European University Institute

DEPARTMENT OF ECONOMICS

Essays in Applied Microeconometrics: Household and Firm Investment

Stefan Lamp

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

Florence, 5 September 2014

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Abstract

The thesis contains three chapters relating to household and firm investment. The first chapter, coauthored with Silvia Albrizio, investigates the relationship between fiscal consolidation, business plans, and firm investment. Based on a detailed narrative of tax changes in Germany covering 40 years of fiscal adjustments, we define and exploit the exogenous variation of tax bills to quantify the effect of tax changes on firms' future investment plans as well as on realized investment. We find that firms in the manufacturing sector revise downward both planned and realized investment subsequently to tax adjustments. Furthermore we find that income and consumption taxes are most harmful to investment and that firms base their investment plans considering laws currently under discussion, anticipating future tax changes. In the second chapter, I investigate if irreversible household investment decisions are affected by behavioral factors, namely Projection Bias (Loewenstein, O'Donoghue, and Rabin (2003)). I use detailed weather data to test if exceptional sunny months have a positive and significant impact on solar photovoltaic (PV) adoption at county level and interpret my findings as strong support for the Projection bias hypothesis given that other weather shocks (temperature, rain, and snow) do not show a significant impact. Results are robust to a wide variety of robustness checks and shock definitions. Elaborating on heterogeneity, I confirm that political ideology can play an important role in expectation formation: counties with higher share of Green voters are more perceptive to Projection Bias in their solar investment decisions. The final chapter investigates the role of economic policy for the installation of solar PV in Germany. After empirically evaluating the variables that play a key role in the household investment decision, I construct a dynamic stochastic discrete choice model of technology adoption to evaluate how different policy dimensions affect the household investment choice and aggregate technology uptake. The simulation exercise shows that an increase in the annual tariff reduction for new installations (degression rate) has the biggest negative impact on investment.

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Preface

This thesis consists of three papers that are related to household and firm investment in the context of sustainability. In recent years, the discussion of sustainability has not only emerged under the background of climate change and "green growth", but due to the financial and economic crisis also with regard to government budgets. Chapter 1 analyzes the effects of fiscal adjustments on investment, a key issue given budgetary pressure in many OECD countries and the need to return to a steady growth path after the recent period of economic downturn. On the other hand, Chapter 2 and 3 refer to investment in sustainable energy. The energy market transformation towards renewables have made households a key player in the provision of decentralized green energy, such as solar photovoltaics (PV). In this context Germany has taken on a leading role with the introduction of targeted support policies that found wide adoption in Europe and other countries worldwide. Nevertheless still little is known about the right choice of policy instruments to incentivize investment while maintaining low policy cost and about the household investment decision per se. Literature from durable goods purchases has furthermore shown that households' choices might not be fully rational and can be affected by behavioral factors. The papers are discussed briefly in turn:

Chapter 1 is joint work with Silvia Albrizio[1] and focuses on the effects of fiscal consolidation measures (tax adjustments) on firm investment. Previous literature (see for example Alesina, Favero, and Giavazzi (2012)) has pointed out that business investment is the main driver of the strong negative effect of tax-based consolidation on aggregate output, however has been unable to provide a causal link between fiscal consolidation, firm expectations and realized investment changes. We aim at closing this gap by combining a detailed narrative of tax changes with firm level investment data that capture both realized and planned investment. For this purpose we revise in detail a narrative of German tax legislation, as developed by Uhl (2013), and merge it with firm level investment data obtained from the IFO investment survey, for which we have data available for the period 1970-2010. We find a strong negative effect on both planned and realized investment. Furthermore we find that income and consumption taxes are most harmful to investment and that firms base their investment plans considering laws currently under discussion, anticipating future tax changes. Not taking into account this anticipation

[1]OECD, EUI

effect would lead to biased estimates.

Chapter 2 on the other hand investigates if irreversible household investment decisions are affected by behavioral factors, namely Projection Bias (Loewenstein, O'Donoghue, and Rabin (2003)). In particular, I combine data from solar photovoltaic (PV) installations in Germany with detailed weather data and test if exceptional sunny months have a positive and permanent impact on technology adoption at county level. I find a strong and robust effect and interpret my findings as clear evidence of Projection Bias, given that only sunshine and no other weather shocks (temperature, rain and snow) have a significant and permanent effect on technology uptake. A one standard deviation shock in terms of monthly sunshine hours leads to an aggregate increase in investment of around 8% when evaluated at the mean. Elaborating on heterogeneity, I find that political ideology can play a key role in expectation formation: counties with higher share of green party voters respond stronger to sunshine outliers in their solar investment decision. These findings are in line with the literature investigating the role of political ideology for the formulation of effective policies (see for example Costa and Kahn (2013)) and should be taken into account when the policy makers objective is to increase investment in climate friendly technologies such as renewables or energy efficient installations.

Finally, Chapter 3 focuses on the role of economic policy for the household investment decision in solar PV in Germany. After empirically evaluating the variables that play a key role in the household investment decision, I construct a dynamic stochastic discrete choice model of technology adoption to evaluate how different policy dimensions affect the household investment choice and aggregate technology uptake. Structural parameters are estimated by simulated method of moments. The simulation exercise shows that an increase in the annual tariff reduction for new installations (degression rate) has the strongest negative impact on investment. The model predicts furthermore that an exogenous increase in electricity prices leads to additional installations, a feature that seems to be present also in the empirical data.

Table of Contents

Chapter 1

The investment effect of fiscal consolidation.

With Silvia Albrizio (OECD, EUI)

1.1 Introduction

Fiscal consolidation represents one of the main challenges that policy makers are currently facing in most OECD countries. Understanding how different fiscal consolidation measures (i.e. spending cuts and tax increases) affect growth is therefore crucial. In a recent paper, Alesina, Favero, and Giavazzi (2012) show empirically that tax-based fiscal adjustments have a statistically significant different effect on output compared to spending-based adjustments. The former ones are not only more costly in terms of output loss than spending adjustments, but they can be also linked to longer-lived recessions. The macro analysis of Alesina, Favero, and Giavazzi (2012) focuses on a large set of OECD countries and points out that the strong effect of tax-based consolidation on output is driven by shifts in business investment. Understanding further the links between fiscal consolidation, business confidence and firm investment is even more crucial in periods of excessive debt and/or deficit, when the economy needs an effective growth policy agenda. Therefore, our analysis focuses on tax adjustments and tries to shed light in the interconnection between tax adjustments, business confidence and investment. Previous studies have been unable to capture the causal link between these elements either due to the aggregate nature of the data, which does not allow matching firm expectations with their investment behavior, or due to the endogeneity of the fiscal policy, as one of the key issues in estimating the impact of economic policy is the identification of exogenous fiscal shocks.

To deal with the unavailability of firm investment expectations, previous literature focuses mainly on realized investment both at the macro and at firm level. Alesina and Perotti (1996), using case studies, stress the "credibility effect" that a decisive discrete change in the fiscal policy stance may have on interest rates which would crowd in private investment. Alesina, Ardagna, Perotti, and Schiantarelli (1999) associate one percentage point of GDP increase in labor tax with a decrease of aggregate investment over GDP by 0.17 on impact and a cumulative effect of about 0.7 in five years. Confirming these results, Cloyne (2011), Mertens and Ravn (2009), and Hayo and Uhl (2013) find a negative, sizable and statistically significant effect of tax increase on investments at the aggregate level. At firm level, previous literature builds heavily on neoclassical models of investment based on the user cost of capital and the Q-theory[1]. In the user-cost framework, higher taxes affect investment negatively through the increase in user cost of capital. Cummins, Hassett, and Hubbard (1996) exploit cross-sectional variation in user cost due to major tax reforms. They find significant effects with an implied long-run elasticity of the capital stock with respect to the user cost between -0.5 and -1.0 [2]. Chirinko, Fazzari, and Meyer (1998) analyze UK firm investment behavior using both the underlying Q-theory and user cost of capital, and their estimated effect reduces to -0.25. Finally, micro evidence based on cointegration models (Caballero, Engel, and Haltiwanger (1995) among others) estimates an average long-run relationship between capital-output ratio and the user cost of -0.1, where estimates range between -0.01 and -2.

Regarding the second limitation, the identification of exogenous fiscal shocks, the economic literature distinguishes three main methodologies. The first branch of literature follows the structural vector autoregressive approach (SVAR). In this approach, exogenous fiscal shifts are unobservable and identification is achieved using sign restrictions derived from economic theory (Mountford and Uhlig (2009)) or by taking into account institutional features of tax and transfer systems (Blanchard and Perotti (2002)). The VAR approach has led to a wide range of estimates of the spending multiplier (see Ramey (2011) for a literature survey). The second group of studies consists mainly of case studies (Giavazzi and Pagano (1990), Alesina and Ardagna (2010), and Alesina and Ardagna (2012)) find that spending based adjustments can have a very small or no output cost at all. Finally, a more recent method that found increasing attention in the economic liter-

[1] See Bond and Van Reenen (2007) for a comprehensive overview of microeconometric models of investment and employment.

[2] Additional firm-level evidence on the user-cost elasticity of the investment rate is given by Schwellnus and Arnold (2008) and Johansson (2008).

ature is the narrative approach. Identification is based on observable exogenous shifts in fiscal stance by considering official documents, and hence by definition focusing only on fiscal adjustments that are motivated by deficit reducing purposes. As pointed out in Mertens and Ravn (2013), an attractive feature of this approach is that the narrative record summarizes the relevant features of a potentially very large information set.

This paper aims at filling the above described research gap, investigating further the set of correlations and causality between tax adjustments and private investment, in order to provide clear insights on the impact of fiscal reforms on firm incentives, and therefore on growth. In particular, we contribute to the debate in three ways: Firstly, by considering micro level data we move one step further in establishing a causal link between tax-based fiscal consolidation, business confidence and investment. Taking advantage of the information on firms' planned investment provided by the IFO investment survey[3], we are not only able to compare our micro-based results with the previous findings from the macro literature, but also to take into consideration forward-looking behavior of the firms. Secondly, the detailed structure of the dataset allows us to disentangle the effect in two different dimensions: a heterogeneous effect depending on firm size and on the industry sub-sector. In line with Romer and Romer (2010) and Pescatori, Leigh, Guajardo, and Devries (2011), we employ the narrative approach to identify exogenous tax adjustments. Based on a detailed narrative created by Uhl (2013) for Germany, we revise 40 years of documented tax legislation (1970-2009) in order to create a dataset of tax adjustments that are not cyclically driven nor dictated by long-term growth considerations. We further investigate the timeline of tax adjustment not only considering the publication date, as provided by Uhl (2013), but also looking for the date when the public discussion of the adjustment started. To do so, based on the LexisNexis database, we collect journalistic documents that discuss each of the tax changes we considered.

Finally, focusing on one country only, we are not only able to consider a much more accurate policy dataset, testing the results for different shock reference dates (discussion date, publication and first implementation date) but also to disentangle the effect according to the type of tax change (income tax, business and corporate tax, or consumption tax). In fact, as pointed out in Mertens and Ravn (2013) and Cloyne and Surico (2013),

[3]EBDC Business Investment Panel, http://www.cesifogroup.de/ifoHome/facts/EBDC.html

there is little reason to expect that the different types of taxes available to governments all have the same impact on the economy.

The remainder of this paper is structured as follows. Section 1.2 introduces the series of exogenous tax shocks as developed by Uhl (2013), and which have been adopted for the purpose of this paper, as well as the firm level investment data. Section 1.3 describes in detail the identification and the estimation strategy, while the main results are discussed in section 1.4. Section 1.5 further elaborates on heterogeneity and section 1.6 performs a series of robustness and sensitivity checks. Finally, section 1.7 concludes.

1.2 Tax shocks and firm investment data

1.2.1 Narrative of German tax changes

The series of tax changes is based on Uhl (2013), who elaborates an extensive record of tax legislation in Germany[4]. In order to identify all relevant tax law changes Uhl (2013) uses in a first step a size criteria of the budgetary impact of tax changes. Tax shocks are thus considered important and are included in the narrative if their budgetary impact reaches 0.1% of GDP in a given year[5]. This first criterion led to the identification of 95 important tax changes that are revised in a detailed fashion in Uhl (2013) and that are classified according to their main motivation in "endogenous" and "exogenous" tax measures in line with the previous literature (see for example Romer and Romer (2010), Pescatori, Leigh, Guajardo, and Devries (2011) and Cloyne (2013))[6].

[4]The analysis in Uhl (2013) is based mainly on the Finanzbericht and Bundesfinanzplan of the Federal Republic of Germany. In order to recover all budgetary details of individual tax laws we revised the Finanzbericht for the years 1970-2009 and the four-year budget plans (Bundesfinanzplan) for the time period 1990-2009.

[5]Tax shocks are also included if the measure is (close to but) below the 0.1% GDP threshold but tax law changes consist of individual well defined measures. Other narratives, such as Pescatori, Leigh, Guajardo, and Devries (2011) do not state a precise cutoff rule, however for their full dataset of fiscal adjustments, only 5 out of 173 fall below the 0.1% rule, none for Germany.

[6]As the previous literature building on the narrative approach we slightly abuse terminology and consider "exogenous" all changes that are not systematically correlated with current or lagged output and investment.

Key in the narrative approach is to identify the exact motivation behind each tax change, as this allows excluding tax policy changes dictated by business cycle fluctuations and changes correlated with the dependent variable through other unobserved factors. As pointed out in Romer and Romer (2010), simply regressing output growth on all legislated tax changes will lead to biased estimates, given the fact that some tax changes might be correlated with the error term. Moreover, this bias might be even more emphasized in case the researcher does not account for the fact that the policy makers might adjust their policy measures to the current state of the economy, for example employing countercyclical policies. Even controlling in the regression framework for known macroeconomic shocks and conditions would not solve the issue of identification, as firstly it would be impossible to proxy for all information about future output movement that the policy maker may have had and secondly the response to tax changes is likely to vary from period to period and may be hence correlated with other unobserved factors in the error term. Thus it is crucial to identify the exact motivation behind individual tax changes.

We align our classification of the motivation of tax changes with Uhl (2013), however we revise each of the Uhl tax shocks and regroup them according to "exogenous" and "endogenous" for our analysis of investment. Uhl (2013) classified spending driven tax changes, countercyclical policies and tax changes due to macroeconomic shocks as "endogenous" measures. On the other hand, "exogenous" measures are those dealing with budget consolidation and structural considerations. While consolidation measures are related only to past spending and are exogenous to the current macroeconomic stance, the category of structural tax changes is more controversial as it includes both measures that aim at long-term growth, incentivizing investment, as well as tax changes that have been induced by court-rulings and that are hence unrelated to investment activity. Therefore, building on the previous narrative-literature, in our reclassification we define as "exogenous" only those structural changes that are not cyclically driven nor motivated by long-term growth considerations and hence aimed at investment. The appendix provides some examples of tax changes and their classifications[7].

Given the fact that we have exact information on the timing of individual tax mea-

[7] For a complete overview of all important tax measures in the Federal Republic of Germany, see Uhl (2013).

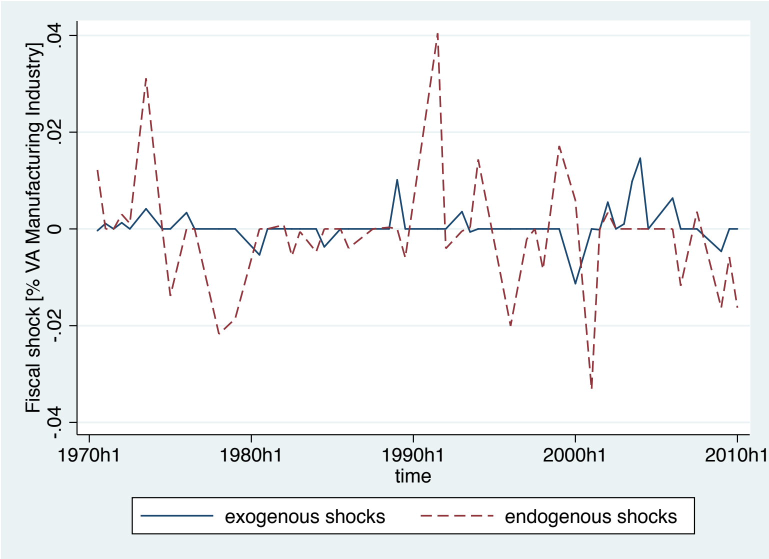

Figure 1.1: Legislated tax changes. Half-yearly frequency

sures - the date the first draft was introduced to the parliament, the date the tax law was published and information on the public discussion in the newspapers - we test for the impact at different dates. Differently from other studies that use this approach, we consider the budgetary impact at announcement. This choice relieves us from difficult considerations regarding revisions that are potentially correlated with investment and the contingent economic situation[8] as well as from potential measurement errors. Furthermore, to avoid heterogeneous displacement effects, we focus on exogenous tax shocks that are announced and implemented within the same period.[9] Figure 1.1 depicts the full series of important tax changes in Germany announced and implemented within the same period for both "exogenous" and "endogenous" motivations for the period 1970-2009, using half-yearly data frequency. As the graph shows clearly, endogenous tax changes are on average larger and more frequent than the exogenous category. In total, we count with 19 exogenous shocks and 31 endogenous ones. The correlation between the two time series is 0.09, and is not statistically significant (p-value of 0.53).

[8]Examples of factors correlated with investment which could drive the revisions are: resistance from trade unions, deterioration of the economic situation, etc.

[9]This is in line with the previous literature. See for example Mertens and Ravn (2011) that exclude tax changes with implementation lag exceeding one quarter. In the robustness section we also control for shocks that are announced but that are implemented in subsequent periods.

Given data availability our main analysis focuses on the period 1970-2010[10]. As explained in more detail in the following section, we group tax changes in both yearly and half-yearly periods in line with our firm level investment data. The original tax shock series, expressed in billions of Euros (governmental budgetary impact), has been first deflated using the gross fixed capital formation deflator for the manufacturing industry[11] and divided by total value added (VA) in the manufacturing industry in 2005, in order to have the main regression variables at a similar scale, which allows for easier interpretation of the coefficients. The exogenous shock series contains both positive and negative tax measures ranging from -0.011 to 0.014 with a mean absolute impact of 0.002 and a standard deviation of 0.004.[12]

In terms of timing, focusing on the subset of exogenous shocks, the average length from the date the draft of the law is introduced to the parliament and the date of publication of the same is around five months [13]. On the other hand the average time between publication and first implementation of the tax measure is two months. However a detailed revision of the shocks brings the fact to light that most of the shocks are induced by a lengthy public discussion prior to the initiation of the legal process of tax change. The media and newspapers report these discussions and we refer to the date of the first article mentioning as "discussion date". In order to check for this possibility we look at the timing of news coverage of tax measures prior to the draft date using the online database LexisNexis. We find that the average time lag between initial discussion of the tax measure and its publication is one year. The appendix provides an overview (Table 1.2) containing discussion, draft and publication date of selected tax shocks[14].

[10]Our last fiscal shock is observed in 2009, however we include one additional year of firm investment data to capture the lagged investment effect.

[11]The deflator is based on STAN Industry Rev. 3, 2008 (OECD) Database. Investment and financial variables are deflated in the same way.

[12]We use the mean absolute impact rather than the simple mean, given both positive and negative shocks. Alternatively the mean impact of the 12 positive shocks has been 0.005 (0.004) shocks, and for the seven negative shocks -0.004 (0.004).

[13]The exact draft date can only be reconstructed for shocks posterior to 1977.

[14]Using LexisNexis, we were able to track back news coverage for tax adjustments for the period 1992 to 2010.

1.2.2 Firm investment data

Data on firm investment is obtained from the IFO investment survey (IVS). As pointed out in Seiler (2012) the IVS was originally introduced in 1955 and considers the manufacturing sector in Germany, however annual investment data is available only from the mid 1960s onwards. While the initial questionnaire has been distributed only once a year, from 1993 onwards the survey has been performed bi-annually, in spring and autumn of the same year, leading to an even richer data structure[15].

The IVS questionnaire focuses mainly on firm investment activity and includes both forward and backward looking statements of realized and planned investment. As the questionnaire includes only a small list of potential control variables, the dataset has been enriched by the Economic and Business Dataset Center (EBDC) with balance sheet data obtained from Amadeus and Hoppenstedt[16]. The merged investment data counts with a total of 202,368 observations that belong to 5,590 firms. In principle the dataset is longitudinal however the number of firm that exit at some point in time the panel is high, so that there are few firms reporting the entire sample period. In terms of representativeness, in 2009 the IVS sample covered 31% of all employment in the German manufacturing sector (7% of companies), with better representation of bigger firms (2% of employment size class < 50 and 66% of employment class size >1000).[17]

For the purpose of our analysis, the original dataset has been first converted to Euros, using the fixed Euro-DM exchange rate and then deflated with the OECD deflator for gross fixed capital formation in the manufacturing industry. Furthermore we drop IFO sector 210 from the analysis, manufacture of mining products, as it does not find a clear correspondence in the ISIC manufacturing classification. Converting the dataset to an annual data structure, and constructing the change in realized investment as log difference of investment at time t and investment at time $t-1$, we are left with 64,310

[15]Data previous to 1991 corresponds to West Germany, while data posterior to 1991 includes also firm from former Eastern Germany.

[16]The exact merging procedure is described in Seiler (2012).

[17]The authors would like to thank Heike Mittelmeier and Christian Seiler from the EBDC for providing this information regarding the IVS.

observations belonging to 5,186 distinct firms[18] [19]

Most of the literature dealing with firm level investment considers as dependent variable the ratio of investment (defined as the change in capital stock) over capital. Even though the IFO data provides a direct measure of investment, it does not provide us with an initial capital stock[20]. Therefore, as alternative measure we normalize investment by firm specific average asset stock over the sample period, which is available for the subset of firms that have been merged with the Amadeus and Hoppenstedt databases. Nevertheless also this procedure reduces the sample coverage considerably. Therefore we use this specification only as robustness check for our findings, estimating a dynamic firm-level investment model as derived in Bond, Harhoff, and van Reenen (2005) (see section 1.6).

Our empirical analysis focuses both on realized investment growth and on updates of planned investment. However updates of planned investment are only available for the subsample period 1993-2010, in which the IVS has been conducted at a bi-annual frequency. In each round firms are asked to provide an estimate for their planned investment for the same year. In addition, in spring firms are asked how much they have been investing in the previous year (realized investment in $t-1$) and, in autumn, how much they are planning to invest next year ($t+1$). Therefore the richness of the IFO investment dataset allows us considering both realized investment changes and updates in planned investment. Formally, realized investment growth in year t is defined as:

$$\Delta \ln(I_t) = \ln(I_{t,A}) - \ln(I_{t-1,A}) \tag{1.1}$$

[18]Conditioning our sample on firms that report in two consecutive periods does not change significantly the size composition: For the full sample (sample in differences) there are 17.6% (15.6%) in size group up to 49 employees, 31.9% (31.2%) in size group up to 199 employees, 34.7% (35.8%) in the size group up to 999 employees and 15.8% (17.3%) in the category >1000.

[19]We allow for zero growth in case a firm reports zero investment in two consecutive years. As robustness check we further experiment with a second specification, imputing a small, but positive number for investment in years t or t-1 in case a firm reports in either of the two periods zero investment. Given that this procedure leads to additional variability, for the analysis we cut the variable at the first and 99th percentile to make the measure outlier proof. We find that our results are not affected by the specification of the dependent variable.

[20]Backtracking the capital stock using inventory methods would be only meaningful for balanced data or data with few gaps.

while the change in planned investment is defined for reference year t, respectively in each period p=1 between 1 October (t-1) and 31 March (t) and p=2 between 1 April (t) and 30 September (t), as:

$$\Delta \ln(PI_{t,1}) = \ln(PI^{t}_{t,S}) - \ln(PI^{t}_{t-1,A}) \tag{1.2}$$

$$\Delta \ln(PI_{t,2}) = \ln(PI^{t}_{t,A}) - \ln(PI^{t}_{t,S}) \tag{1.3}$$

where the subscript indicate the year and the survey round (S=spring, A=autumn) when the plan is revealed, while the superscript refers to the forecast horizon, i.e. the year the investment is supposed to take place. The exact timing of the half-yearly investment structure is depicted in Figure 6 in the appendix.

1.2.3 Summary statistics and representativeness

Table 1.1 shows the main variables of interest for our analysis at annual frequency for the full sample period and two subsample periods 1970-1990 (West Germany only) and 1991-2010. The main dependent variable, realized investment growth is small in absolute terms, however as the standard error suggests there exists considerable variation across firms. The alternative measure (investment over average capital stock) has a mean of 0.25 (median of 0.18), which however includes more bigger firms. The exogenous fiscal shock measured in terms of total value added in the manufacturing industry is very similar for the two time periods in terms of the average, however the standard error in the later period (1991-2010) is almost the double. For comparative purposes Table 1.1 also reports the aggregate control variables for the interest rate as well as sales growth and firm size (number of employees), as these variables are reported for all firms in the questionnaire [21]. While the interest rate has been around 1% higher in the early subsample (1970-1991), average sales growth was nearly double compared to the second sample period. These tendencies are related to general structural changes in the German economy.

In order to provide further evidence on the representativeness of our data, Figure 1.7 in the appendix compares realized changes in aggregate investment in the manufacturing sector in Germany obtained from STAN (OECD, Rev.3 2008) with aggregation based

[21] As mentioned, other financial covariates, such as assets and liabilities, are only available for a subset of firms (those listed in either Amadeus or Hoppenstedt and that could be merged).

	Total sample: 1970-2010		Subsample: 1970-1990		Subsample: 1991-2010	
	Mean	std	Mean	std	Mean	std
Realized investment change	-0.0110	(-1.046)	0.0297	(0.965)	-0.0424	(1.104)
Investment / Average total assets	0.2520	(0.229)	0.2580	(0.234)	0.2487	(0.226)
Exogeneous fiscal shock	0.0011	(-0.006)	0.0013	(0.004)	0.0010	(0.007)
3 month interbank rate	2.4670	(-1.616)	3.0911	(1.904)	2.0205	(1.186)
Sales growth	0.0231	(-0.261)	0.0312	(0.225)	0.0164	(0.288)
Total employment last year	837	(5195)	948	(5247)	753	(5154)
Observations	64310		27936		36374	

Note: Investment / Average total assets counts with a total of 39751 observations.

Table 1.1: Summary statistics: main variables

on our sample data. The figure indicates that the series co-move closely over the entire sample period but that our aggregation based on firm data shows slightly more variability than the official statistics. Furthermore the appendix provides some first evidence for the negative correlation of our fiscal shock measure and aggregate investment growth. The two series show a correlation coefficient of -0.15 (Figure 1.8). We present the same evidence by ISIC 3 industry sub-sector and by size group (Figure 1.9 and Figure 1.10 in the appendix).

1.3 Identification and empirical specification

As pointed out above, the key assumption behind the narrative approach is that both the tax changes itself and their composition are "exogenous" i.e. tax changes are not dictated by business cycle fluctuations nor long-term growth concerns. In line with the previous literature (see for example Cloyne and Surico (2013)), we test for exogeneity using a four-variable VAR at annual frequency including the tax shock series (for both the endogenous and exogenous category), GDP growth, the three month interbank rate and the average investment change as main dependent variable [22]. We construct the aggregate change in investment as log difference of average investment in period t and t-1 weighted by employment shares [23]. The selection-order criterion suggests in most

[22] In an alternative specification, we also account for the structural break due to the German reunification (1990) and the recent financial and economic crisis (post 2007); our results are robust to the inclusion of these exogenous dummies.

[23] We also test for other measures of aggregation, using changes in total investment from period t to period $t + 1$, and hence conditioning on firm presence in two consecutive years, or using simple unweighted

specifications unanimously a lag structure of order one for the VAR. Table 1.3 in the appendix provides evidence from the granger causality tests, showing that the exogenous tax shock series implemented in the same period of the publication date cannot be predicted neither by macroeconomic conditions in the last year, nor by past investment activity. On the other hand, the "endogenous" tax adjustments can be predicted by economic growth (p-value 0.063). The three excluded series jointly (investment growth, GDP growth and interest rate) moreover carry information to forecast the endogenous fiscal shock series at 10%. These results strongly support our key identification assumptions [24].

As second test for exogeneity of our fiscal shock series we run an ordered probit regression to see if the government's decision to adjust taxes can be predicted by past macroeconomic data. The same approach has been taken by Cloyne and Surico (2013) and Mertens and Ravn (2009). We hence construct an indicator variable ω_t equal to 1 if the government implements a positive fiscal shock, zero if no action has taken place and -1 if there has been a negative fiscal adjustment. Results are presented in Table 1.4 in the appendix and indicate that while movements in the exogenous shock cannot be predicted neither by lagged changes in aggregate investment nor by lagged levels of GDP, the endogenous shocks are correlated to lagged investment growth. As additional test, we run the ordered probit model on official data from the manufacturing sector (Table 1.5) using both changes in gross fixed capital formation (GFCF) and levels of GFCF from the OECD (STAN) database. While the results for GFCF growth are fully comparable with our in-sample findings (only lag 2 of GFCF growth) is significantly correlated with the endogenous shock, for the levels equation we find strong evidence that movements in the endogenous series are highly correlated with both lagged levels of investment and GDP. The shocks that have been classified "exogenous" on the other hand are not predictable.

Using the exogenous tax adjustment series, our analysis first focuses on the revision

average investment change. The main results hold for all definitions of aggregate investment. We furthermore test that the investment series are stationary, using an augmented Dickey-Fuller test.

[24] Given the fact that our tax shock series includes both structural and consolidation motivated shocks, as sensitivity check, we furthermore exclude all shocks with structural motivation. The presented findings are robust to the selection of shocks.

of investment plans, and secondly, we study how realized investment is affected. Both analysis are based on the following main regression specification:

$$\Delta I_{i,j,t} = \alpha + \beta_m(L_m)\tau_t + \psi m_{t-1} + \rho g_{t-1} + \nu \Delta z_{i,t-1} + D_{90} + D_{07} + \theta_j + \epsilon_{i,j,t} \tag{1.4}$$

where $\Delta I_{i,j,t}$ is the growth rate of realized investment for firm i, in sector j, in period t. The investment changes are defined separately for realized and planned investment as introduced in section 1.2. The fiscal shock τ_t is the exogenous tax adjustment published at time t, and is uncorrelated with other shocks to investment by construction. Macro-level controls consist of the monetary policy stance m_{t-1} (previous period three-month interbank rate) and economic condition g_{t-1} (lagged levels of GDP). Dummies to account for the crisis period 2007-2010 (D_{07}) and for the structural change 1990 (D_{90}) are included in the regression equation[25]. Finally, lagged sales growth at firm level ($\Delta z_{i,t-1}$) is part of the regression controls to proxy for current and future demand conditions at firm level. In all specifications we include furthermore sectorial fixed effects θ_j and standard errors are clustered at firm level [26]

1.4 Main regression results

The following section presents the main regression results for both planned and realized investment growth at firm level. Table 1.13 in the appendix also provides some evidence for the effect of fiscal shocks on realized investment changes aggregated at sub-sector level.

1.4.1 Planned investment

As previous contributions have suggested (see for example Alesina, Favero, and Giavazzi (2012)), business confidence and private investment are found to be the main drivers of

[25] To account for the structural break in the statistical data more than the actual historical date of the German reunification.

[26] Given the fact that our main explanatory variable is aggregated at annual level, we potentially could cluster on years, however clustering on year assumes that firm level errors are uncorrelated from one year to another, an assumption that is unlikely to hold. Alternatively we test for clustering at industry sub-sector (branch). The main findings are unaffected by the choice of the clustering variable.

the output effect of fiscal consolidation. Studying the change in future investment plans at micro level helps to understand and pin down the business expectation and confidence channel. As mentioned in section 1.2, in the IVS firms are asked about their investment plans for next period. Given the opportunity cost of investments, these plans, and in particular their revisions, incorporate business expectations and anticipation about future economic and policy conditions.

Insert Table 1.6 here

We observe updates on planned investment for the period 1993 to 2010 at a bi-annual frequency. For this period, we count with a total of 10 exogenous fiscal shocks with a mean impact of 0.001 and a standard deviation of 0.0048. Moreover given the fact that our analysis focuses on the announcement effect of fiscal policy, we use the shock publication date. Table 1.6 presents the estimates of the effect of a tax change equal to 1% of total manufacturing value added on the revision of planned investment. Block 1 (column (1) - (3)) includes only lags of the fiscal shock, while block 2 (column (4) - (6)) includes also leads. For the rest, the two blocks include the same set of covariates: the first column of each block includes a set of aggregate controls (lagged GDP, lagged three month interbank rate, and a dummy accounting for the recent financial crisis) in addition to industry fixed-effects, the second column includes additionally lagged firm level sales growth, and finally the third column includes firm level fixed effects. In all specifications we furthermore include a separate dummy for the second half-year (autumn), in order to account for potential differences in volatility of the two revisions[27], which results to be highly significant in all specifications.

Block 1 shows that there is a significant and negative effect of tax shocks on planned investment. A shock equal to one standard deviation of the exogenous fiscal shock[28] hence translates to a decrease in planned investment of around 1.2% in the next investment plan. Once we additionally include leads, in order to test for a potential anticipation

[27] Due to a lower degree of uncertainty, the autumn investment update might be more accurate and hence less volatile than the spring update. The authors would like to thank Antonello d'Agostino for pointing this out in his discussion at the Banca d'Italia Fiscal Policy Workshop 2014.

[28] As the shock can take on both positive and negative values, we standardize using a standard deviation measure. Alternatively we could use the mean of the absolute shock impact in order to quantify the shock impact on investment growth, which is very similar in magnitude.

effect in block 2, the lagged effect on planned investment becomes quantitatively larger. We furthermore confirm that agents anticipate the fiscal adjustment as both lead 1 and 2 show up to be significant in all three specifications. Note additionally that all control variables (but lagged GDP in some specifications) show up to be statistically significant with the expected sign. The R^2 is low even when including firm level fixed effects, which indicates that investment changes are indeed very lumpy and volatile [29].

The forward looking behavior of the firms can be explained by the average length of the legislative process for tax changes in Germany. To test this hypothesis we investigate in a more detailed fashion the legislative timing, starting from the moment when the draft of the law is discussed in the public (media coverage in major German newspapers and news magazines). Therefore we search for news contents related to the discussion of fiscal shock measures employing the database LexisNexis [30]. In fact we find clear evidence that between the time of public discussion and publication of the law, on average, there passes one year. Compared to the draft date, the date when the law is officially introduced in the parliamentary discussion, the public discussion happens around half a year earlier. Table 1.2 in the appendix provides an overview of mayor exogenous tax shocks since 1992 including their official publication dates, draft dates and periods of public discussion in the media (discussion dates). Given these findings, we re-estimate our main regression model focusing on the discussion date as "true" announcement date of the shock.

The results are reported in Table 1.7. We find that once we consider the media discussion date, controlling for firm-level sales growth or using firm-level fixed effects, no forward lag shows up to be significant. In fact compared to the publication date, the fiscal shock is only significantly (and negatively) correlated with changes in planned investment at impact, i.e. when the news is announced. [31] Generally, using the discussion date, we find quantitatively similar, but more stable effects of downward revision of -3.5% to -4% for a shock equal to 1% value added in the manufacturing industry. A shock

[29] Note furthermore that the R^2 from the firm level fixed effect regressions, column (3) and (6) are adjusted and hence lower than the other columns, that report an unadjusted regression fit.

[30] LexiNexis contains all major German newspaper and covers news contents from the beginning of the 1990s.

[31] We also tried alternative specifications including additional lags up to lag 4, but the only significant impact remains at lag zero.

equal to one standard deviation hence led to a downward revision of investment plans by 1.9% for the sample period 1993-2010.

Insert Table 1.7 here

To sum up, when firms make their plans for next period investment, they are influenced by laws currently under discussion and laws published in the previous half year. Given the fact that we are interested in identifying the announcement effect of fiscal consolidation measures on planned and realized investment, we hence use the discussion date as main specification in the remaining sections of this paper.

1.4.2 Realized investment

After analyzing firm behavior in terms of investment expectation, it is interesting to apply a similar analysis to realized investment in order to be able to compare our findings with the previous macro-level results. We consider firms' annual investment growth from 1970 to 2010 as defined in section 1.2. Table 1.8 presents the point estimates of the effect of a tax change equal to 1% of total manufacturing value added on investment growth. Column (1) does not include any controls while column(2) includes aggregate controls and column (3) furthermore lagged sales growth at firm level. Column (4) presents the results for realized investment for the period 1991-2010, while column (5) for the earlier period and Western Germany alone (1970-1990).

Insert Table 1.8 here

Interestingly, we find that the fiscal shock has a negative and significant impact on realized investment that is strongest in the year of public discussion[32] but has also a lagged effect. The initial impact is stable to the inclusion of additional aggregate and firm level controls (column 2 and 3), however once we include the set of controls, we find a more persistent effect. Adding up the significant lags in column 3, the total impact of a one percent tax shock on investment growth is around -15.6%, which however is smaller when evaluated at the mean absolute impact or the standard deviation measure: -5.7%.

[32]Using as true announcement date the date of public discussion as introduced in the previous section.

In fact, for the annual shock series, there are a total of 19 fiscal shocks with a mean value of 0.0007 and a standard deviation of 0.0037. All aggregate control variables show up to be significant and show the expected sign. The sample split in column 4 and 5 suggests two clearly different patterns: while in the more recent period 1991-2010, the fiscal shock shows quantitatively the same impact as for the entire sample period (-8.8%), the earlier subsample shows a significant lagged effect that is biggest at lag 1. As for the half yearly analysis there are 10 shocks for the subsample post 1991, with a mean impact of 0.00096 (0.0047) and 9 shocks for the first subsample referring to column 5 with a mean impact of 0.0004 (0.0027). Hence the different fiscal policy over the period considered translates into bigger and more volatile shocks in more recent years. In addition to differences in the fiscal shock series, firms might have changed their behavior over the last 20 years, using more technology and respond faster to changes in the companies legal and fiscal environment.

Generally, the results are in line with the macro level findings even though the magnitudes are not directly comparable. Alesina, Favero, and Giavazzi (2012) for instance find that a one percent GDP tax shock has a negative and significant lagged effect on fixed capital formation growth in Germany that increases from -4% in the first quarter after the adjustment to around -6% one year after the adjustment. In fact, while in the macro literature the shock is standardized by GDP, in our micro set-up it makes more sense to re-scale the expected budgetary impact using the value added of the total manufacturing sector. Moreover, another difference between our framework and the macro analysis is the difference in timing.

In order to verify that fiscal shocks, defined as exogenous, are not correlated with the shocks that were announced in the past but implemented at time t, we reestimate our regression model including both the previously announced shocks and in a second step also the shocks that we classified as endogenous. Running our main specification (column (3), containing both aggregate and firm level controls), and including the shocks previously identified as endogenous, we get results very much in line with those presented in Table 1.7. While the leads do not show up to be significant, at impact we estimate an effect of -7.65, at lag1 of -5.87 and at lag 2 of -2.95, all significant at 1%[33]. On

[33]This results hold independent of the inclusion of control variables.

the other hand, including the anticipated tax shocks, we confirm these findings: while the leads are not statistically significant, at impact we estimate an effect of -8.29, at lag1 of -6.39 and at lag2 of -4.89. These findings can be seen as a first robustness check for our main regression results.[34]

While section 1.5 reports the results for heterogeneity of realized investment changes depending on type of tax adjustment, firm size and the sub-sector of the manufacturing industry, section 1.6 performs further robustness checks, providing also evidence for the negative and significant effect of tax adjustments using a rigorous difference-in-difference strategy that allows us controlling for other unobserved factors potentially correlated with the fiscal shock series and investment growth.

1.5 Heterogeneous effects

The long time span of available data for realized investment growth allows us studying the effect of tax changes by looking at three main dimensions: type of tax adjustment, heterogeneous effects by firm size and by manufacturing sub-sector as well as their interactions.

Looking at GDP per capita, Johansson (2008) find that corporate taxes are most harmful for growth, followed by personal income taxes and consumption taxes. To test for the effect of exogenous tax changes on realized investment we group the shocks in different categories. As depicted in Figure 1.2, we distinguish three main tax categories:

- personal income tax, pension & savings tax
- corporate & business tax, energy tax, property tax
- consumption tax

Breaking down the tax shock into these subcategories, we are able to distinguish 11 tax measures for the first category, 11 for category two and 7 for the third category. In

[34] Table 1.13 presents the effects of fiscal consolidation at industry level, provides similar evidence. Including previously announced shocks or shocks considered endogenous does not alter our main findings.

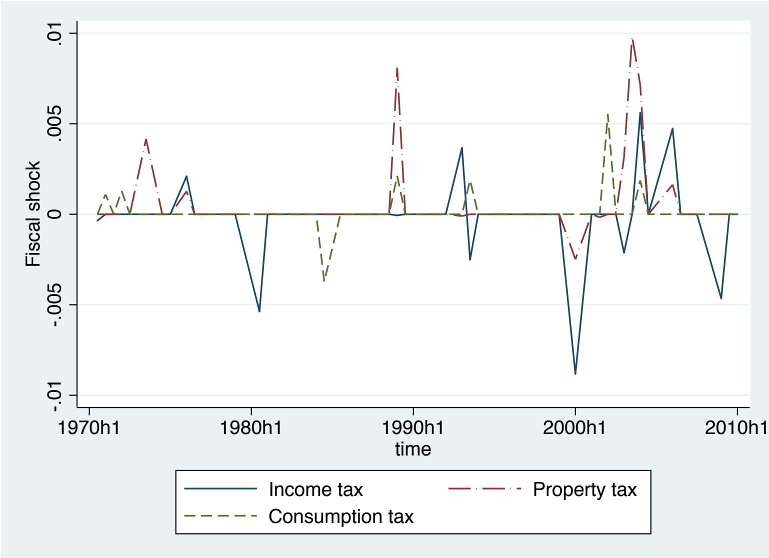

Figure 1.2: Exogenous tax adjustments; by tax type

order to identify these categories we revised a total of 42 tax law changes that consist of 184 individual tax measures.

Insert Table 1.9 here

Including the three fiscal shock series in our reduced form estimation, both in the same regression (Table 1.9, column 1) and in separate regressions, we find important differences with respect to the previous estimates found in Johansson (2008): consumption tax shocks have a strong negative and lagged impact, while tax adjustments affecting income tax seem to have the biggest impact within the same year. Property and corporate taxes, on the other hand, have a smaller effect at impact. These findings support a recent hypothesis[35] which highlights the importance of the demand channel for the transmission of fiscal shocks. Consumption taxes affect demand and consequently firms' investment in the successive periods through future demand expectations.

In order to compare our results with the aggregate findings on realized investment (section 1.4), we look at the standard deviation measure of the distinct categories of fiscal shocks and find that while income (0.0021) and property (0.0022) adjustments nearly

[35] See for example the discussion of Aghion and Kharroubi (2013) at the annual BIS conference (June 2013) by Reichlin.

have the same variability, consumption shocks are smaller, almost half (0.0011). Using the estimated coefficients from column (1) this leads to an effect of a standard deviation fiscal adjustment on investment growth of -4.1% for income tax, -1.76% for property tax and -1.9% for consumption tax. In order to contrast these results, we aggregate fiscal shocks in an alternative way, considering income and property tax as direct taxes and the consumption tax as indirect taxes. Results are presented in Table 1.10 and show the same pattern that is stable to the inclusion of additional controls, fixed effects and also to the inclusion of previously excluded tax shocks. While direct taxes show a negative effect at impact, indirect taxes only lead to a downward revision of realized investment in the subsequent period, and hence providing further evidence for the demand channel hypothesis.

Recent firm-level literature has furthermore stressed the importance of considering heterogeneous and distributional effects of fiscal and other policies in general. To test for different impact in terms of firm size we use the IFO firm class sizes of employees (1-49, 50-199, 200-999, $>$1000) and run the regression for each subgroup separately. Given the potential residual correlation across size classes, we adopted a seemingly unrelated regression (SUR) framework. The results highlighted in Figure 1.3 show that at impact all size classes are negatively and significantly affected by the tax adjustment. Furthermore the effects are larger for firms that belong to size group 1 to 3. The largest firms show the smallest coefficient. Moreover we confirm that the lagged effect is present for all size classes but for the smallest firms (size group 1), where lag1 does not show up to be significant. This finding might be due to the fact that the smallest group is highly heterogeneous, as it is also suggested by the wide confidence band. The magnitude of the effect is in line with the aggregate findings for the impact and slightly larger for lag1.

In a next step, we investigate if distinct tax shocks have different effects by firm size. The tax effects might differ as firm size can be also seen as a proxy for legal status. Figure 1.4 shows the results for direct and indirect tax shocks at impact and for lag1 for the distinct size groups. As pointed out above, given the strong heterogeneity in the smallest size group, we cannot confirm any significant effect for either tax category. On the other hand we do confirm the main pattern that we found when looking at type of tax shocks. Direct tax adjustments have a negative impact at lag 0 that is quantitatively smaller than the impact for indirect (consumption) taxes at lag 1. Furthermore the impact is larger for smaller firms (coefficient for size group 2 $>$ size 3 $>$ size 4, for both direct and indirect taxes), which might indicate that smaller firms are on average more credit constraint and hence a fiscal shock translates to a stronger effect (see Zwick and Mahon (Working Paper) for recent evidence from the US).

A final dimension of heterogeneity that we test is the response by sub-sectors of the manufacturing industry. For that purpose, we divide the firms in our sample into 12 sub-sectors based on the two-digit ISIC 3 classification with some aggregations[36]. We apply the same SUR methodology as used for firm size, and regress investment growth on contemporaneous and lagged fiscal shocks, including furthermore our set of control variables. The results for lag 0 are displayed in Figure 1.5 [37]. We find that almost all sub-sectors show a negative and significant impact at lag 0, but the sub-sectors "food, beverages & tobacco", "leather", "non-metallic mineral products", and "transport equipment"[38]. The significant coefficients range from -5 to -11 and are hence in line with our previous findings.

Using the narrative identification for fiscal shocks allows us considering and aggregating a wide range of shocks, and thus identifying a robust average effect of tax adjustments; however, at the same time, and given the shock heterogeneity, the narrative approach makes it difficult to pin down a single channel.

[36]The manufacturing industries covered are food, beverages and tobacco (1516), textiles and wearing apparel (1718), Leather industry (1900), wood (2000), pulp, paper and printing (2122), chemical, rubber, plastics and fuel products (2325), other non-metallic mineral products (2600), basic metals and fabricated metal products (2728), machinery and equipment n.e.c. (2900), machinery and equipment (3033), transport equipment (3435) and manufacturing n.e.c. and recycling (3637).

[37]For lag one we only find a significant (and negative) effect for sub-sectors 1718, 2122, 2900, and 3033.

[38]While "food, beverages & tobacco" are a very heterogeneous group of firms, "leather" and "non-metallic mineral products" are very small and specialized sub-sectors within the German manufacturing industry. The fact that we do not find a significant effect for the transport equipment sector might be related to the strong export orientation of this sub sector, which includes the entire German car industry.

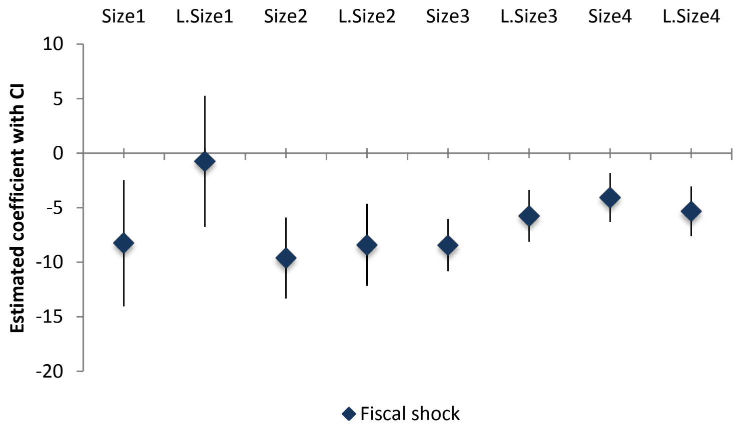

Figure 1.3: Heterogeneous effect by firm class size

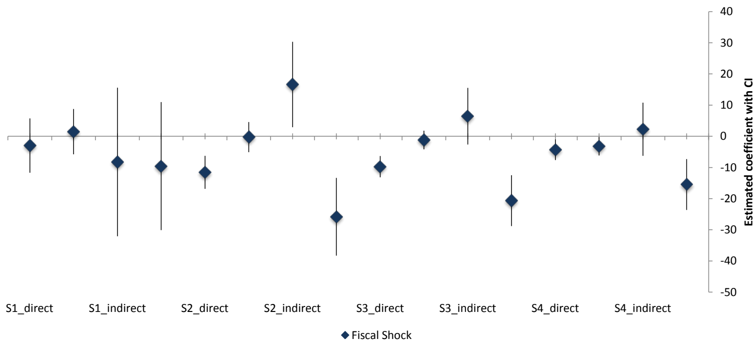

Figure 1.4: Heterogeneous effect by size and tax type

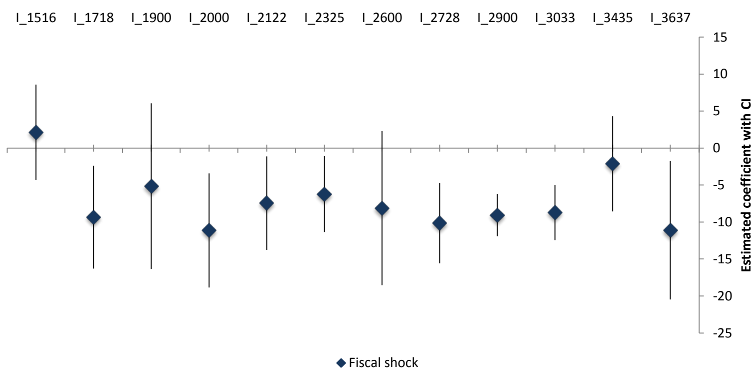

Figure 1.5: Heterogeneous effect by ISIC sector classification: at impact

1.6 Robustness

1.6.1 Sensitivity analysis

In addition to the first model checks presented in the main section, we further elaborate on robustness in the present section. First, given the strong impact that the recent financial and economic crisis had on the economic activity in Germany (negative changes in realized investment of around 30 % in 2009 alone), a first sensitivity check consists of excluding the period 2007-2010 from our analysis. As pointed out in the methodological section, in the original regression specification we already control with a dummy for the recent crisis period, however excluding the period completely represents a good robustness check for our findings. Dropping the period post 2007, we are left with 38,950 observations. For our preferred regression specification, including both aggregate and firm-level controls we find that the leads are not predictable and that the estimated coefficients for the fiscal shocks show the same sign and magnitude as before: -8.76, -5.54, and -3.05 for lag 0 to lag 2.

Another important robustness check is to exclude the biggest single sub-sector within manufacturing (manufacture of machinery and equipment) and to see if our results are stable. Dropping 17,710 observations from the annual dataset does not affect our results to an important degree and the estimated coefficients are directly aligned with our analysis of annual realized investment changes: -7.99, -4.21, and -2.96 for lag 0 to lag 2. Moreover, given the potential concern that structural shocks differ from consolidation shocks in their nature, i.e. they are based on "structural" considerations, these shocks might be correlated to past output and investment levels. We hence exclude them from our regression analysis and re-estimate the model using only shocks that are labeled unambiguously consolidation shocks in both Uhl (2013) and our classification. Again, our results are strongly aligned with the ones presented previously.

Finally, and in order to follow the literature on firm level investment, we model firm investment as in Bond, Harhoff, and van Reenen (2005). We hence estimate a dynamic model of firm investment focusing on the investment rate rather than on investment growth [39]. Due to data availably, we normalize investment by average assets of the com-

[39]The interested reader is referred to Bond, Harhoff, and van Reenen (2005), where the error correction

pany rather than by the capital stock at time $t-1$. The investment model specifies that current investment, the dependent variable, is explained by lagged investment, current and lagged sales growth, levels of sales, current and lagged cash flow to capital ratio and the second lag of the difference between capital stock and sales $(k-y)$. As explained in Bond, Harhoff, and van Reenen (2005), for consistency with the error correction specification, we require the coefficient of $(k-y)$ to be negative. For stability we furthermore require that the coefficient of lagged investment is lower than one in absolute terms.

As the investment rate depends on investment in the previous period, the model has to be estimated by general method of moments (GMM) [40]. Given the fact that the GMM estimator is a large N, small T estimator, we focus on the sample period 1991 to 2004 in order to maximize the numbers of tax shocks and firm observations, but repeat the exercise for the full sample with very similar findings. In a first step, we estimate the model as in Bond, Harhoff, and van Reenen (2005), including time fixed effects, in order to account for the economic cycle and other unobserved factors (Table 1.11, column 1). In order to estimate the effect of our annualized fiscal shocks, we replace the time fixed effects by aggregate controls (column 2) and confirm that the main results do not change. Finally, the fiscal shock is included in column (3). Similar to our previous findings on investment growth, we find a negative and significant effect for fiscal shocks on the investment rate at impact and lag1. The coefficients can be interpreted as a 1% tax adjustment in terms of VA in the manufacturing industry leads to a decrease in investment by -1.4% at impact and -1.1% at lag one, and hence a total aggregate effect of -2.5%. The test statistics for column 3 indicate that the Hansen-statistic of non-valid instruments can be rejected, while the model shows clear evidence of autocorrelation only at lag1.[41].

model of firm investment is derived in detail.

[40] For efficiency considerations, we adopt the system GMM approach as in Bond, Harhoff, and van Reenen (2005)

[41] As additional model check we ignore the potential correlation between lagged investment and the error term and estimate the investment equation by both OLS and fixed effect regression. Given the induced bias the true value for lagged investment should be in-between the two naive approaches. We find that his is the case with an OLS estimate of 0.45 and FE estimate of 0.09 for the lagged investment coefficient.

1.6.2 Towards a causal interpretation

Using a narrative identification strategy for fiscal shocks should overcome any type of endogeneity by construction. Nevertheless, taking advantage of the micro-level dataset and the detailed shock breakdown, we can provide further evidence that the investment response is indeed driven by the fiscal shock and that there are no unobserved factors driving the investment response, using a difference-in-difference approach. In order to do so, we focus on one specific type of shock that is likely to affect only some sub-sectors of the manufacturing industry. This identification strategy can help us to get closer to a causal interpretation of investment impact of fiscal consolidation.

For this purpose, we focus on tax changes that affect the cost of energy. Our assumption is that controlling for a set of aggregate and firm level factors, some energy intensive sectors will be highly affected by this type of tax adjustment, while other sectors will not respond to this tax change. Key is that both sectors, belonging to the manufacturing industry, share the same unobserved trends and hence any difference in outcome can be assigned to the effect of the tax shock. The pulp and paper industry seems a good candidate to test this hypothesis, given its high energy dependence[42]. As control groups we consider the food and tobacco industry (ISIC 1516) and the group of non-classified manufacturing (ISIC 3637). Even though some firms in the food and tobacco industry might be dependent on energy in their production process, both control sectors are highly heterogeneous in terms of products and production processes and hence it is likely for energy tax changes not to show any aggregate effect.

Our "treatment" group "paper" consists of 10,357 observations and the combined group of "controls" has a total of 10,946 observations for the sample period 1970-2010. For this period we count a total of 4 energy shocks[43]. Investment change for the entire sample period for the control group has a mean value of -0.012 (1.01) and for the treatment group 0.001 (1.36). The regression results are reported in Table 1.12, where the first col-

[42]On a worldwide scale the pulp and paper industry is considered the fifth largest consumer of energy. One additional advantage of the pulp and paper industry is that the products and manufacturing processes are highly standardized and hence a shock on energy prices (tax increase) is likely to affect all companies in the industry in a very similar fashion.

[43]Shocks in 1972, 1980, 1987 and 2001. Given the small number of shocks, we focus on realized investment changes rather than updates in planned investment.

umn (1) refers to a pooled regression, column (2) includes fixed effects for the individual sub-branches summarized in the two categories, and column (3) includes firm level fixed effects. The results show that there exists a strong negative lagged effect for pulp and paper, while the control sector does not show any significant response to energy tax increases. Adding firm level fixed effects in column (3) alters the estimated coefficients only slightly, but leads to a higher level of significance for lag 1. In order to compare the magnitude of the coefficients with our previous findings, we evaluate them at the mean impact of energy shocks. Given a standard deviation of energy shocks of 0.002, firms in the pulp and paper industry respond to an average shock by reducing their investment growth by -4.8%. The results are hence highly aligned with our previous findings.

1.7 Conclusion

Private investment has been shown to be one of the main drivers of aggregate output during periods of fiscal consolidation. Nevertheless, previous literature has failed to provide a causal link between fiscal adjustment, business confidence and firm investment. The urge for understanding this channel is even more relevant in periods of excessive debt and/or deficit when the economy needs an effective growth policy agenda.

Based on a detailed narrative record for tax changes in Germany (Uhl (2013)), we reclassify 40 years of fiscal shocks into "exogenous" and "endogenous" changes with respect to investment and to the contingent state of the economy. Exploiting this exogenous variation, we study the effect of a tax change on firms' realized and planned investment, considering the IFO investment survey dataset. We find that recently published laws and laws under current discussion in the media and in the parliament shape future investment plans. Taking into account the forward looking behavior and adjusting the announcement dates according, we find that an increase in tax equal to 1% of the value added of the total manufacturing industry leads to a lagged decrease in planned investment of about 4%. For realized investment growth we estimate an average effect of 8%

Finally, the use of micro-level firm data allows us to elaborate further on heterogeneity in terms of firm size, industry sub sector as well as by type of tax shock. Differently from the previous literature, we find that consumption taxes and income tax adjustments are most harmful for growth as they have the strongest negative and persistent effect on investment growth at firm level. The finding thus support recent hypotheses that highlight the importance of the demand channel in the transmission of fiscal policies, and may act through future demand expectation.

1.8 Appendix

1.8.1 Narrative & firm investment data

This section shows some examples of tax changes as discussed and classified in Uhl (2013). For our purpose of analyzing the effect of exogenous fiscal tax changes on investment we revise all structural and consolidation tax measures in Uhl and reclassify them accordingly in "endogenous" and "exogenous" measures.

An example for an exogenous structural tax measure is given by shock number 20 in Uhl (2013) ,"Gesetz zur Fortentwicklung der oekologischen Steuerreform". It corresponds to the continuation of the ecological tax reform, published on 22 December 1999, with a total budgetary impact of 10,635 billion Euros it represents a tax measure with structural motivation that is included in our analysis. Even though the revenues from the original ecological tax reform were aimed at reforming the retirement scheme in Germany from a pure pay-as-you go system to a more capital oriented system (the so-called "Riester Rente"), and hence might have indirect impact on investment, the continuation law discussed here did not directly contribute to the structural reform of the pension scheme, and revenues were not used to reduce the contribution rates to the social security system. The main argument that dominated the parliamentary debate was that that additional block grants were used to avoid future increases. We label the tax measure structural and include it in our analysis.

On the contrary, shock number 28 in Uhl (2013) " Gesetz zur Senkung der Steuersaetze und zur Reform der Unternehmensbesteuerung", represents a good example of structural shock that we consider endogenous, differently from Uhl (2013) . It refers to a law that has the objective to decrease taxes and reform company taxation (published in October

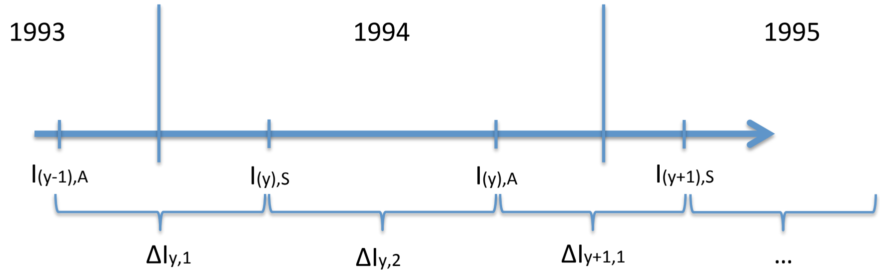

Figure 1.6: Timing of the half-yearly investment survey

2000). This law implemented one of the most extensive tax reforms in Germany and substantially reduced income - and corporate tax burden. Furthermore the corporate tax imputation system was replaced by a 50 percent income taxation rule. The introduction of the bill clearly postulated that the motivation behind the law is to promote growth and employment by reducing the tax burden. Tax reductions were supposed to stimulate consumption, employment and investment. Therefore we do not included it in our analysis as it is directly aimed at increasing firm investment activity.

Finally, a good example for a consolidation shock is given by shock number 62 in Uhl (2013), a law published in March 1981, with the objective to increase petroleum tax and taxes on spirits (Mineraloel und Branntweinsteuer-Aenderungsgesetz 1981). As pointed out in Uhl (2013), the main motivation behind the law was budgetary consolidation. Although structural effects cannot be excluded completely (in order to improve the structure of tax revenues), consolidation considerations dominated the discussion.

Tax shocks: Number in Uhl (2013)	Parliament Publication date	Parliament Draft date	Newspaper coverage Discussion date	Comments
No 5. Law for the continuation of the legal situation 2006 for commuter's tax allowances	Dec-08	Mar-2009, Constitutional court ruling(Dec-2008)	Oct-07	Case rulings in 2007 made clear that the constitutional court likely declares the previously introduced measure for the "Pendlerpauschale" unconstitutional.
No 10. Tax reform act 2007	Jul-06	May-06	Nov-05	Negotiation of the coalition agreement in November 2005 defined list of important changes, amongst others the commuter's allowance.
No 12 .Law for limitation of the loss incorporation in the context of tax deferral	Dec-05	Nov-05	Apr-04 to Jun-05	Already in April 2004 changes in the classification of certain type of life insurances. End of 2004, same applies to closed real estate investment funds. Law as extension of these measures.
No 13. Law to increase tax compliance	Dec-03	Jul-03	Feb-03	Presentation of a white paper by the Financial Ministry in February 2003 to increase the declaration of unreported earnings from abroad.
No 15. Reform of the retirement income (AltEinkG)	Jul-04	Dec-03	Mar-03	Commission established in 2002. Report on the reformation of the pension scheme published in 2003.
No 16. Act for the change of the tobacco tax and other consumption taxes	Dec-03	Jul-03	May-03	First press news in May 2003, however possibility to increase consumption taxes due to financial situation has been already discussed in coalition negotiations after the federal elections in autumn 2002.
No 20 Law for the continuation of the ecological tax reform	Dec-02	Nov-02	Jun-01	Discussion of the further development of the ecological tax.
No 24. Law for the reform of the pension insurance and the promotion of capital pension schemes (AVmG)	Jun-01	Nov-00	Early 2000	Discussion of aging society and unsustainability of the Pay-as-you-go pension scheme in early 2000. Presentation of the pension scheme reform in May 2000.
No 42. Law for the new regulation of the interest taxation	Nov-92	Apr-92	Jan-92	Press notes on the discussion of the consistency with the constitution of the revised interest taxation in early January 1992.
No 44. Law for the implementation of the federal consolidation package (FKPG)	Jun-93	Mar-93	Feb-91	Coalition agrees on substantial tax increases in order to finance the burden of the German reunification. Biggest impact has the solidary surcharge on income and wages.

Table 1.2: Previous news coverage of fiscal shocks

1.8.2 Summary statistics

This section presents evidence for the representativeness of our sample data for the overall manufacturing sector in Germany. We compare aggregate firm level data, obtained as log difference of total change at time t and time t-1 (d_inv_t) and a size-weighted average measure of investment changes (d_inv_a_w), with the benchmark for realized investment changes (gross fixed capital formation data obtained from STAN Industry Rev.3 2008 (OECD).

Table 1.3 and Table 1.4 present results from the aggregate VAR analysis and provide evidence that the shock series cannot be predicted by macroeconomic variables or lagged investment changes. On the other hand, all announced shocks at time t seem to have an impact on changes in investment (Table 1.4); the null hypothesis of no granger causality can be rejected at the 10% significance level.

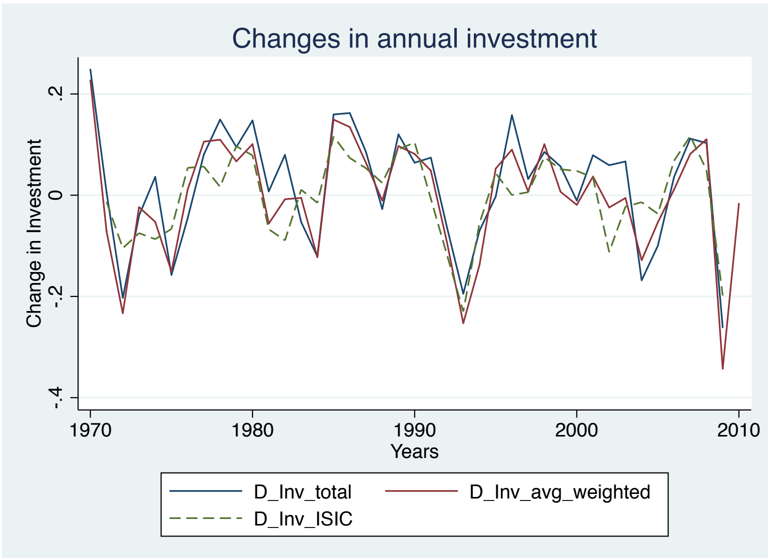

Figure 1.7: Change in aggregate investment: STAN vs. sample aggregation

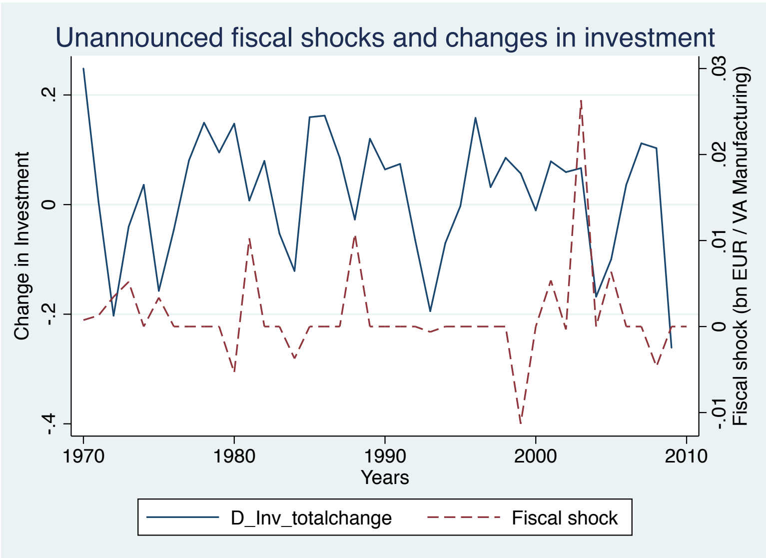

Figure 1.8: Change in aggregate investment vs. exogenous fiscal shock series

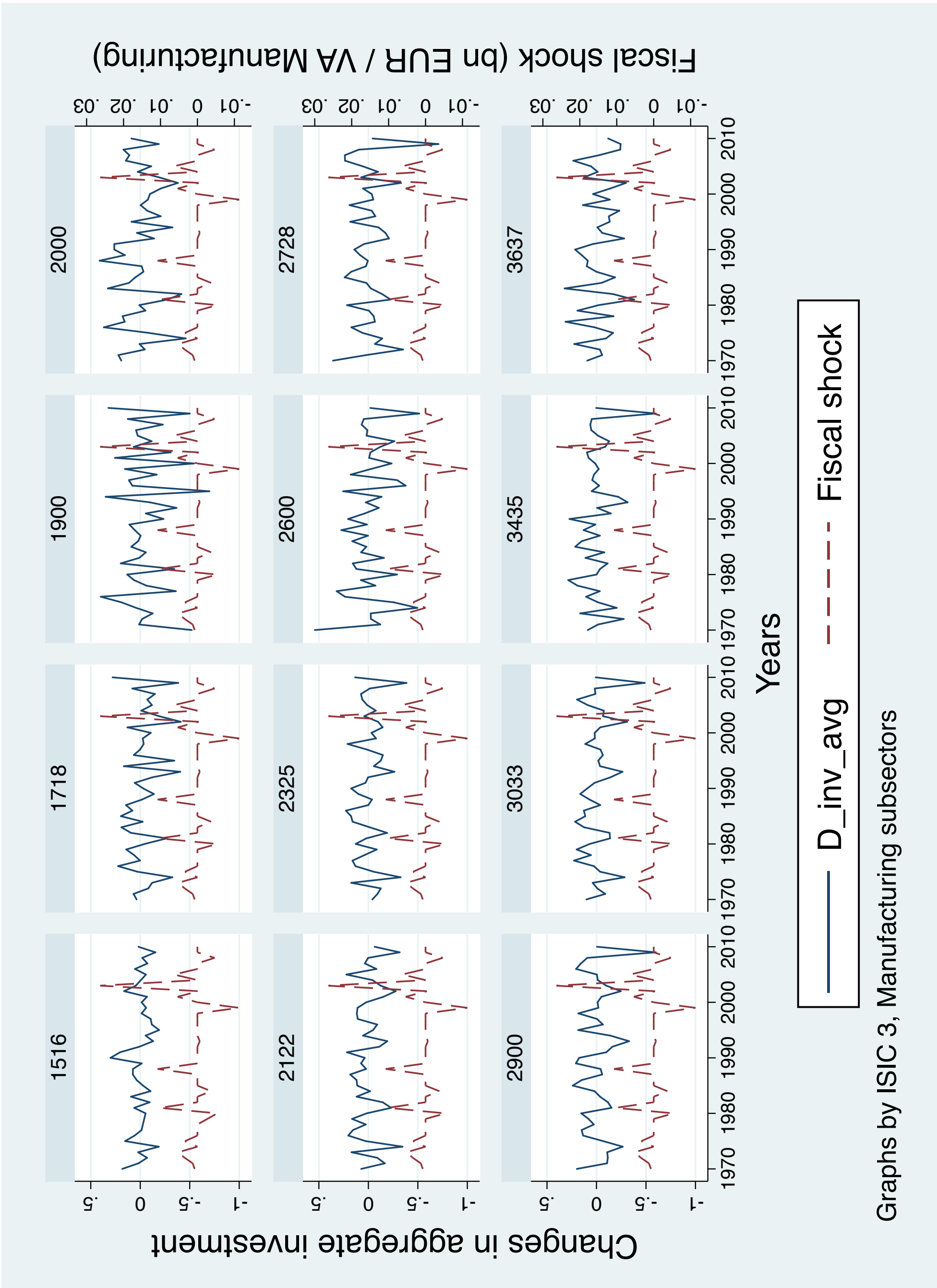

Figure 1.9: Change in aggregate investment in ISIC3 sub sectors vs. exogenous fiscal shock series

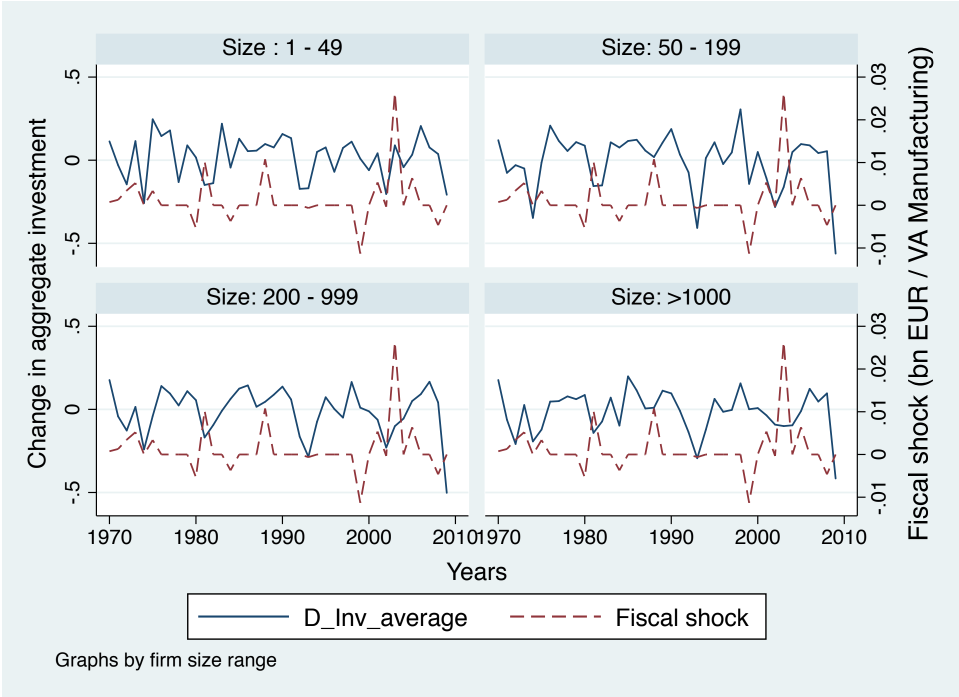

Figure 1.10: Change in aggregate investment by size class vs. exogenous fiscal shock series

Equation	Excluded	chi2	df	Prob > chi2
Exog. fiscal shock	Interest rate (3month)	0.003	1	0.959
Exog. fiscal shock	GDP growth	0.689	1	0.407
Exog. fiscal shock	Change in investment	0.172	1	0.678
Exog. fiscal shock	ALL	1.461	3	0.691
D.investment	Exog. fiscal shock	0.020	1	0.887
D.investment	Interest rate (3month)	1.426	1	0.232
D.investment	GDP growth	1.620	1	0.203
D.investment	ALL	2.732	3	0.435

Exogenous fiscal shock and investment change (39 obs.)

Equation	Excluded	chi2	df	Prob > chi2
Endog. fiscal shock	Interest rate (3month)	2.572	1	0.109
Endog. fiscal shock	GDP growth	3.447	1	0.063
Endog. fiscal shock	Change in investment	2.141	1	0.143
Endog. fiscal shock	ALL	6.283	3	0.099
D.investment	Endog. fiscal shock	0.297	1	0.586
D.investment	Interest rate (3month)	1.040	1	0.308
D.investment	GDP growth	1.964	1	0.161
D.investment	ALL	3.028	3	0.387

Endogenous fiscal shock and investment change (39 obs.)

Table 1.3: Granger causality test based on 4 variable VAR

1.8.3 Regression tables

Dependent variable: Exogenous fiscal shock		
	beta	se
L.1 Change in investment	-2.626	(2.108)
L.2 Change in investment	1.670	(1.942)
L.1 GDP	0.000	(0.000)
L.2 GDP	0.000	(0.000)
Observations	39	
Pseudo R2	0.06	

For the sample period 1970-2010 there are 6 negative adjustment, 25 periods of no action and 10 years with positive shocks.

Dependent variable: Endogenous fiscal shock		
	beta	se
L.1 Change in investment	-0.335	(-2.005)
L.2 Change in investment	4.766**	(-2.099)
L.1 GDP	0.000	(0.000)
L.2 GDP	0.000	(0.000)
Observations	39	
Pseudo R2	0.09	

For the sample period 1970-2010 there are 14 negative adjustment, 15 periods of no action and 12 years with positive shocks.

Table 1.4: Ordered Probit: Insample

Dependent variable: Exogenous fiscal shock		
	beta	se
L.1 GFCF	-2.93E-11	(7.81e-11)
L.2 GFCF	5.03E-11	(6.73e-11)
L.1 GDP	-.000	(0.000)
L.2 GDP	0.000	(0.000)
Observations	38	
Pseudo R2	0.05	

For the sample period 1970-2010 there are 6 negative adjustment, 25 periods of no action and 10 years with positive shocks.

Dependent variable: Endogenous fiscal shock		
	beta	se
L.1 GFCF	1.82E-10**	(8.15E-11)
L.2 GFCF	-7.13E-11	(6.71E-11)
L.1 GDP	-0.002**	(0.001)
L.2 GDP	0.001**	(0.001)
Observations	38	
Pseudo R2	0.12	

For the sample period 1970-2010 there are 14 negative adjustment, 15 periods of no action and 12 years with positive shocks.

Table 1.5: Ordered Probit: Official Statistics (OECD STAN)

Table 1.6: Revision in planned investment

Dependent variable: Revision in planned investment	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)	(4) β / (SE)	(5) β / (SE)	(6) β / (SE)
F2.fiscal shock				−5.520***	−4.021*	−5.012**
				(2.076)	(2.148)	(2.175)
F.fiscal shock				−2.945*	−4.141**	−4.033**
				(1.769)	(1.830)	(1.928)
Fiscal shock	−1.601	0.103	−0.398	0.050	2.504	1.838
	(2.170)	(2.264)	(2.370)	(2.071)	(2.184)	(2.201)
L.fiscal shock	−2.573*	−3.750**	−2.149	−5.293***	−6.575***	−5.816***
	(1.544)	(1.755)	(1.892)	(1.631)	(1.691)	(1.901)
L2.fiscal shock	−1.587	−2.018	−0.794	−0.187	−0.325	0.289
	(1.681)	(1.815)	(1.833)	(1.679)	(1.790)	(1.839)
Dummy_autumn	0.095***	0.099***	0.102***	0.083***	0.084***	0.086***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
Dummy_crisis	−0.089***	−0.061***	−0.050**	−0.130***	−0.116***	−0.113***
	(0.018)	(0.020)	(0.021)	(0.020)	(0.021)	(0.023)
L.GDP	0.000	−0.000	−0.000*	0.000***	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L.3 month interbank rate	−0.030***	−0.042***	−0.031**	−0.025***	−0.026***	−0.027**
	(0.009)	(0.011)	(0.013)	(0.009)	(0.010)	(0.012)
L.Sales growth		0.090***	0.046		0.100***	0.061*
		(0.029)	(0.032)		(0.028)	(0.032)
Observations	25189	19525	19525	23151	19525	19525
R^2	0.006	0.009	0.007	0.007	0.009	0.006
Industry FE	Y	Y	N	Y	Y	N
Firm FE	N	N	Y	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at firm level in parentheses.

Table 1.7: Halfyearly: discussion date of the fiscal shock

Dependent variable: Revision in planned investment	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)
F2.fiscal shock	−4.831**	−3.149	−3.268
	(2.452)	(2.551)	(2.645)
F.fiscal shock	1.566	1.632	0.933
	(2.265)	(2.287)	(2.406)
Fiscal shock	−4.132***	−3.418**	−3.941**
	(1.498)	(1.565)	(1.590)
L.fiscal shock	−1.548	−1.736	−1.810
	(1.510)	(1.564)	(1.651)
L2.fiscal shock	−1.910	−0.813	−1.012
	(1.816)	(1.888)	(1.892)
Dummy_autumn	0.081***	0.081***	0.085***
	(0.014)	(0.015)	(0.015)
Dummy_crisis	−0.116***	−0.100***	−0.097***
	(0.020)	(0.021)	(0.022)
L.GDP	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)
L.3 month interbank rate	−0.017**	−0.018**	−0.020*
	(0.008)	(0.008)	(0.010)
L.Sales growth		0.095***	0.056*
		(0.028)	(0.032)
Observations	23151	19525	19525
R^2	0.007	0.008	0.006
Industry FE	Y	Y	N
Firm FE	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors at firm level in parentheses.

Table 1.8: Annual: realized investment change

Dependent variable: Investment growth	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)	(4) β / (SE)	(5) β / (SE)
F2.fiscal shock	2.659***	1.239	0.584	2.126*	3.085
	(0.922)	(0.940)	(0.945)	(1.150)	(2.022)
F.fiscal shock	0.895	0.056	−0.020	0.642	4.563**
	(0.896)	(0.904)	(0.910)	(1.208)	(1.923)
Fiscal shock	−8.949***	−8.502***	−8.724***	−8.789***	−2.359
	(0.952)	(0.960)	(0.960)	(1.245)	(1.811)
L.fiscal shock	−2.901***	−4.682***	−4.853***	−1.704	−7.072***
	(0.849)	(0.876)	(0.883)	(1.056)	(1.824)
L2.fiscal shock	0.858	−1.757*	−2.164**	0.529	−3.275*
	(0.941)	(0.986)	(0.993)	(1.248)	(1.895)
Dummy_90		−0.270***	−0.276***		
		(0.018)	(0.018)		
Dummy_crisis		−0.098***	−0.097***	0.065	
		(0.032)	(0.036)	(0.051)	
L.GDP		0.000***	0.000***	−0.000	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
L.3 month interbank rate		−0.028***	−0.028***	−0.047***	−0.047***
		(0.002)	(0.003)	(0.009)	(0.005)
L.Sales growth			0.032	0.053	0.000
			(0.031)	(0.034)	(0.056)
Observations	43738	43738	42046	23024	19022
R^2	0.003	0.007	0.008	0.007	0.013
Industry FE	Y	Y	Y	Y	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors at firm level in parentheses.

Table 1.9: Heterogeneous effects: Tax type

Dependent variable: Investment growth	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)	(4) β / (SE)
Income tax	−13.956***	−18.096***		
	(2.298)	(1.925)		
L.Income tax	−5.670**	−5.808***		
	(2.403)	(1.963)		
Property and Corp tax	−7.958***		−12.959***	
	(2.052)		(1.575)	
L.Property and Corp tax	0.947		−6.606***	
	(2.037)		(1.474)	
Consumption tax	0.176			−6.754***
	(2.998)			(2.533)
L.Consumption tax	−17.392***			−17.800***
	(3.044)			(2.550)
Dummy_90	−0.225***	−0.213***	−0.239***	−0.191***
	(0.016)	(0.015)	(0.016)	(0.015)
Dummy_crisis	−0.227***	−0.207***	−0.240***	−0.216***
	(0.017)	(0.016)	(0.016)	(0.016)
L.GDP	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
L.3 month interbank rate	−0.023***	−0.026***	−0.027***	−0.024***
	(0.002)	(0.002)	(0.002)	(0.002)
L.Sales growth	−0.002	−0.002	0.002	0.006
	(0.022)	(0.022)	(0.022)	(0.022)
Observations	54261	54261	54261	54261
R^2	0.008	0.007	0.007	0.006
Industry FE	Y	Y	Y	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors at firm level in parentheses.

Table 1.10: Heterogeneous effects: direct vs. indirect taxes

Dependent variable: Investment growth	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)
Direct taxes	−9.720***	−10.228***	−9.869***
	(1.086)	(1.114)	(1.102)
L.Direct taxes	−0.906	−1.641	−0.959
	(1.081)	(1.106)	(1.087)
Indirect taxes	3.054	2.449	3.298
	(3.053)	(3.097)	(3.160)
L.Indirect taxes	−16.265***	−15.903***	−16.055***
	(2.778)	(2.822)	(2.844)
Observations	53164	53164	53164
R^2	0.01	0.01	0.01
Controls	Y	Y	Y
Anticipated shocks	N	N	Y
Industry FE	Y	N	Y
Firm FE	N	Y	N

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at firm level in parentheses.

Table 1.11: Results from GMM Model (Bond et. al (2003))

Dependent variable: Investment / Assets	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)
L. Investment / Assets	0.222***	0.218***	0.236***
	(0.020)	(0.020)	(0.021)
Sales growth	0.294***	0.256***	0.254***
	(0.088)	(0.081)	(0.111)
L.Sales growth	0.145***	0.137***	0.153***
	(0.026)	(0.023)	(0.030)
L2.(Assets - Sales)	−0.103***	−0.100***	−0.124***
	(0.022)	(0.020)	(0.030)
F.fiscal shock			−0.094
			(1.001)
Fiscal shock			−1.461**
			(0.681)
L.fiscal shock			−1.101*
			(0.665)
Hansen (p-value)	0.01	0.05	0.13
Arellano-Bond (AR1)	-17.34	-17.72	-15.91
Arellano-Bond (AR2)	1.67	1.75	1.76
Observations	10761	10761	9524
Firms	1875	1875	1798
Year FE	Y	N	N
Aggregate controls	N	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimation by SYS-GMM using the one-step estimator. Hansen test (p-value) for over identification restrictions reported. We follow the same selection of instruments as in Bond et. al (2003)

Table 1.12: Results from Diff-in-Diff: Energy tax

Dependent variable: Investment growth	(1) (β / (SE)	(2) (β / (SE)	(3) (β / (SE)
Energy tax X paper industry	3.608	3.410	6.921
	(13.553)	(13.554)	(14.011)
L.Energy tax X paper industry	−23.134*	−23.532*	−24.323**
	(12.269)	(12.272)	(12.289)
L2.Energy tax X paper industry	−20.403	−20.356	−20.427
	(12.683)	(12.697)	(13.105)
Energy tax	−1.535	−1.517	−3.133
	(8.436)	(8.435)	(8.806)
L.Energy tax	4.927	5.158	4.569
	(7.952)	(7.958)	(7.972)
L2.Energy tax	−10.747	−10.927	−12.773
	(9.005)	(9.020)	(9.230)
Pulp & Paper		0.039***	
		(0.013)	
Observations	12960	12960	12960
R^2	0.004	0.004	0.004
Controls	Y	Y	Y
Industry FE	N	Y	N
Firm FE	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at firm level in parentheses.

Table 1.13: Aggretated results: by ISIC 3 subsector

Dependent variable: Investment growth	(1) β / (SE)	(2) β / (SE)	(3) β / (SE)	(4) β / (SE)
Fiscal shock	−3.689***	−3.689***	−2.301*	−2.278**
	(1.120)	(0.816)	(1.054)	(0.864)
L.fiscal shock	−2.674**	−2.682***	−2.279**	−2.958***
	(1.182)	(0.760)	(0.772)	(0.740)
L2.fiscal shock	−.635	−0.640	−1.091	−1.493
	(1.557)	(2.124)	(2.065)	(2.021)
Fiscal shock anticipated			−0.018	
			(0.689)	
L.fiscal shock anticipated			0.181	
			(0.421)	
L2.fiscal shock anticipated			2.011*	
			(0.989)	
Fiscal shock endog.				1.209*
				(0.649)
L.fiscal shock endog.				−1.129
				(0.679)
L2.fiscal shock endog.				−3.316***
				(0.589)
Dummy_90	−0.248***	−0.249***	−0.253***	−0.202***
	(0.0402)	(0.027)	(0.029)	(0.038)
Dummy_crisis	−0.151***	−0.151***	−0.176***	−0.1678***
	(0.043)	(0.037)	(0.046)	(0.034)
L.GDP_index	0.696***	0.697***	0.689***	0.589***
	(0.135)	(0.101)	(0.097)	(0.122)
L.3 month interbank rate	−.0171***	−0.171***	−0.0183***	−0.011*
	(0.006)	(0.004)	(0.004)	(0.005)
Observations	465	465	465	465
R^2	0.11	0.11	0.12	0.16
Industry FE	N	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors at firm level in parentheses.

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Chapter 2

Projection bias in household investment? The case of solar photovoltaics in Germany.

2.1 Introduction

Core theory in economics builds on a simple but powerful model of behavior (DellaVigna (2009)). The neoclassical theory hence assumes that decision makers are fully rational, incorporate all available information, and base their decisions on expected returns. However, general evidence from psychology suggests that this is not always the case. When optimal decision-making includes a prediction of future tastes, it seems that although people understand qualitatively how tastes change over time, they systematically underestimate the magnitudes of such changes. Behavioral economists developed theories that could explain such deviation from the classical rational utility maximizers.[1] Loewenstein, O'Donoghue, and Rabin (2003) show with a simple model in which optimal decision-making depends on the correct anticipation of future tastes, that when future tastes might differ from current ones due to habit formation, mood fluctuations, social influences, or changes in the exogenous environment, *Projection bias* can lead to dynamic inconsistency. They furthermore show that *Projection bias* can be especially important in the context of durable good buying decisions and irreversible investment where it can lead to misguided (impulse) purchases.

When Loewenstein, O'Donoghue, and Rabin (2003) formally introduce the framework of *Projection bias* to the economic literature, most evidence was based on experiments and so far only a limited number of economic studies exploits field data to look at this potentially important phenomenon. Conlin, O'Donoghue, and Vogelsang (2007) look at

[1]A detailed discussion for the psychological evidence of *Projection bias* is provided by Loewenstein and Schkade (1999).

Projection bias in catalogue orders of cold-weather items and find that people's choices are over-influenced by the weather at the time they make decisions. In addition to reduced form estimates, they provide a structural model to measure the magnitude of the bias and find it to be rather important. Simonsohn (2010) on the other hand provides field evidence for the student's decision to enroll to college. Documenting the evidence that cloudiness increases the appeal of academic activities, he finds that an increase in cloud-cover of one standard deviation on the day of the campus visit is associated with an increase in the probability of enrollment of 9 percentage points. In a recent working paper Busse, Pope, Pope, and Silva-Risso (2012) find further evidence of *Projection bias* in two important consumer markets: the car and housing market in the U.S. The authors analyze how weather impacts consumer's purchasing decision and show that sales for 4-wheel-drives and convertibles are highly influenced by idiosyncratic variation in weather variables. Furthermore, using hedonic house price models they find evidence that certain house characteristics are valued differently throughout the year[2].

This paper investigates the presence of *Projection bias* in the context of an irreversible household investment decision: the decision to install solar PV. Given the threat of climate change, European policy makers (and most OECD countries) agree that large investment in renewable energy sources is necessary. Germany is taking a pioneer role in this transition process with the so called "Energiewende"[3], a key policy concern for coming decades. Resulting support policies for renewables have made the installation of solar PV an interesting investment opportunity for households.[4] I investigate if household investment decisions are over-influenced by short-lived weather phenomena such as an exceptionally sunny month. Finding evidence of *Projection bias* in an important household investment decision could have implications for other consumer choices (see

[2]Other papers providing evidence on *Projection bias* are Mehra and Sah (2002) and Grable, Lytton, and O'Neill (2004), where *Projection bias* is however linked to mood fluctuations. Alternative interpretations for deviations from rational choice are consumer myopia (see for example Busse, Knittel, and Zettelmeyer (2013) for a recent contribution) or habit formation.

[3]The *Energiewende*, is one of the key concerns for German policy in the current legislative. In 2011 the goal has been approved to reduce long-term greenhouse gases by 80-95%, to establish renewable energy targets of 60%, and to increase energy efficiency by 50% by 2050.

[4]The German renewable energy act, EEG for its letters in German, provides households with fixed "feed-in tariffs" that allow long-term planning security and above market returns for solar PV plants. The institutional features of the market for solar PV are discussed in detail in section 2.3.

Loewenstein, O'Donoghue, and Rabin (2003) and Busse, Pope, Pope, and Silva-Risso (2012)), the policy maker should be aware of. The present paper makes three main contributions to the literature.

First, given the financial commitment, planning and installation horizon together with the information cost, the investment choice in solar PV can be clearly labeled a high stake decision. Second, my research design tackles the potential relevant *Projection bias* in an environment where weather (sunshine) can be linked to utility through financial returns, as sunshine is a direct input to electricity production and hence expected returns. Third, given the political importance of solar PV diffusion, this paper contributes to the policy discussion by testing if household choices are affected by short-lived weather phenomena, and hence gives further insights, how targeted information campaigns might help to reduce the cost of technology promotion and to achieve a fast uptake, e.g. testing for heterogeneous effects, I confirm that certain political groups are more preceptive to *Projection bias*[5].

Using exogenous variation in sunshine hours, I estimate the causal effect of sunshine and other weather shocks on the household investment decision in solar PV. In order to do so, I create a unique dataset, merging the universe of all registered household solar PV installations in Germany with highly precise weather information for the period 2000-2008. The official data for sunshine hours and temperature are available on a km-by-km grid, which allows me to identify the impact of weather shocks at the county-month level. My identification takes furthermore advantage of the fact that the average time of installation in Germany is 5-8 weeks and hence current weather does not affect directly the profitability of the investment decision. The results indicate that *Projection bias* is potentially an important factor for household investment in solar technology. For the period 2000-08, a sunshine realization one standard deviation above the long-term average in a given county-month leads to approximately 0.5 additional installations, which represents an increase of 8% when evaluated at the sample mean. This increase is not driven by displacement (harvesting), but I find a lasting effect which is furthermore robust to shock definition and model specification.

[5]For a recent contribution on the impact of political orientation on environmental behavior see Costa and Kahn (2013).

For the full sample, I test as well for temperature shocks, which do not have any significant effect. I furthermore perform robustness checks employing a reduced sample of 62 weather stations, for which I can observe additional weather covariates such as rain and snow as well as data at higher frequencies. The reduced sample confirms my main findings, however only at the monthly level. Weekly sunshine shocks do not seem to have a significant impact on the uptake behavior of households, which could be a result of the noisiness of weekly weather patterns. Finally, I confirm that there exists important heterogeneity for *Projection bias* which can be linked to political ideology. As pointed out in a recent paper by Costa and Kahn (2013), political ideology can have an important impact on non-market mechanisms to reduce (electricity) consumption. Using county data from federal elections outcome, I confirm that counties in which the green party had their strongest results in the federal elections 2002 and 2005, are influenced more by extreme sunshine outliers.

The paper proceeds as follows. In the next section I introduce the theoretical framework of *Projection bias* as developed by Loewenstein, O'Donoghue, and Rabin (2003) to the extent relevant for the purpose of this analysis. Section 2.3 describes the institutional features of the German market for solar PV and shows how climate and weather phenomena affect the profitability of solar PV plants. Section 2.4 introduces the data used for the analysis of this paper while section 2.5 presents the empirical strategy and the main results. Section 2.6 elaborates further on robustness. Finally, section 2.7 concludes.

2.2 A theoretical framework for Projection Bias

Based on experiments and previous studies (see for instance Loewenstein and Adler (1995)), Loewenstein, O'Donoghue, and Rabin (2003) introduce formally the theory of *Projection bias* to the economic literature. They give evidence that individuals tend to mispredict their future sequence of preferences in a sense that they systematically exaggerate how future tastes resemble present tastes. *Projection bias* can have important implications in the case of durable goods purchase, with multiple buying opportunities and irreversibility. This section follows closely Loewenstein, O'Donoghue, and Rabin (2003) and shows how *Projection bias* can be seen as the main influencing channel when it comes to the question what triggers the investment decision in a solar PV plant.

Suppose that a person's instantaneous utility can be written as $u(c, s)$, where c is consumption good and s is the state that parameterizes the tastes of the decision maker. In case of a *Simple Projection bias*, people with current state s' form linear expectations about their future utility in state s. Thus, the person's predicted utility lies in between the true future tastes $u(c, s)$ and the current tastes $u(c, s')$ which implies that a person's behavior needs not to correspond to correct inter-temporal utility maximization[6].

In the specific case of durable good purchases, suppose furthermore that a person's valuation in period t is given by a random variable μ_t, which is identically and independently distributed across periods and has a finite sample mean $\overline{\mu}$. The realization of μ_t is known at the beginning of the period and the durable good lasts M months [7]. Finally, the good is not consumed in the month of purchase. If a person decides to buy at period 1, she obtains utility from the purchase, but has to pay price P which implies that she foregoes consumption of the other goods. Assume that the utility for the durable good is additively separable from utility of other goods and the current state is equal to the random variable, $s_t = \mu_t$. Then, in a one-time buying decision, the *true* expected inter-temporal utility is given by:

$$E_1[U_1] = E_1[\sum_{k=1}^{M} \mu_{1+k} - P] = M\overline{\mu} - P$$

While in the presence of *Projection bias* we have that

$$E_1[\widetilde{U_1}] = E_1[\sum_{k=1}^{M} [(1-\alpha)\mu_{1+k} + \alpha\mu_1] - P] = M\overline{\mu} + \alpha M(\mu_1 - \overline{\mu}) - P$$

Clearly $\mu_1 > \overline{\mu}$ implies $E_1[\widetilde{U_1}] > E_1[U_1]$ and vice versa. Thus if the period 1 valuation is larger than the average and the consumer predicts this into the future, she will be

[6] Loewenstein, O'Donoghue, and Rabin (2003) hence define simple projection bias as: $\widetilde{u}(c, s|s') = (1-\alpha)u(c, s) + \alpha u(c, s')$, where α measures the degree of *Projection bias*, i.e. $\alpha = 0$ implies correct prediction of future utility and $\alpha = 1$ implies fully myopic habits.

[7] Loewenstein, O'Donoghue, and Rabin (2003) assume D days, however given the time horizon of the investment in solar PV, M months seem more reasonable. Furthermore, for simplicity reasons they assume that there is no discounting of future utilities; the results do not depend on this assumption.

prone to overvaluation of the durable, or in other words, the persons buying decision is too sensitive to the valuation at the purchasing time.

In the more realistic case of multiple buying decisions, the consumer can buy at most once in any period $t \in \{1,2,...\}$. A rational person would buy the good in period 1 or never, i.e. she buys if and only if $M\overline{\mu} - P \geqslant 0$.[8] In the case of solar PV, given the average time it takes from the decision to invest to complete the installation, the solar plant is not functional in the month of purchase and the net expected value of investment is hence independent of the valuation of the day (month) of purchase. On the other hand, a person with *Projection bias* similarly would like to buy immediately or not at all, however her buying decision is influenced by her current valuation. Then a high valuation $\mu_H > \overline{\mu}$, implies that $M\overline{\mu} + \alpha M(\mu_H - \overline{\mu}) - P > 0$, or in other words, *Projection bias* can lead to overbuying. The person always buys when she should buy and sometimes when she should not buy. In the case where the buying decision is highly irreversible, as in the case of a solar plant, *Projection bias* can lead to impulse purchases.[9]

2.3 Institutional features of the market under consideration

2.3.1 The market for solar PV in Germany

By the end of 2009[10], the German market for solar PV represented 52% of the total world market[11]. The success of solar energy in Germany has been widely attributed to the introduction of the renewable energy source act (EEG, for its letters in German) and the related FIT support scheme in 2000. However even before the introduction of the renewable energy source act, renewable energy was supported by the so called 'Stromein-

[8] In the case of solar PV, the setup is slightly more complicated as in the dynamic setting the consumer has to form expectations on the evolution of the feed-in tariff, the technology cost (including capital cost) and technology improvements. Furthermore the discount rate and knowledge about the technology play an important role that are not considered here.

[9] As pointed out in Loewenstein, O'Donoghue, and Rabin (2003), another possible explanation for overconsumption is hyperbolic discounting, which however is more likely in the case of repeated consumption purchasing decisions.

[10] This subsection follows closely Jacobs (2012)

[11] European Photovoltaic Association

speisungsgesetz', in force since 1991. This act was focused on the integration of smaller power plants, mainly hydroelectric, into the electricity grid. Only the introduction of the EEG, together with the so called 100,000 roof program that provided investors with subsidized loans led to an initial boom in solar. Figure 2.1 shows the number of newly added household installations per year as well as the cumulative uptake of small scale solar PV installations in Germany over the period 2000-2011.

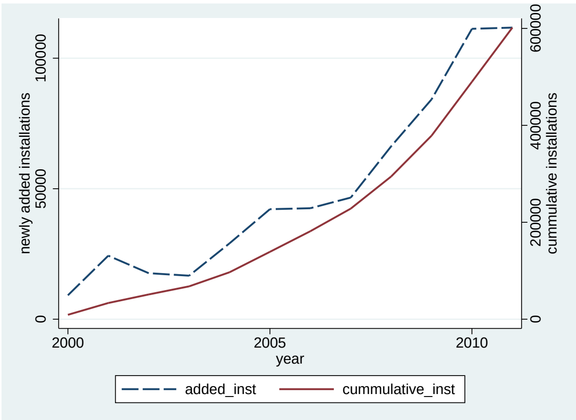

Figure 2.1: New solar PV household installations in Germany

The German FIT guarantees investors access to the electricity grid for a period of 20 years and a fixed remuneration for every unit of electricity produced and sold to the network. In order to account for technological cost-decrease and adoption behavior, the legislator additionally introduced an annual degression rate of 5%, which applies for new installations only. The initial EEG was limited to a total amount of new solar PV capacity of 350 Mega Watt Peak (installed nominal capacity), which however was reached by 2003. In order to provide also new installations with the FIT scheme, the federal government acted in late 2003 and introduced the interim law for PV (Photovoltaik Vorschaltgesetz), the first reform of the EEG enacted in January 2004.

Annual degression rates have been kept stable at 5% until the introduction of the revised version of the EEG in 2009. This reform brought several changes for new solar PV installations: First, the lawmaker decided to introduce a so called sliding degression, i.e. if the total amount of newly installed capacity is above a predicted corridor, the guaranteed tariffs will be reduced further in the following year. This measure was mainly introduced to deal with the massive costs related to the FIT support schemes.

This change in policy is important, as it can lead to higher variability in the investment decision. If households observe that total added capacity is close to the maximum amount for a given year, this policy might lead to a run on installations and hence can have potentially an important impact on the decision when to invest. Second, the EEG 2009 gave new incentives to use electricity generated at home locally and not to sell off the full amount to the network. In the first years, only few solar panel owners decided to make use of this possibility, which however changed importantly in more recent years. The reform of the EEG in 2009 hence represents a structural break in the FIT support policies and I reduce my sample to the period 2000-08 in order to have comparable investment incentives across time.

Furthermore as shown in Figure 2.2, the prices for solar modules continued to decrease sharply from 2009 onwards. In 2009 alone prices fell by more than 30% which led to three tariff reductions in 2010 (January, July and October) and a very volatile demand response. The last revision of the EEG has taken place in June 2011, to be implemented in January 2012. Given the cost development of the EEG surcharge, the new law cut importantly the incentives for solar PV and puts more emphasize on self-consumption and electricity storage.

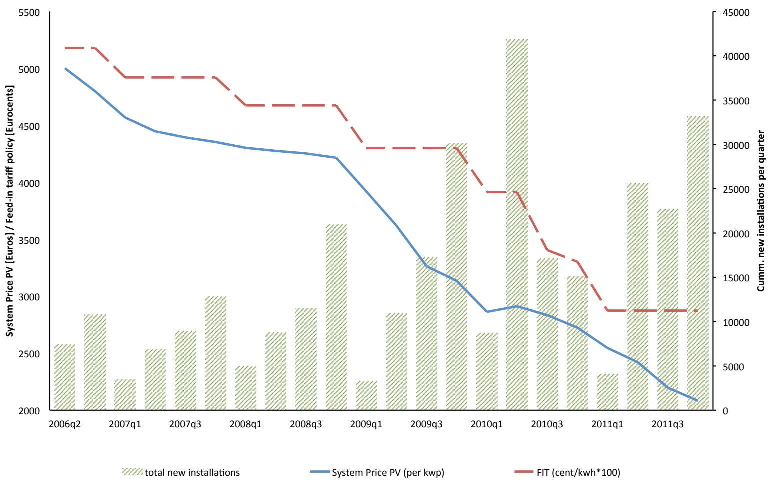

Figure 2.2: FIT, Price of solar module and aggregate installations

2.3.2 How does weather affect the profitability of solar PV?

As pointed out in King, Boyson, and Kratochvil (2002), energy produced by a photovoltaic module is directly related to the availability of *solar energy* and is hence site dependent, but can be influenced by the module's orientation relative to the sun. Annual solar radiation in Germany typically lies between 950 kwh and 1150 kwh per square meter and is generally higher in the southern German regions of Bavaria and Baden-Wuerttemberg [12]. Given average sunshine radiation and FIT support policies, solar panels are profitable all over Germany.

Temperature on the other hand can affect the performance of the cells negatively. Both the electrical current generated and its voltage are influenced by the operating temperature: an increase in temperature leads typically to a decrease in voltage and an increase in current. However the change in current is not as great as the change in voltage and given the fact that the solar module is made up of a number of cells connected in series, the output voltage decrease due to temperature may become significant [13]. Cell's performance in laboratory are typically measured at a cell temperature of 25 degrees Celsius, thus a module's performance will decrease where cell temperature is above that reference measure. This means that hot days in the summer month can lead to less electricity production. However generally speaking for Germany temperature is a factor benefiting electricity production from solar compared to other countries with more solar radiation[14].

Cloud cover and shade are the enemies of solar production, as they can reduce electricity produced by solar cells significantly (50% and more[15]), depending on the thickness of the cloud cover. However, an alternative phenomenon can emerge when the sun moves between the clouds, as then solar cells will receive direct sunlight plus the one reflected from the clouds which may even lead to a higher peak output compared to cloudless

[12] Solar radiation maps are freely available online and can be obtained for example from: http://www.deutschesolar.de/en/solar-power/solar-radiation-map/ (Company information) or from the European Commission (http://re.jrc.ec.europa.eu/pvgis/countries/europe/g13y_de.png)

[13] http://www.elec.uow.edu.au/apqrc/content/technotes/UOW009_Tech%20Note%2010_AW_screen.pdf

[14] Annual average temperatures ranges between 7 and 10 degrees Celsius for Germany

[15] http://www.sunfarmers.com/do-solar-panels-work-when-its-cloudy

days[16]. Similarly a rainy day (with thick cloud cover) can reduce the production from solar energy by as much as 90%. As described above, the peak output can be higher on a mixed day due to additional sunlight reflection and the cooling effect of rain and or clouds. However, these extreme high peak outputs are typically short-lived and should not affect the monthly average return.

Other extreme weather events such as snow and ice can affect the quantity of sunlight absorbed by the solar panel when they block the sun, and again, a very thin snow cover can even have beneficial effect on the electricity amount produced due to additionally reflected sunlight.

2.4 Data sources and summary statistics

2.4.1 Data sources

The present study uses a unique dataset combining the universe of all household solar PV installations in Germany for the period 2000-2008 with highly detailed weather information obtained from the German Weather Service.[17]

Installation Data for renewable energies are available from the online platform of electricity network transmission operator[18]. The data contains all installations that are connected to the electricity network and that are subject to the German FIT policy, which implies practically all household solar PV plants[19]. Even though installation data is available until the end of 2011, I limit my sample to the period January 2000 to December 2008. The choice of this sample period is mainly due to changes in the FIT policy schemes for solar PV, as outlined in the previous section. The total number of individual PV installations in Germany for that time period is 452,854. However this number is likely to be too high as the data contains duplicates and observations that are locally not assignable.

[16]http://www.streetdirectory.com/travel_guide/125965/computers/effects_of_clouds_on_a_solar_panel.html
[17]Deutscher Wetter Dienst, DWD
[18]http://www.eeg-kwk.net/de/index.htm
[19]Given the technology cost, installations have been economically feasible only through FIT support policies. Further technological limitations in electricity storage imply that households with PV have to be connected to the electricity network. The number of plants used completely in autarky is negligible.

After cleaning for observations that do not provide a local identifier and report zero capacity (31 observations), I restrict my sample to household plants with an installed capacity smaller or equal to 10 kilowatt peak (kwp)[20]. This reduces my sample to a total of 294,460 registered installations. In order to check for possible duplicates, I compare day of installation, exact address, installed capacity and plant identification number[21]. All mentioned identifier variables coincide in 76,894 cases, while date, address and capacity coincide in additional 3,237 cases. Hence my final sample of solar PV installations consists of 214,329 individual household installations, which I aggregate at county-month level.

Weather data is provided by the German Weather Service (DWD). In the present analysis I employ two distinct datasets. First, and in order to be able to merge all county-month PV plants to weather data, I acquire highly detailed 1 x 1 kilometer grid climate data for the entire Republic of Germany. The data provides aggregate monthly sunshine hours and monthly average temperature for the period 2000-2008. I merge the grid data to counties using Geographic Information System (GIS) Software[22]. This software allows me to overlay the grid image with county polygons and merge the two datasets using their relative geographic position. The appendix (Figure 2.5) provides a visual sample of the overlay. In a next step, I take averages of sunshine hours and temperature for each county in a given month. In order to identify weather shocks, I calculate the long-term mean within a given county-month, e.g. January in county A [23]. I follow two strategies to identify weather shocks: 1) I use the demeaned sunshine hours and temperature data at county level and assign a dummy equal to one when the weather realization is in the 90th percentile and 2) I assign a shock dummy if the county-month weather lies outside the one standard deviation, of a typical month in that county.

As outlined above, I use a second, reduced sample of 62 freely available weather stations. This sample allows me to contrast my findings in different dimensions. First, given

[20]This is in line with previous literature that focuses on household PV installations in Germany.

[21]Duplicates may arise in the case that individual plants have been disconnected and newly registered in case of a change of network operator.

[22]MapInfo Professional

[23]For the full sample I construct the weather averages over the period 2000-2011. For the reduced sample, I follow the same approach, but additionally control for long term averages within each county using the meteorological 30-year reference period 1970-2000 (as well as 1980-2010).

the fact that these weather stations report daily observations for a longer time span, I can contrast the long term averages per county and moreover estimate my empirical model using higher frequency data (weekly observations). Second, given the fact that these monitors include additional weather covariates, such as rainfall and snow, I am able to test for the impact of further weather phenomena and if sunshine is indeed the main channel affecting investment.

Finally, I include additional covariates to the sample in order to control for time varying differences across counties and to test for heterogeneous effects. Data at this level of disaggregation is available only at annual frequency from the regional statistics database provided by the German national statistical agency[24].

2.4.2 Summary statistics

I combine the above described weather and installation data to a fully balanced panel at county-month level. For the full weather sample, I am able to merge 342 out of around 400 counties in Germany[25]. This leads to a total number of 36,936 observations for the sample period 2000-2008. Table 2.1 in the appendix provides simple summary statistics for the main variables of interest, namely newly added PV installations per county-month, the distribution of weather shocks (sunshine and temperature) and a list of covariates. The first of the three columns refers to the full sample, while columns two and three refer to counties whose average number of monthly installations is above/below the median.

For the full sample period 2000-08, the mean of new installations is 5.48, however there is strong heterogeneity across counties. The above median counties install on average around 4.7 times as many solar PV panels than the below median counties. Weather shocks sun_1sd and sun_p90 [26] are equally distributed across the columns.[27]

[24]https://www.regionalstatistik.de/genesis/online/logon

[25]Land reforms and differences in coding made it difficult to match all counties from the two datasets unambiguously.

[26]Dummy equal to 1 if the sunshine hours in a given county is outside the 1standard deviation (90 percentile) compared to the long-term average in that county-month.

[27]Note further that the demeaned values are zero when considering the entire sample period over which the averages have been drawn (2000-11).

Insert Table 2.1 here

Covariates are only available for the sub period 2002-08, but as Table 2.1 suggests, some differences in the uptake behavior might be explained by observables such as population and number of total houses, which are higher for the above median group. However, one can also see that the counties that adopt more solar are on average richer, have considerably less unemployment, are more likely to participate in elections. The fact that the center-right party (CDU) scores higher for the second column, is mainly driven by the state of Bavaria, which have traditionally a very strong center-right inclination and happens to be as well the state with most installations. Note that the number of high school graduates (as proxy for education), the agricultural surface as well as the number of home sales adjusted for the size of population in each county do not differ between the two groups. Table 2.2 in the appendix provides the same summary statistics for the reduced sample of 62 counties and shows that while the number of newly added installations as well as weather variables are similarly distributed compared to the full sample, the subsample seems to capture on average bigger counties (population, number of houses), which might be due to the location of weather monitors, as those are typically placed in proximity to airports and hence urban areas. The appendix (Figure 2.9) provides an overview of the geographic position of freely available weather monitors, which are distributed all over Germany.

Figure 2.6 on the other hand shows differences in solar PV uptake behavior across German states (Laender) for the time period 2002-2008. Even though the Laender follow a similar pattern, mainly driven by changes in the FIT schedule and an increasing trend, the data also shows an increase in variability over time. The empirical specification will take this into consideration.

2.5 Empirical strategy and findings

This section explains in detail the empirical model and identification strategy employed in this paper. Moreover it discusses the main regression results.

2.5.1 Identification and empirical model

As pointed out in Busse, Pope, Pope, and Silva-Risso (2012), a challenge involved with empirically testing *Projection bias* is that the weather at time of purchase should not impact agents that do not have *Projection bias.* The advantage of the market under consideration is that solar PV plants are highly durable with an average time of usage of 20-30 years and fixed FIT support policies for 20 years. More importantly there is a time lag between the point in time when the decision to invest is taken and the time the installation is completed. For 2011 the average time of installation has been 5.3 weeks with a standard deviation of 2.2 weeks[28], and has not been shorter in preceding periods. Hence on average, from the point the purchase decision was made until the completion of installation, there passes at least one month of time. This means that the weather in a given period does not affect the utility of the investor directly, but that a response to weather shocks can be interpreted as a sign of *Projection bias.* Moreover, given the time lag, weather this period does not affect directly the profitability of the investment in the same period and hence is uncorrelated with the error term. Following this argumentation, a positive and significant coefficient for lag1 and lag2 of the sunshine shocks could be interpreted as a first indication of *Projection bias.* Given randomness of weather, weather shocks provide a credible exogenous variation that fulfill the formal requirements for an unbiased and consistent OLS estimation. In a first step I estimate the following reduced form model:

$$\Delta inst_{c,t} = \alpha + \sum_{i=0}^{M} \beta_i(L_i)weather_{c,t} + \sum_{j=2}^{12} \delta_j m_j + \theta_t + \epsilon_{c,t} \tag{2.1}$$

where the dependent variable $\Delta inst_{c,t}$ captures newly added PV installations in county c at time t, $weather_{c,t}$ contains the weather shocks, i.e. positive deviations from county-month long term means in aggregate sunshine hours, mean temperature, rain, and snow [29]. As introduced in the data section, I rely on two different shock definitions, which are coded according to a zero-one dummy. Current and lagged weather shocks have no direct impact on profitability and assuming randomness holds, do not carry information about future weather states (i.e. learning) and hence should not affect the in-

[28] Seel, Barbose, and Wiser (2013) show in a scoping analysis that mean installation labor in Germany is around 39 man hours per system. The author would like to thank furthermore Joachim Seel for sharing his individual survey results regarding total installation times in Germany.

[29] Given data availability, rain and snow are only tested for the reduced sample.

vestment decision of investors without *Projection bias*. Given the timing of installations, I expect lag 0 not to have any significant effect. On the other hand if lagged sunshine in period 1 and period 2 have a significant impact on the newly added installations, I interpret this as a sign of *Projection bias*, as likely investors project the current weather state and perceived utility into the future when making their buying decision. The baseline definition additionally accounts for time fixed effect in order to control for nationwide trends, such as the level of FIT and prices of solar panels. Monthly dummies account for the strong seasonality introduced by the announced changes of FIT each year, leading to bunching of installations in the last months of the year. As weather shocks are defined according to a demeaned measure at county level, any differences in absolute weather, i.e. levels of sunshine is taken into account.

One additional concern might be observable differences across counties and regions that lead to differences in uptake behavior. I introduce a list of covariates, such as population, income per capita, number of houses, voting participation, voting for green party, agricultural surface and unemployment per county that might be correlated with the number of installations. Moreover, even though weather is random, aggregating and averaging at monthly level could introduce some correlation between weather covariates, (un)observable county characteristics and the number of newly added installations per county due to local and temporal correlation of weather shocks. Similar to Cesur, Tekin, and Ulker (2013), who control for selection on observables by introducing a flexible set of time trends and fixed effects, I take this possibility into account by controlling for potential correlation between weather shocks and time varying covariates.

I test for potential correlation between the shocks and county characteristics in Table 2.3 and find that the total number of houses, income per capita, the unemployment rate, percentage of green voters as well as percentage of high school graduates and number of residential buildings to population are significantly correlated with the shock. Controlling for aggregate time fixed effects, but more importantly for county time trends as well as state-by-year fixed effects, makes this correlation disappear. Hence, the set of fixed effects is necessary to account for the potential bias due to omitted factors that may be correlated with both the number of new installations and the distribution of sunshine outliers. The fixed effects also control for time varying unobservables such as local availability and awareness of the technology, and hence relax the parallel trend assumption. There might have been local support and information campaigns for solar PV that are not captured by the nationwide trends. Figure 2.7 and 2.8 in the appendix show exemplary differences in time trends of newly added solar PV installations in a high-adoption county and low-adoption county. The county fixed effect additionally allows for permanent differences across counties. I hence estimate the following augmented model:

$$\begin{aligned} \Delta inst_{c,t} = \alpha + \sum_{i=0}^{M} \beta_{1,i}(L_i) weather_{c,t} + \beta_2 X_{c,t} + \sum_{j=2}^{12} \delta_j m_j + \theta_t + \\ + \psi_c t + \nu_c t^2 + \gamma_{y,l} + \lambda_c + \epsilon_{c,t} \end{aligned} \tag{2.2}$$

Where in addition to equation (2.1) I introduce a linear ($\psi_c t$) and quadratic time trend ($\nu_c t^2$) for each county as well as state-by-year fixed effect ($\gamma_{y,l}$), and in the most stringent specification county fixed effect (λ_c). The set of additional control variables are captured by $X_{c,t}$.

2.5.2 Main findings

This section describes the main results obtained from estimating the empirical model for a number of specifications, shock definitions, and subsamples. In a first step, and in order to obtain benchmark results, I regress the number of newly added installations per county on lagged sunshine shock dummies as introduced in the data section. I use two different definitions: First I use demeaned aggregate sunshine hours that lie outside the 1 standard deviation of a typical county-month and second, I look at the more extreme outliers, using the outliers that are above the 90th percentile of the demeaned sunshine hours in a given county and month. I take into account the possibility of correlation between weather shocks and unobservable county characteristics by introducing time trends and state-by-year fixed effects that furthermore account for the dynamic uptake behavior across counties. The results in Table 2.4 show the estimation results for different set of controls.

Insert Table 2.4 here

While only regressing the lagged sunshine shocks on the new number of installation produces negative estimates, that are large in magnitude and significant, introducing aggregate time fixed effects, county specific time trends, and state-year fixed effects leads to more convincing results. In specifications (3) - (5), lag zero is never significant, both lag1 and 2 of sunshine show a positive and highly significant estimate (but lag1 for model 3). The county specific time trends could be interpreted as baseline growth rate for each county.[30] The accumulated effect for lagged sunshine shocks is about 0.5 new installations or an increase of 7-8% evaluated at the mean. The standard errors, reported in parenthesis are county-cluster adjusted in order to account for potential heteroskedasticity and correlation within counties.

Comparing these results to a sunshine shock definition according to the 90 percentile definition (Table 2.5), the results are robust to shock definition. The same lags show up to be significant now for all models (3) - (5) and, as expected, the effects are slightly larger in magnitude. One concern for the here presented results could be that abnormal weather might cause a short run substitution effect, i.e. rational decision maker plan their investment and make the purchase whenever it happens to be a sunny period. I can test for this alternative hypothesis in two ways. First, in order to directly address short-run inter-temporal substitution of purchases, I look more closely at the coefficients related to the distributive-lag model as estimated. Following the analysis of Busse, Pope, Pope, and Silva-Risso (2012) and other papers looking at inter-temporal substitution using weather shocks (Jacob, Lefgren, and Moretti (2007) and Deschenes and Moretti (2009)) I add up all significant lagged coefficients and verify if these add up to an effect different from zero. In case it is zero, it is likely to be the case that an exceptional sunshine month only displaces the installations from one month to another (harvesting effect). However, I do not find such evidence for the present data in any of my specifications. Second, I can test for the "sunny-day" hypothesis by looking at other related factors, such as rain. One possible interpretation would be that people decide rationally about investing, but wait for a sunny period (a nice day) to go and actually make the deal. I can test for the impact of rain using the reduced sample of 62 counties at both monthly and weekly data frequency. The results, presented in the next section indicate that a rainy month does not have a clear impact on the investment decision of the household. I interpret these findings that the main channel through with sunshine affects the investment choice is

[30]The results do not depend on the inclusion of the county time trends; regressing model specification (4) with a linear time trend alone or without time trend does not alter the main findings. Lag1 and Lag 2 are positive and highly significant with a magnitude of around 0.5

indeed *Projection bias*.

Before looking at the effect of both sunshine and temperature outliers, I perform two initial model specification tests. Table 2.6 in the appendix additionally includes a forward lag. When using the 90 percentile definition, agents should not be able to forecast weather shocks in the next period and base their investment decision on this. The inclusion of the forward lag shifts slightly the significance of lag 0, however the significant negative effect at lag 0 is counterbalanced at lag 1, with a zero-net effect. Lag 2 in this specification shows still an aggregate effect of about 0.5 and is highly significant. Moreover, Table 2.7 on the other hand includes in addition to time and county fixed effects the set of time varying control variables. Note that due to data availability this reduces the sample size to the period 2002-08, and hence provides a further robustness check. Including only the set of controls to the simplest OLS regression (1), leads to negative and very large effects. As outlined above, these results are biased strongly due to the correlation of the sunshine shock with other unobserved covariates. However, taking this into account, introducing a rich set of fixed effects, the results are aligned with the previous findings, and show a slightly higher effect for the period 2002-08.

Insert Table 2.8 here

In Table 2.8, I look also at the potential impact of temperature on investment. I run the different models including both sunshine and temperature shocks (using the 90 percentile definition). In addition to the question if temperature triggers investment, the inclusion of further shocks are a good robustness check due to the correlation of sunshine and temperature. While for model specification (4) and (5) lag 1 and lag 2 of the sunshine shock are highly significant ($p < 0.01$) and show a very similar size than beforehand, non of the temperature lags, but lag 3 at model (5) are of importance. I conclude that it is indeed sunshine that triggers investment in solar PV.

One concern with weather data are non-linear effects, as it has been highlighted by the previous literature (see for example Zivin and Neidell (2010)). Figures 2.3 and 2.4 show the impact of different bins for demeaned sunshine in a given county-month on new installations[31]. The empirical model follows specification (4) and includes time FE,

[31] 95% confidence intervals plotted together with the point estimates. Category 4 (zero mean) omitted.

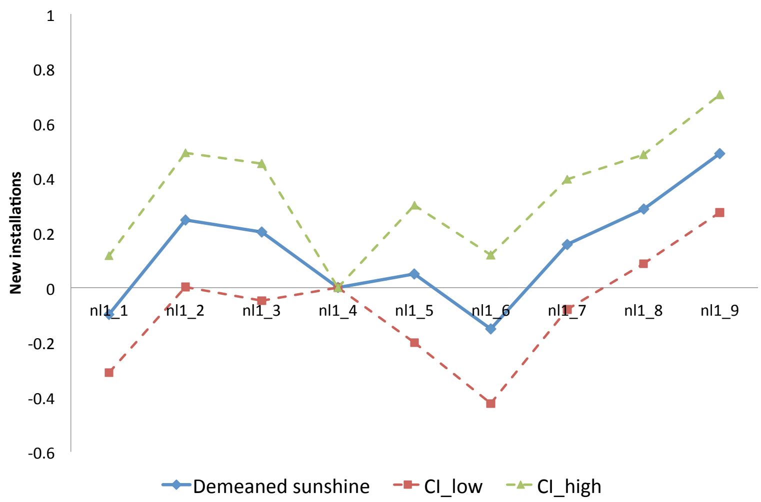

Figure 2.3: Non-linear effects for lag1 demeaned sunshine

county time trends and state-by-year FE. While for lag 1 only bins 8 and 9, the highest outliers, are significantly different from zero and positive, for lag 2 bins 7 to 9 are significant and positive. No other bin is significant which gives further credit to the findings above that it is indeed the positive extreme sunshine deviation that trigger new installations. Negative deviations do not seem to have any effect[32].

Finally looking at heterogeneous effects for *Projection bias*, Table 2.9 summarizes the estimation results following the main regression specification (4). In line with Costa and Kahn (2013), I would like to test whether political ideology has an influence on the uptake behavior in solar PV. As presented in the summary statistics, the voting outcome for the green party in above and below median counties in terms of solar PV installations does not vary significantly, however political ideology could play an important role in terms of how beliefs are shaped. Given the fact that solar PV installations, a "green technology", can be strongly identified with the green party program, I am interested to see whether in counties where the political engagement and the green party had strong results in the 2002 and 2005 federal elections, I can find any differences in technology uptake due to *Projection Bias*[33]. For this purpose I interact the treatment variable "sunshine

[32]Note furthermore that the non-linear regression model does not depend on the definition of the cut-off rule for extreme events, but includes all demeaned sunshine categories.

[33]Green voters might be more idealistic and hence be easier influenced by short-lived weather shocks and their investment decision in solar PV.

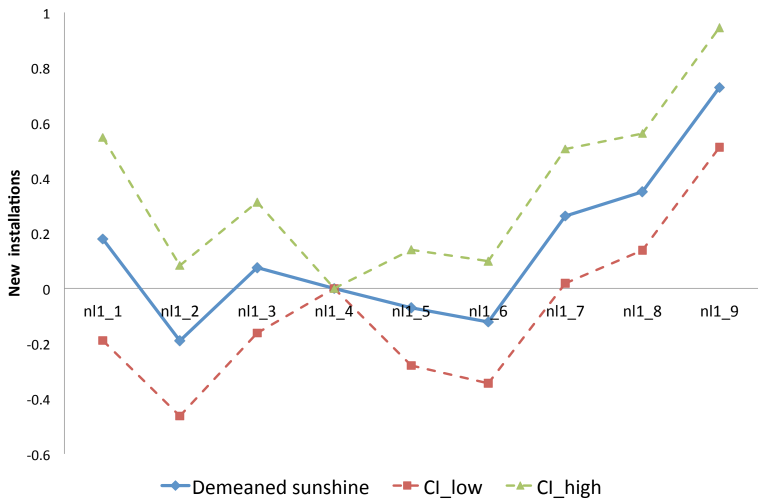

Figure 2.4: Non-linear effects for lag2 demeaned sunshine

shock" with a dummy equal to 1 if in a given country the vote participation has been above the median ($\text{VotePart}_{p(50)}$) in order to capture political engagement, if the green party's election results have been above the median (column 2) or the 75 percentile (column3)[34] Finally, column 4 to column 6 of the same table test for heterogeneity in terms of economic covariates: household income (column 4), unemployment rate (column 5) and living in Eastern Germany (column 6).

Insert Table 2.9 here

While the coefficients for the sunshine shock are in line with the previous findings, the heterogeneity results reveal that political orientation and involvement matter, but economic covariates seem not to play an important role. I find that in counties where the vote participation in the federal elections has been above the median lag 2 of the interaction term is positive and significant at 5%. Looking specifically at the outcome of the green party, as proxy for environmental orientation, I find that in case I use the above median definition, both lag1 and lag2 are significant and positive at 10%, i.e. the effect of *Projection bias* is more pronounced in green counties. These results gain even more momentum when looking at those counties in which the green party received their highest voting shares (p75). In this case I find that compared to the average effect the effect in green counties is double the size. Hence, this might indeed indicate that green

[34] Typically the vote participation is higher in counties where smaller parties yield stronger results as these tend to mobilize their electorate more than the bigger parties.

voters are more idealistic and can be easier influenced by short-lived weather phenomena. Interestingly, the differences in income and unemployment as well as East vs. West Germany do not have any impact on the presence of *Projection bias*.

2.6 Robustness

In addition to the specification tests presented in the previous section, I perform a series of robustness checks, employing a second, reduced, sample of 62 stations which contains additional weather covariates at higher frequency. Figure 2.9 in the appendix provides the geographic position of these freely available weather stations.

First, and in order to check for consistency, I reestimate the original model to compare the results qualitatively and quantitatively. Table 2.10 in the appendix provides the main results and shows that specification (5) is able to reproduce the same results as we've seen with the full sample. In this case, lag 2 is significant at 5% and shows a magnitude of 0.436. All other lags are not significant for the 90 percentile sunshine shock definition. On the other hand, looking at specification (3) and (4) lag zero appears to be the only significant lag at 10% significance, which however is endogenous to the investment decision and should not play any important role. Note moreover that the individual point estimates for lag 1 and lag 2 are in line with the previous findings, only the standard errors are broader due to the reduced sample size, leading to non-significant estimates.

Table 2.11 includes all lag zero to lag three sunshine, temperature, snow and rain shocks, defined according to the 90 percentile rule. For model (5) only lag 2 of sunshine shows up to be significant, with an point estimate of 0.48 which is very much aligned with the overall findings. All other weather shocks do not seem to have an impact on the investment decision. Again, focusing on the impact of sunshine shocks, the point estimates for model (4) are similar to the findings in specification (5), but with a lower significance.

In a last step, I use the reduced sample and look at weekly data frequency. Table 2.12 shows the weekly results for sunshine shocks according to the 90 percentile rule. For model (3)-(5) only week 6 shows up to be significant, but negative. No other lag seems to play an important role. Adding other weather shocks to the analysis (Table 2.13), can help to shed further light into the analysis. The negative sunshine lag 6 seems to be compensated by a positive sign of a similar magnitude for temperature at the same lag. However given the potential correlation between sunshine and temperature these effects are difficult to disentangle. Other weather phenomena seem to play only a minor role. Rain shows a negative effect at lag 9 in specification (1), (4) and (5), indicating that a very rainy week might actually lead to less installations compared to the baseline. This could indicate that a negative weather shock leads to some displacement. On the other hand, and due to the negative correlation between rain and sunshine, this findings could be also interpreted as a sign of *Projection bias.* The positive correlation for snow at lag 7 is puzzling.

Overall, the weekly analysis does not provide clear-cut evidence in favor or against the *Projection bias* hypothesis. Weekly data however allows me to perform another model specification test, namely to test if bad weather conditions, such as a heavy week of snow, leads to significantly less installations in the regression framework. Table 2.14 provides such evidence. For all model specifications (3) - (5) an extreme week of snow at lag zero shows a negative and significant impact for county-week installations, with a 0.2 magnitude. Interestingly this effect is reversed at lag 3, showing a positive and significant effect of the same size, leading to a zero aggregate effect. To conclude the analysis of weekly data, the fact that I am not finding clear evidence for *Projection bias* at higher frequency, might indicate that weekly weather is too volatile and thus households do not base their long-term investment decisions on it. My findings indicate that it needs a period of stable weather (a month outlier in sunshine) to trigger investment decisions that have an effect on aggregate uptake.

One potential shortcoming of the present paper is the focus on the demand side only and thus the analysis does not account for potential general equilibrium effects, i.e. one could think of the theoretical possibility that lagged sunshine shocks have an impact on current demand, which makes suppliers react and adjust prices upwards. Hence weather shocks would be correlated with prices, which could potentially lead to biased estimates. However, given the strong supply side (technology) driven cost decrease of solar energy in the sample period, this is rather a hypothetical possibility; using furthermore a rich set of fixed-effects allows to take care of such possibility. Moreover, if sunshine shocks make the sellers react, promoting their technologies or making special offers, my estimates capture a joint effect between increases in demand and selling effort, which is nevertheless not less important. Generally, the impact of *Projection bias* on supply, remains a possibility for future research.

Another possible interpretation of the results could be given in the light of Li, Johnson, and Zaval (2011), that investigate how believes about climate change are affected by daily temperature. They confirm that survey respondents that thought the day was warmer than usual believed more in and had greater concern on global warming. Given the available data, I cannot distinguish between investors that build future return expectations on the current state of the weather, and thus showing clear evidence of *Projection bias*, and those that form rational expectations but build them on a wrong forecast. However, climate change beliefs are influenced by temperature and not by sunshine, and as pointed out in the results section, there is no evidence for a significant effect of temperature shocks on investment. In any case, for rational investors short term weather fluctuations should not have a significant impact on their adoption decision, if these weather shocks do not contain direct information about future climatic developments.

2.7 Conclusion

This paper provides clear evidence that household investment decisions in an irreversible good are affected by *Projection bias*. Using data from solar PV installations in Germany, I show that an extremely sunny month has a significant impact on the number of new installations per county. A one standard deviation shock in terms of monthly sunshine hours leads to additional 0.5 solar installations in a given county, translating to an approximate increase of 8% for the sample period 2000-08. Households hence project current weather states into the future when forming expectations about investment profitability. Weekly sunshine outliers as well as other weather variables (temperature, rain, and snow) do not seem to have any influence on technology uptake. The results are robust to a wide range of shock definition, specification, and robustness checks.

The findings furthermore indicate that *Projection bias* can differ by political ideology. In the present case, solar PV can be directly linked to the political belief of the

Green party voter, I find that *Projection bias* is indeed stronger in counties where the Green party received its highest voting shares. The policy maker could build on these insights to formulate more efficient and better targeted information campaigns. On the other hand, providing evidence for *Projection bias* in an irreversible investment decision means that likely also other important household decisions are influenced by *Projection bias* (Busse, Pope, Pope, and Silva-Risso (2012)). The policy maker should be aware of this possibility.

2.8 Appendix

2.8.1 Summary statistics

Figure 2.5 presents an overlay of monthly sunshine hours (1 x 1 km grid) with county limits. The shading intensity refers to aggregate sunshine hours at each grid point, where darker areas represent more sun. The data plot displays data for one month only (April 2000) and clearly indicates heterogeneity in terms of aggregate monthly sunshine hours across Germany.[35]

[35]Long-term average sunshine radiation does not necessarily coincide with the here presented graph, which is thought to show heterogeneity at monthly level as well as the GIS overlay. The darker areas in central Germany correspond to areas that also have higher average sunshine hours due to geographic conditions.

Table 2.1: Sample Characteristics by technology adoption: full sample

	all	> median inst.	<= median inst.
PV installations and weather: 2000-08			
new installations county month	5.48	9.03	1.93
sun_1sd	0.15	0.15	0.15
sun_p90	0.08	0.08	0.08
demean_sunhours	-0.31	-0.18	-0.44
temp_1sd	0.16	0.16	0.16
temp_p90	0.09	0.09	0.10
demean_temp	1.30	1.21	1.39
Observations	36936	18468	18468
Covariates: 2002-08			
houses	40195	50368	30082
HHinc_pc	17400	18109	16696
population	176687	206450	147098
unemploy_percent	10.77	8.18	13.34
highschool_rat	0.30	0.24	0.37
surf_agricul_rat	31.97	32.22	31.72
buildings_residential_rat	0.19	0.22	0.17
home_sales_rat	0.13	0.13	0.12
vote_particip	78.13	80.06	76.21
p_vote_cdu	39.29	44.71	33.91
p_vote_spd	35.62	33.11	38.12
p_vote_green	6.98	6.97	6.99
p_vote_fdp	8.23	8.46	8.00
p_vote_linke	6.40	3.36	9.43
p_vote_other	3.48	3.39	3.56
Observations	28644	14280	14364

Table 2.2: Sample Characteristics by technology adoption: reduced sample

	all	> median inst.	<= median inst.
PV installations and weather: 2000-08			
new installations county month	5.18	8.72	1.64
sun_1sd	0.16	0.16	0.16
sun_p90	0.09	0.09	0.08
demean_sunhours	0.14	0.29	-0.01
temp_1sd	0.16	0.16	0.16
temp_p90	0.10	0.10	0.10
demean_temp	0.11	0.10	0.12
Observations	6696	3348	3348
Covariates: 2002-08			
houses	43553	56854	29792
HHinc_pc	16826	17649	15910
population	223356	269074	176061
unemploy_percent	12.66	9.74	15.68
highschool_rat	0.34	0.26	0.43
surf_agricul_rat	28.47	32.35	24.46
buildings_residential_rat	0.18	0.23	0.13
home_sales_rat	0.12	0.13	0.10
vote_particip	76.50	79.19	73.73
p_vote_cdu	37.16	42.38	31.75
p_vote_spd	34.76	33.81	35.74
p_vote_green	7.52	7.85	7.17
p_vote_fdp	7.96	8.41	7.49
p_vote_linke	9.12	4.47	13.93
p_vote_other	3.49	3.08	3.92
Observations	4956	2520	2436

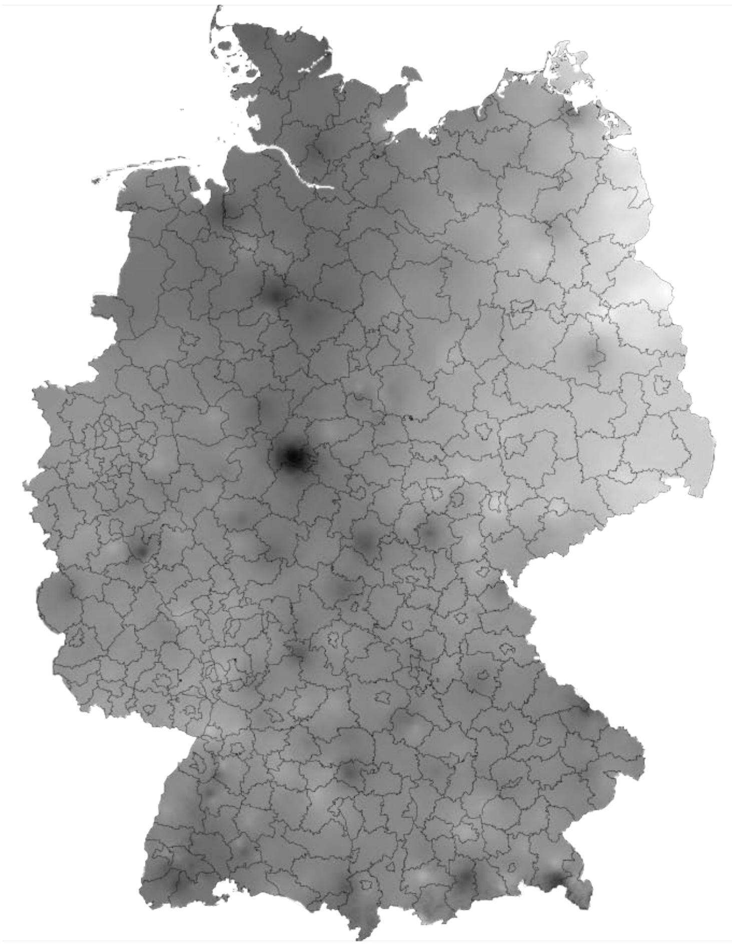

Figure 2.5: Overlay monthly sunshine data and county boundaries.

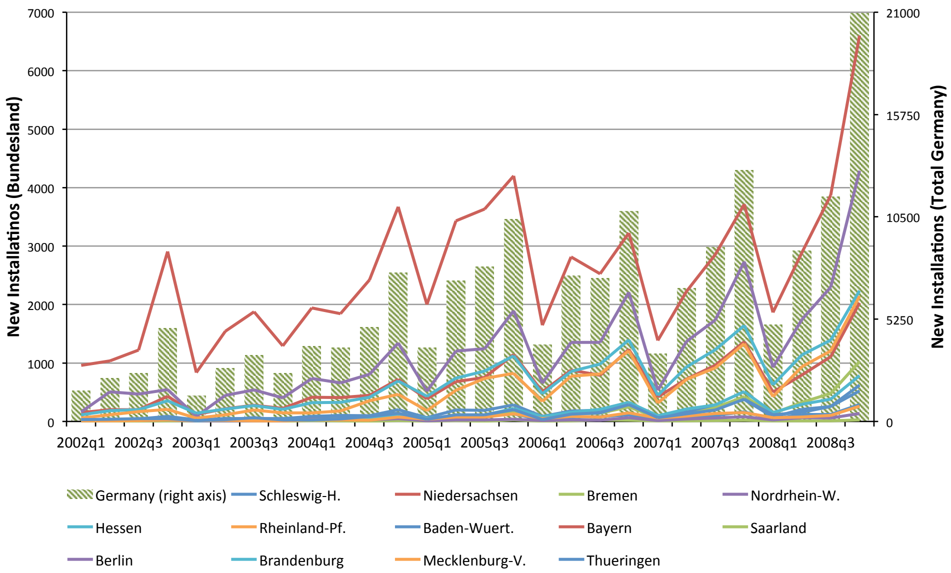

Figure 2.6: Newly added installations by state (Bundesland)

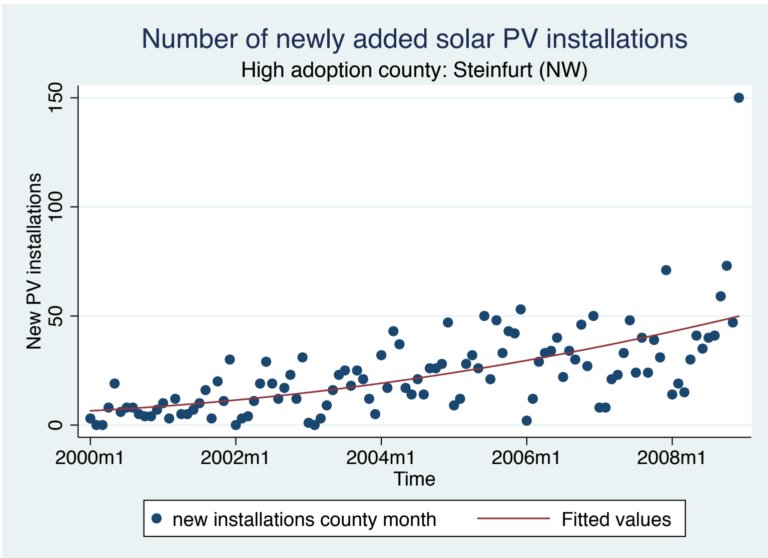

Figure 2.7: Evolution of solar PV diffusion in a high-adoption county

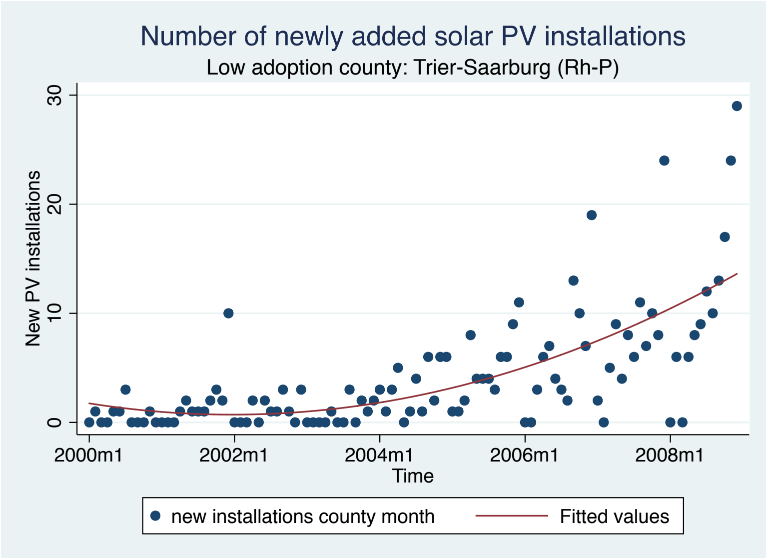

Figure 2.8: Evolution of solar PV diffusion in a low-adoption county

2.8.2 Regression results

Figure 2.9: Geographic position of freely available weather stations in Germany (DWD).

Table 2.3: Model selection: Predictability of sunshine shock - 1sd definition

Dependent variable: Sunshine shock	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Total houses	0.000***	0.000***	−0.000***	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HH income per capita	0.000***	−0.000**	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Vote participation	−0.001	0.000	−0.001	−0.002	0.000
	(0.000)	(0.001)	(0.001)	(0.003)	(0.004)
Unemployment rate	0.005***	0.001	−0.013***	−0.003	−0.005**
	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Vote Green	0.177***	0.098	0.221	−0.347	−0.840
	(0.062)	(0.068)	(0.278)	(0.380)	(0.647)
High school (%)	−3.096**	−0.006	−1.594	−4.295	−6.581
	(1.264)	(1.010)	(3.005)	(4.514)	(4.961)
Agric. surface (%)	−0.007	0.012**	0.271	0.418	0.659
	(0.007)	(0.006)	(0.529)	(0.497)	(0.679)
Resid. buildings (%)	21.059***	0.008	−8.389*	−3.814	−4.662
	(2.249)	(1.663)	(4.304)	(3.327)	(4.042)
Sales cases	−0.060	0.051	−3.948	−1.036	0.725
	(2.340)	(1.651)	(4.439)	(3.632)	(4.509)
Observations	32736	32736	32736	32736	32736
R^2	0.004	0.240	0.279	0.292	0.291
Time FEs	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.4: Different model specifications: Sunshine shock - 1sd definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	−0.371***	−0.323**	−0.040	0.068	0.038
	(0.097)	(0.129)	(0.096)	(0.094)	(0.091)
L.sun	−0.760***	−0.199*	0.097	0.253***	0.225***
	(0.086)	(0.112)	(0.078)	(0.083)	(0.081)
L2.sun	−0.222***	0.102	0.314***	0.438***	0.413***
	(0.086)	(0.130)	(0.086)	(0.085)	(0.084)
L3.sun	−0.330***	−0.770***	−0.276***	−0.134	−0.152*
	(0.097)	(0.125)	(0.088)	(0.081)	(0.082)
L4.sun	−0.499***	−0.459***	−0.128*	−0.052	−0.065
	(0.085)	(0.112)	(0.072)	(0.075)	(0.073)
Observations	35568	35568	35568	35568	35568
R^2	0.002	0.216	0.600	0.623	0.487
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.5: Different model specifications: Sunshine shock - p(90) definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	−0.591***	−0.732***	−0.147	0.018	−0.060
	(0.119)	(0.148)	(0.126)	(0.121)	(0.119)
L.sun	−0.613***	−0.296**	0.248**	0.461***	0.382***
	(0.104)	(0.123)	(0.099)	(0.100)	(0.098)
L2.sun	0.009	−0.040	0.342***	0.542***	0.451***
	(0.098)	(0.124)	(0.098)	(0.099)	(0.098)
L3.sun	−0.378***	−1.020***	−0.248**	−0.081	−0.168*
	(0.093)	(0.131)	(0.098)	(0.096)	(0.096)
L4.sun	−0.337***	−0.622***	−0.095	−0.015	−0.088
	(0.088)	(0.118)	(0.084)	(0.080)	(0.081)
Observations	35568	35568	35568	35568	35568
R^2	0.001	0.216	0.600	0.623	0.487
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Table 2.6: Different model specifications: Include forward lag - p(90) definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
F.sun	0.113	−0.269**	−0.065	0.154	0.110
	(0.118)	(0.137)	(0.103)	(0.100)	(0.103)
sun	−0.875***	−1.184***	−0.537***	−0.294***	−0.352***
	(0.095)	(0.145)	(0.105)	(0.104)	(0.105)
L.sun	−0.405***	−0.524***	0.032	0.298***	0.238**
	(0.100)	(0.134)	(0.097)	(0.101)	(0.099)
L2.sun	0.251***	−0.140	0.288***	0.527***	0.461***
	(0.096)	(0.126)	(0.093)	(0.095)	(0.095)
L3.sun	−0.131	−1.013***	−0.359***	−0.177*	−0.239**
	(0.089)	(0.132)	(0.098)	(0.096)	(0.095)
L4.sun	−0.090	−0.581***	−0.105	0.010	−0.046
	(0.087)	(0.121)	(0.085)	(0.082)	(0.083)
Observations	35226	35226	35226	35226	35226
R^2	0.001	0.179	0.581	0.601	0.434
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Table 2.7: Different model specifications: Adding Controls - p(90) definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
sun	-1.354^{***}	-0.727^{***}	-0.008	0.108	0.096
	(0.131)	(0.155)	(0.129)	(0.123)	(0.120)
L.sun	-1.421^{***}	-0.265^{*}	0.397^{***}	0.593^{***}	0.572^{***}
	(0.127)	(0.135)	(0.107)	(0.107)	(0.105)
L2.sun	-0.783^{***}	-0.085	0.409^{***}	0.591^{***}	0.558^{***}
	(0.104)	(0.136)	(0.104)	(0.106)	(0.103)
L3.sun	-1.150^{***}	-1.055^{***}	-0.119	0.020	-0.024
	(0.111)	(0.143)	(0.102)	(0.101)	(0.099)
L4.sun	-1.050^{***}	-0.620^{***}	0.020	0.035	-0.007
	(0.104)	(0.126)	(0.087)	(0.083)	(0.083)
Observations	27280	27280	27280	27280	27280
R^2	0.008	0.223	0.677	0.700	0.550
Controls	Y	Y	Y	Y	Y
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Table 2.8: Different model specifications: Including both sunshine and temperature shocks (p90)

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	−0.405***	−0.760***	−0.134	0.027	−0.053
	(0.129)	(0.152)	(0.131)	(0.127)	(0.125)
L.sun	−0.238**	−0.218*	0.221**	0.479***	0.400***
	(0.112)	(0.126)	(0.101)	(0.105)	(0.102)
L2.sun	0.057	−0.190	0.270***	0.489***	0.395***
	(0.102)	(0.129)	(0.104)	(0.103)	(0.103)
L3.sun	−0.366***	−0.991***	−0.206**	−0.027	−0.114
	(0.104)	(0.132)	(0.099)	(0.097)	(0.096)
L4.sun	−0.154*	−0.643***	−0.177**	−0.057	−0.134
	(0.088)	(0.120)	(0.088)	(0.084)	(0.085)
Temperature shock:					
temp	−0.727***	−0.058	0.015	0.015	0.020
	(0.099)	(0.105)	(0.091)	(0.097)	(0.096)
L.temp	−1.096***	−0.157	0.198	−0.018	−0.015
	(0.100)	(0.141)	(0.123)	(0.133)	(0.131)
L2.temp	0.024	0.544***	0.465***	0.110	0.130
	(0.088)	(0.120)	(0.113)	(0.113)	(0.113)
L3.temp	0.121	0.160	0.281***	−0.198*	−0.174
	(0.111)	(0.133)	(0.091)	(0.113)	(0.111)
L4.temp	−0.537***	0.021	0.445***	0.021	0.044
	(0.103)	(0.108)	(0.091)	(0.096)	(0.095)
Observations	35568	35568	35568	35568	35568
R^2	0.003	0.216	0.600	0.623	0.487
Time FE	N	Y	Y	Y	Y
State trend	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.9: Heterogeneous effects - Main regression specification (4)

Dependent variable: New PV installations (county-month)	VotePart$_{p(50)}$ β / SE	VoteGreen$_{p(50)}$ β / SE	VoteGreen$_{p(75)}$ β / SE	HhInc$_{p(75)}$ β / SE	Unemp$_{p(75)}$ β / SE	East β / SE
L.sun	0.510***	0.361**	0.382***	0.460***	0.512***	0.566***
	(0.099)	(0.141)	(0.114)	(0.109)	(0.121)	(0.103)
L2.sun	0.392***	0.414***	0.470***	0.504***	0.619***	0.591***
	(0.101)	(0.124)	(0.098)	(0.094)	(0.105)	(0.092)
L.sun x treat	0.066	0.346*	0.596***	0.328	0.087	−0.217
	(0.200)	(0.198)	(0.195)	(0.206)	(0.158)	(0.155)
L2.sun x treat	0.358**	0.296*	0.358**	0.258	−0.168	−0.206
	(0.179)	(0.169)	(0.168)	(0.191)	(0.147)	(0.152)
Observations	27962	27962	27962	27962	27962	27962
R^2	0.704	0.704	0.704	0.704	0.704	0.704
Treatment variable	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
FE & time trends	Y	Y	Y	Y	Y	Y

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustered standard errors in parentheses.

Table 2.10: Reduced sample: Monthly observations - p(90) definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
Sunshine shock:					
sun	−0.534***	−0.572**	−0.606***	−0.363*	−0.284
	(0.183)	(0.228)	(0.182)	(0.204)	(0.187)
L.sun	−0.344	−0.071	−0.125	0.108	0.188
	(0.249)	(0.284)	(0.244)	(0.215)	(0.190)
L2.sun	0.414*	0.449*	0.192	0.349	0.436**
	(0.245)	(0.264)	(0.223)	(0.229)	(0.209)
L3.sun	−0.119	−0.439	−0.363	−0.231	−0.149
	(0.213)	(0.263)	(0.224)	(0.229)	(0.196)
L4.sun	−0.136	−0.232	−0.237	−0.206	−0.131
	(0.263)	(0.295)	(0.194)	(0.170)	(0.164)
Observations	6448	6448	6448	6448	6448
R^2	0.001	0.171	0.542	0.575	0.411
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.11: Reduced sample: All weather shocks - p(90) definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
L.sun	−0.160	0.073	−0.037	0.143	0.219
	(0.265)	(0.278)	(0.245)	(0.210)	(0.193)
L2.sun	0.367	0.450*	0.250	0.411*	0.480**
	(0.266)	(0.249)	(0.229)	(0.225)	(0.210)
L3.sun	−0.247	−0.434*	−0.356*	−0.165	−0.091
	(0.227)	(0.241)	(0.213)	(0.221)	(0.195)
L.temp	−0.774***	0.013	0.301	0.128	0.070
	(0.194)	(0.253)	(0.205)	(0.229)	(0.223)
L2.temp	−0.162	0.387*	0.368	0.049	−0.001
	(0.174)	(0.226)	(0.233)	(0.220)	(0.208)
L3.temp	0.258	0.239	0.256	−0.127	−0.180
	(0.245)	(0.276)	(0.192)	(0.225)	(0.227)
L.snow	2.191**	0.795	0.589	0.498	0.513
	(0.898)	(0.786)	(0.510)	(0.429)	(0.421)
L2.snow	0.320	0.149	0.092	0.088	0.130
	(0.747)	(0.747)	(0.392)	(0.352)	(0.374)
L3.snow	0.536	0.730	0.424	0.441	0.460
	(0.790)	(0.853)	(0.546)	(0.522)	(0.491)
L.rain	−0.664**	0.121	−0.006	−0.288	−0.177
	(0.273)	(0.189)	(0.172)	(0.175)	(0.180)
L2.rain	−0.275	−0.074	−0.200	−0.371*	−0.250
	(0.271)	(0.214)	(0.180)	(0.186)	(0.185)
L3.rain	−0.241	−0.302	−0.314	−0.431**	−0.312
	(0.298)	(0.251)	(0.215)	(0.204)	(0.190)
Observations	6510	6510	6510	6510	6510
R^2	0.005	0.173	0.541	0.576	0.412
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.12: Reduced sample: weekly data - p(90) sunshine shock

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
L5.sun	−0.157***	−0.046	−0.034	−0.024	−0.028
	(0.041)	(0.037)	(0.038)	(0.034)	(0.035)
L6.sun	−0.186***	−0.098***	−0.105***	−0.097***	−0.101***
	(0.040)	(0.035)	(0.033)	(0.029)	(0.030)
L7.sun	−0.071	0.006	−0.022	−0.016	−0.020
	(0.049)	(0.044)	(0.040)	(0.038)	(0.039)
L8.sun	−0.059**	−0.004	−0.020	−0.018	−0.021
	(0.027)	(0.032)	(0.028)	(0.027)	(0.026)
L9.sun	−0.033	0.033	0.012	0.017	0.014
	(0.059)	(0.062)	(0.062)	(0.061)	(0.060)
L10.sun	−0.054	0.018	−0.002	0.001	−0.002
	(0.042)	(0.035)	(0.033)	(0.032)	(0.033)
L11.sun	−0.060*	−0.003	−0.015	−0.006	−0.009
	(0.033)	(0.032)	(0.035)	(0.032)	(0.033)
L12.sun	−0.119***	−0.038	−0.043	−0.039	−0.042
	(0.039)	(0.038)	(0.040)	(0.037)	(0.036)
Observations	28272	28272	28272	28272	28272
R^2	0.001	0.102	0.277	0.294	0.184
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.13: Weekly data: all weather shocks - p(90) definition

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
L6.sun	−0.190***	−0.082**	−0.107***	−0.097***	−0.099***
	(0.038)	(0.033)	(0.034)	(0.029)	(0.029)
L7.sun	−0.087*	0.016	−0.030	−0.021	−0.024
	(0.048)	(0.042)	(0.039)	(0.038)	(0.039)
L8.sun	−0.065**	−0.000	−0.028	−0.022	−0.025
	(0.030)	(0.032)	(0.028)	(0.028)	(0.028)
L9.sun	−0.039	0.029	0.002	0.009	0.006
	(0.060)	(0.063)	(0.062)	(0.061)	(0.061)
L6.temp	0.024	0.008	0.087**	0.072**	0.073**
	(0.044)	(0.039)	(0.038)	(0.034)	(0.034)
L7.temp	0.022	−0.046	0.009	−0.004	−0.004
	(0.025)	(0.029)	(0.028)	(0.028)	(0.028)
L8.temp	−0.067	−0.014	0.022	0.010	0.010
	(0.042)	(0.030)	(0.026)	(0.026)	(0.027)
L9.temp	−0.050	−0.018	−0.006	−0.017	−0.017
	(0.045)	(0.042)	(0.036)	(0.036)	(0.036)
L6.rain	0.079	0.149	0.126	0.118	0.120
	(0.120)	(0.130)	(0.130)	(0.130)	(0.130)
L7.rain	−0.054	0.027	0.008	−0.002	−0.001
	(0.039)	(0.042)	(0.038)	(0.036)	(0.036)
L8.rain	−0.044	−0.014	−0.017	−0.032	−0.030
	(0.035)	(0.037)	(0.031)	(0.030)	(0.030)
L9.rain	−0.112***	−0.028	−0.047	−0.063**	−0.061**
	(0.040)	(0.036)	(0.032)	(0.030)	(0.030)
L6.snow	0.200	−0.069	−0.076	−0.053	−0.030
	(0.131)	(0.124)	(0.080)	(0.075)	(0.073)
L7.snow	0.273**	0.173	0.189*	0.191*	0.208**
	(0.134)	(0.127)	(0.100)	(0.100)	(0.102)
L8.snow	0.101	0.051	0.050	0.064	0.083
	(0.161)	(0.153)	(0.140)	(0.136)	(0.136)
L9.snow	−0.112	−0.011	−0.000	0.004	0.025
	(0.116)	(0.118)	(0.069)	(0.067)	(0.069)
Observations	28458	28458	28458	28458	28458
R^2	0.001	0.103	0.278	0.295	0.186
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

Table 2.14: Weekly data: model selection - p(90) rain and snow

Dependent variable: New PV installations (county-month)	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
rain	0.004	0.096*	0.066	0.063	0.068
	(0.061)	(0.052)	(0.053)	(0.054)	(0.053)
L.rain	−0.217***	−0.125***	−0.148***	−0.149***	−0.145***
	(0.044)	(0.037)	(0.034)	(0.034)	(0.034)
L2.rain	−0.129***	−0.008	−0.029	−0.035	−0.031
	(0.040)	(0.036)	(0.027)	(0.028)	(0.028)
L3.rain	0.016	0.076*	0.052	0.043	0.046
	(0.036)	(0.039)	(0.037)	(0.036)	(0.036)
snow	−0.123	−0.157	−0.212**	−0.224**	−0.208**
	(0.132)	(0.129)	(0.102)	(0.092)	(0.093)
L.snow	0.030	0.026	−0.010	−0.006	0.006
	(0.104)	(0.100)	(0.081)	(0.071)	(0.074)
L2.snow	0.134	0.090	0.053	0.059	0.072
	(0.101)	(0.097)	(0.072)	(0.066)	(0.067)
L3.snow	0.449***	0.228*	0.203***	0.215***	0.234***
	(0.133)	(0.119)	(0.073)	(0.067)	(0.068)
Observations	28830	28830	28830	28830	28830
R^2	0.002	0.104	0.278	0.296	0.188
Time FE	N	Y	Y	Y	Y
County trends	N	N	Y	Y	Y
State-yr FE	N	N	N	Y	Y
County FE	N	N	N	N	Y

* p < 0.1, ** p < 0.05, *** p < 0.01. Clustered standard errors in parentheses.

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Chapter 3

The impact of feed-in-tariffs on household investment in photovoltaics.

3.1 Introduction

Increasing private investment in renewable energy sources (RES) is an important public policy target. In addition to the climate change goals decided upon by the member states of the European Union in 2007, [1] Germany adopted the far-reaching goal to increase the share of renewable sources in gross electricity production to 35% by 2020. The commitment to increase investment in renewables has been further reinforced by the nuclear incident in Japan in March 2011, which led to the immediate shutdown of eight out of the originally 17 nuclear power plants and to the plan to completely resign from nuclear energy by 2022.[2]

In order to support RES deployment, the German government introduced in 2000 a novel policy tool: feed-in tariffs (FIT). FIT offer long-term contractual agreements to producers of renewable energy that guarantee access to the electricity network at a fixed rate above the electricity market price. This policy tool was designed to guarantee ex-ante planning security and profitability for producers of renewable energy with the objective to incentivize investment. FIT policies typically distinguish type and size of installation, and in the case of solar PV, were especially targeted towards private households[3]. Thanks to financial incentives, solar PV installations have found increasing popularity in recent years. However, even though FIT can be considered successful in reaching their principal objective, to increase the participation of RES in the overall energy mix[4], they

[1]The so called 20-20-20 targets involve a reduction of 20% in greenhouse gases from 1990 levels, 20% of energy consumption produced by renewables, and an improvement of 20% of the European Union's energy efficiency.

[2]Nuclear energy accounted for 23% of gross electricity generation in 2010.

[3]Small scale roof mounted household installations receive the highest FIT remuneration.

[4]As pointed out by the European Commission and the International Energy Agency, one key element

are also expensive. In 2009 alone, a total of 10,779 million Euros had to be covered in form of an additional surcharge in order to pay for FIT. Around one third of this amount can be attributed directly to the support of solar PV[5]. Finding the optimal way to incentivize investment in solar while taking into consideration cost developments hence has important welfare implications.

This paper has the objective to analyze further how FIT support policies affect the investment decision of households in solar PV and how changes in the FIT schedule matter for the aggregate technology uptake. Given the dynamic nature of household investment decisions, I build my analysis on a dynamic stochastic discrete choice model based on the economic literature on household optimization problems in durable goods, such as Adda and Cooper (2000) or Adda and Ottaviani (2005).

Investigating household energy behavior has a relatively long tradition in the economic literature. Most of the papers follow an applied approach and focus on the quantification of household energy demand (see Taylor (1975) for an early survey), or empirical specification of demand elasticities Dubin and McFadden (1984) or Reiss and White (2005). In recent years, a growing literature has emerged dealing with household investment in RES, and in particular in solar PV. Lobel and Perakis (2011) develop a consumer choice model for forecasting demand and designing incentives for solar technology applied to the case of Germany. They use a random utility demand model to describe the household purchase behavior and in a second step solve a dynamic optimization problem for the optimal subsidy policy. Their findings show that it would be more cost efficient to have higher subsidies in the near future and to phase-out subsidies faster than proposed by the current law. In another paper Wand and Leuthold (2011) follow closely the modeling approach by Benthem, Gillingham, and Sweeney (2008) in order to analyze the FIT policy in Germany from a more generalized welfare perspective. Using a partial equilibrium approach, they evaluate the FIT policy by weighing the benefits from induced learning and avoided environmental externalities against the social costs of promoting residential PV. Similarly, Creti and Joaug (2012) study the optimal

in the success of the penetration through renewables have been FIT, first experienced by Germany's 2000 RES Act.

[5]See position papers from the regulating authority for renewable energy in Germany, available at http://www.bundesnetzagentur.de

FIT policies from the policy maker perspective, but directly focus on the optimal FIT schedule and its adjustment in a theoretical setting (see also Shrimali and Baker (2012) or Alizamir, de Véricourt, and Sun (2012)).

Unlike these papers, that focus on the policy maker optimization problem, I explicitly model the household environment of the investment decision as a dynamic stochastic discrete choice model.[6] In order to do so, in a first step I use data from a representative household survey in Germany (the socio-economic panel, GSOEP) and evaluate the variables that play a key role in the investment decision. I find that both income and saving at the individual level are important determinants of investing in a solar PV plant. Using furthermore insights from a random-effects Probit model indicates that also the FIT policy and electricity prices are correlated with the investment decision. I incorporate these findings in my model, which moreover allows for learning-by doing, in a sense that the cost of solar is endogenous to aggregate technology uptake in the economy. Given the sharp decrease in solar PV cost paired with the increasing utilization of this technology, this seems an important data feature and should be taken into consideration, as it has been done by the other studies (Lobel and Perakis (2011), Wand and Leuthold (2011), or Benthem, Gillingham, and Sweeney (2008)).

The model estimation is performed in two steps: First, I estimate the income process and the learning rate using micro-level data from GSOEP as well as aggregate data on the cost of solar PV and the number of installations. Secondly, I estimate the structural model parameter using simulated-method of moments (SMM), matching jointly the aggregate sales path and a set of micro-level moments. Finally, the model is used to perform a series of policy experiments and to quantify how changes in the FIT policy parameters affect the household decision to invest and how these changes influence the aggregate technology uptake. I find that changes in the individual policy parameters have a different impact on aggregate uptake. An increase in the degression rate seems to have the strongest negative impact on uptake. An increase in the exogenous electricity price on the other hand leads to additional installations, as households seem to invest in order to insure themselves against higher electricity prices.

[6] Lumpiness of household durables has been widely documented for example in the car and housing market, where it is common to build the analysis on micro-founded demand models.

The rest of the paper is structured as follows. Section 3.2 gives a more detailed overview on the market for solar PV in Germany and the system of feed-in-tariffs in general. Section 3.3 introduces the data as well as the empirical evidence, while section 3.4 describes in detail the theoretical model. Section 3.5 explains the estimation strategy while section 3.6 performs a series of policy experiments. Finally, section 3.7 concludes.

3.2 The German market for solar PV

The German market for solar PV[7] is the single biggest world market, representing 52% of its total share by the end of 2009[8]. The success of solar energy in Germany has been widely attributed to the introduction of the renewable energy source act (EEG, for its letters in German) and the related FIT support scheme in 2000.

Before the year 2000, renewable energy has been supported by the so called 'Stromeinspeisungsgesetz', in force since 1991; however this act mainly focused on the integration of smaller power plants (hydroelectric) into the electricity grid. Only with the introduction of the EEG and the so called "100,000 roof program", that provided investors with subsidized loans for solar PV installation, technology uptake grew considerably.

The German FIT guarantees investors access to the electricity grid for a period of 20 years (defined as policy horizon) and a fixed remuneration for every unit of electricity produced and sold to the network. In order to account for technological driven cost-decrease and adoption behavior, the legislator additionally introduced an annual FIT degression rate of 5%, which applies for new installations only. For instance, if a household decides to invest at time t, the FIT that applies in that specific year t, is guaranteed for the entire policy horizon (20 years), while if a household invests in $t+1$ the FIT will be 5% less. Hence the policy can be summarized in three main parameters: the initial level of FIT, the annual degression rate and the horizon.

When the EEG was introduced in 2000, support for new solar PV was initially limited to a total amount of 350 Mega Watt Peak[9] of total added capacity. However, this

[7]This section follows closely Jacobs (2012)
[8]European Photovoltaic Association
[9]Installed nominal capacity

threshold was reached by 2003, and, in order to provide new installations with the FIT scheme, the federal government acted in late 2003 and introduced the interim law for PV (Photovoltaik Vorschaltgesetz) - the first reform of the EEG enacted in January 2004. The tariffs were revised upwards, but the annual degression rate was kept stable at 5% until 2009. The reformed EEG in 2009 brought several changes for new installations. Firstly the lawmaker decided to introduce a so called "sliding degression": if the total amount of newly installed capacity is above a predicted corridor, the guaranteed tariffs will be reduced further in the following year. This measure was mainly introduced to deal with the massive costs related to the FIT support schemes. Secondly, the EEG 2009 for the first time gave incentives to use the generated electricity locally and not to sell off the full amount to the network. Nevertheless, in the first period only very few households adopted this possibility and it became only important with the 2012 revision of the law that made partial self-consumption mandatory for new installations.

For the analysis, and in order to have a comparable time horizon in terms of policy incentives, I hence focus on the period 1990 - 2011, as the latest EEG reform might have changed importantly the incentives of the household to invest.

3.3 Empirical evidence

3.3.1 Data

Figure 3.1 shows the aggregate path of household PV installations as well as the average cost of installing one kilowatt peak in Germany for the period 2000 to 2011[10]. While the total number of installations has been growing exponentially from a few thousand to nearly half a million installations in 2011, the average cost has decreased from around 6500 EUR per kilowatt peak in the year 2000 to around 2200 EUR in 2011. This cost decrease has been attributed to learning-by-doing in the solar industry (see for example Wand and Leuthold (2011), Lobel and Perakis (2011), and Benthem, Gillingham, and Sweeney (2008)). An increase in aggregate output hence leads to direct reduction of aver-

[10] As pointed out in the previous literature (see for example Wand and Leuthold (2011)), I define all plants with a installed capacity of $\leqslant 10$ kilowatt peak as household installations. The cost refers to the average system price paid for small scale household PV installations in Germany.

age technology cost. The aggregate number of installations are obtained from individual level data that are available from the electricity network carrier [11] and that contain the universe of solar PV installations. Residential specific solar price data for Germany, on the other hand, is only available for the period posterior to 2006[12]. I hence use a simple regression model to back-cast the residential price series, using global prices.[13]

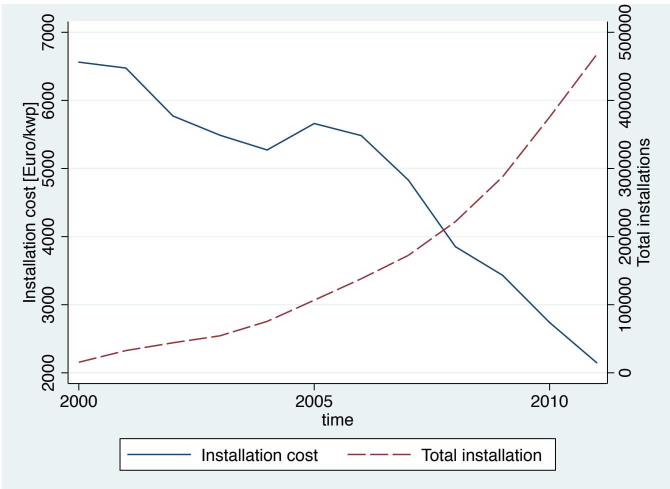

Figure 3.1: Total number and cost of household solar PV installations.

Moreover, I make use of household level data from the German Socio Economic Panel (GSOEP), a representative longitudinal study of German households. While the full data consists of around 21,000 households, it is only from 2007 onwards that the questionnaire includes variables related to renewable energy installations (solar) and only from 2010 detailed information on household electricity consumption. Moreover, the GSOEP does not allow to identify the exact timing of solar installations and it does not have information on plant size. I hence use individual level solar PV installation data and aggregate them at annual level in order to obtain the aggregate technology adoption path. Secondly, I use the data from the network carrier to obtain estimates of the average plant size. Even considering these shortcomings, the GSOEP dataset has the main

[11] http://www.eeg-kwk.net/de/index.htm
[12] German Solar Industry Association
[13] Given the high and sustained market share of Germany in the worldwide solar PV market, this relationship is likely to hold over time. In fact, the predicted price gets arbitrary close to the true price data for the in-sample period (2006-11) with a mean absolute error of 310 Euros (standard deviation of 262), which represents a deviation of around 6% in 2006.

advantage that it contains longitudinal information for household and personal characteristics such as income, age, education and living standard variables, that potentially play an important role in the decision to invest in solar PV and that are included in the empirical analysis of this paper.

Tables 3.6 and 3.7 in the appendix provide summary statistics for the main variables of interest. Table 3.6 focuses on those households that have been reported for the full sample period 1990-2011 (i.e. a "balanced" subsample based on 2,681 households (out of 21,673) with 58,982 observations). However, given the fact that solar PV ownership is only recorded from 2007 onwards, my sample reduces to a total of 13,000 observations. For the estimation of the lifecycle model I focus on this balanced subsample for which I can observe both income and savings over the entire time horizon.

As shown in Table 3.6, for this subsample, around 7% of all households own a solar panel. Moreover the data shows some differences between solar panel owners and non-owners: income and savings are higher for the group of solar panel owners, they are on average better educated, the head of household is younger, and they are more likely to be the owner of the house. Finally, the group of solar panel owners is more likely to live in newer houses[14] and rural areas.[15] Nevertheless, none of these differences are statistically significant. In order to contrast the statistics from the reduced sample with the full GSOEP sample, Table 3.7 reports the same statistics for all observations, where the differences in earning and saving between the two groups become even more evident.

3.3.2 Empirical analysis

In order to evaluate which variables play an important role for the household investment decision, I use data from GSOEP and run a probability model (Probit) on pooled data for both the balanced and unbalanced dataset. The results are reported in Table 3.8 to 3.10 in the appendix.

[14]construction year = 1 if built before 1980, 2 if built between 1980 and 2000, and 3 if later than 2000

[15]The table also provides different opinion variables on noise and air pollution, adequacy of green fields and parks. These variables can serve as a proxy for living conditions and environmental attitudes.

The dependent variable in the Probit model is whether the household owns a solar installation or not. As it is shown in Table 3.8, log income is significantly correlated with the solar variable in all specifications, but when including lagged savings (column 5) [16]. On the other hand, higher education (education above high school omitted), younger age of head of household, household size, house ownership, recent year of construction (after 2000),[17], and location (outside of the urban areas) are all factors that are positively correlated with owing a solar PV plant.

Contrasting these findings with the full sample (Table 3.9), I find very similar point estimates, which are however more precisely estimated, due to the bigger sample size. For instance, in Table 3.9 additional control variables show up to be statistically significant and both income and lagged savings are positively correlated with owing a solar PV plant. Including furthermore aggregate variables (feed-in-tariffs, cost of solar PV installation, and electricity price), only the price of electricity shows up to be positively and significantly correlated with solar PV ownership at 1%, indicating that solar PV might serve as insurance against increasing electricity prices.[18] As further robustness check, I run a random-effect Probit model and find a very similar pattern (results reported in Table 3.10). Interestingly in the panel model both the level of FIT and the electricity price are positive and statistically significant.[19] The next section builds on the insights obtained from the empirical analysis and I construct a model of household investment in solar PV.

[16]Note that log income and log savings are highly correlated with a correlation coefficient of .39, statistically different from zero at 1%

[17]Changes in building standards might have an impact on the decision to invest in either solar PV or solar heating when building a new house or renovating an old building.

[18]Given the increase in household electricity price in recent years, including the price of electricity in the regression captures a possible time trend. In fact, the findings are robust to including a linear and quadratic time trend in the regression.

[19]The Random effects (RE) model depends on the assumption that the unobserved individual effects are uncorrelated with other explanatory variables. If the RE Probit is the true model, the reported rho value being close to unity implies that the panel-level variance component is rather important and thus the results differ from the pooled estimator.

3.4 The theoretical model

The here presented dynamic model of discrete choice describes the decision of a household to investment in a solar PV system. I consider a household that receives in each period of life stochastic income y. The household faces the choice of how much of his income to save (A_{t+1}) and how much to consume (c). Furthermore, he has the choice of how much electricity (x) to consume and whether or not to invest in a solar PV plant. Consumption of both in-kind goods and electricity yields utility. As in Reiss and White (2005) I do not consider electricity to be consumed directly, rather a demand for electricity is derived from the flow of services provided by household's durable energy-using appliances. Hence the amount of electricity consumed can be thought of as a proxy for the service flow from (durable) appliances[20]. I follow the literature on durables in a life-cycle context, similar to Fernandez-Villaverde and Krueger (2011), and assume that the period utility function is of the standard constant relative risk aversion (CRRA) type:

$$u(c_t, x_t) = \frac{(g(c_t, x_t))^{1-\gamma} - 1}{1-\gamma}$$

where $g(\cdot)$ is an aggregator function of the service flows from electricity and consumption good. A general choice for the aggregator is of the constant elasticity of substitution (CES) type of the form

$$g(c_t, x_t) = [\nu c_t^{\tau} + (1-\nu)x_t^{\tau}]^{\frac{1}{\tau}}$$

such that both $c_t \geqslant 0$ and $x_t \geqslant 0$. Following Fernandez-Villaverde and Krueger (2011), for the numerical simulation and solution, I set the elasticity of substitution τ equal to zero, given the high sensitivity of τ to the overall specification of preferences and the limited empirical evidence on substitutability between (service flow from) electricity and consumption good. Setting τ equal to zero implies that the aggregator takes the form of a Cobb-Douglas function [21].

$$u(c_t, x_t) = \frac{(c_{t,}^{\nu}(x_t)^{1-\nu})^{1-\gamma} - 1}{1-\gamma}$$

[20] Alternatively, as in Jacobsen, Kotchen, and Vandenbergh (2012), electricity is also found to be modeled to yield direct utility.

[21] Figure 3.10 in the appendix provides evidence on the positive relationship between log income and log electricity using data from GSOEP. Higher income is hence related with higher electricity consumption.

The representative household maximizes the expected lifetime utility over T periods, subject to the following constraints:

$$\max_{c_t, x_t} E_t \sum_{t=1}^{T} \beta^{t-1} u(c_t, x_t)$$

$$\text{s.t.}$$

$$c_t + A_{t+1} + (1 - \alpha(1 - I_a))x_t p_e + (G(Q_{t-1}) + \pi)I_G \leqslant y_t + A_t(1 + r) + I_a F_{t=t_I}$$

$$A_t \geqslant 0$$

$$A_{T+1} = 0$$

$$y_{t+1} = (1 - \rho)\mu_y + \rho y_t + \varepsilon_{y,t+1}$$

$$F_t = (1 - df)F_{t-1}, F_1 \, given$$

$$G(Q_{t-1}) = a(Q_{t-1})^b$$

where in addition to the above introduced parameters, p_e is the price of electricity, $I_G$is an indicator variable equal to one in the period the household decides to invest. When investing the household has to pay a one time set-up cost $G(Q_{t-1})$, that depends on the cumulative technology uptake in the economy at the beginning of the period (equation 1). The parameter π on the other hand will be structurally estimated and can either represent an additional information and search cost (if positive) or capture the idea that investors receive some kind of "warm glow" when doing something good for the environment and evaluate their cost below the true technology cost (Kotchen (2006)). I_a is an indicator variable equal to one in all periods following investment for which the household receives FIT. The length of payment of the policy is determined by the policy parameter horizon h. $I_a = 1$ hence implies that the household receives the annual feed in tariff $F_{t=t_I}$. After h years, the household is still able to profit from the solar plant, reducing his annual electricity bill by a share α. Finally, the household can invest in bonds at the annual risk-free interest rate r in order to build up a savings stock and to smooth the consumption profile while facing stochastic income, which evolves according to the above specified AR(1) process, with $\varepsilon_{y,t}$~$N(0, \sigma_\varepsilon^2)$.[22]

[22]The full model estimated in the next section furthermore includes a random i.i.d. utility shock.

Given the constraint $A_t \geqslant 0$, the borrowing limit is effectively set to zero, which means that the household has to build up assets in order to realize investment in a solar plant.[23] By assumption, households live for T periods and given that there is no bequest motive ($A_{T+1} = 0$) it is optimal to consume all savings as well as the remaining net present value of the solar installation in the last period. For the numerical simulation, I choose to replicate the time horizon 1990-2011. Given the fact that solar installations are typically maintenance free and have a life duration exceeding the policy horizon, I do not model this component. Finally, I make the assumption that each household can only invest in one plant of average size, and once the household installs this capacity, the system cannot be replaced, i.e. there is no resale, destruction or replacement of technology.[24]

Recursive formulation

In recursive formulation, the state space at time t is given by the vector

$$\Omega_t = [y, A, G(Q), F, a, \epsilon]$$

Where y is the household income, A the stock of assets, $G(Q)$ the cost of investment as a function of cumulative technology uptake, F the Feed-in-tariff policy, a the age of the plant, that is necessary to determine the duration for which F is paid, and ϵ, a random utility shock[25]. As pointed out above, FIT policy actually depends on three policy parameters that jointly determine F in each period: the initial FIT level, the degression rate and the policy horizon. Conditional on the states, the household chooses in each period of life optimally consumption (savings), electricity as well as whether or not to invest in a solar PV plant. The investment decision is determined by the following discrete choice:

$$V(\Omega_t) = \max \{V^N(\Omega_t), V^I(\Omega_t)\}$$

[23] More realistically, I could experiment with different set of borrowing limits related to the income profile and the value of the solar plant, however this feature would not add additional insight to the discussion while considerably increasing complexity.

[24] This assumption is rather realistic for the case of solar PV given customized installation of plants and the fixed incentive schemes.

[25] The random utility shock is introduced in order to obtain additional variability in the aggregate uptake path, when matching the data. I allow for three different values and make furthermore the assumption that the utility shock and the income shock are independent from each other.

where the superscript N refers to "not investing" and the superscript I refers to "investing". As outlined above, the one time installation and setup cost $G(Q)$ enters the household budget constraint only in the period of investment. Similar to Cooper and Haltiwanger (1993), I assume that the installed system becomes productive immediately[26], and also FIT are paid within the same period of installation. Once the investment decision is taken, FIT are locked in at a level $F_{t=t_I}$ and paid for a years ($a \leqslant h$).

Income is modeled as an autoregressive process of order one with unconditional mean μ, autocorrelation coefficient ρ_y , and error ε.

$$y' = (1-\rho_y)\mu + \rho_y y + \varepsilon'$$

Following the Tauchen (1986) procedure, this process can be approximated by a Markov transition matrix [27] The autocorrelation coefficient as well as the standard deviation of the income shock have been estimated with GSOEP data. I moreover assume the price of electricity p_e to be fixed in order to focus on the impact of the policy channel. F follows an exogenously given deterministic discount rates d_f, set by the policy maker, while the cost of technology $G(Q)$ is endogenously determined, depending on the cumulative uptake in the previous period.

$$F' = (1-d_f)F, \text{ with } d_f < 1$$

Substituting in the budget constraint for consumption, the household determines savings (assets next period, A') and the optimal amount of electricity x. Note that while A' is a dynamic choice, the optimal electricity choice is static.

The value function for investing $V^I(\cdot)$ is given by

$$V^I(\Omega_t) = \max_{A',x}\{\epsilon(u(y + A(1+r) + FI_a - (1-\alpha(1-I_a))xp - A' - I_G G(Q), x) +$$
$$+\beta E_{y',\epsilon'|y} V^I(y', A', F, a', \epsilon'))$$

[26]In 2011 the average time of installation has been 5.3 weeks with a standard deviation of 2.2 weeks for Germany (Seel, Barbose, and Wiser (2013)).
[27]I allow for seven income states.

On the other hand, the value function for not investing $V^N(\cdot)$, is the utility of consumption of the household in the current period $y + A(1 + r) - xp - A'$ plus the continuation value $V(\cdot)$ which depends upon the choice of investing in the successive periods. Hence $V^N(\cdot)$ is defined as

$$V^N(\Omega_t) = \max_{A',x}\{\epsilon(u(y + A(1+r) - xp - A', x) + \beta E_{y',\epsilon'|y} V(y', A', G', F^{'}\epsilon')\}$$

Both subject to the constraints:

$$\begin{aligned} A' &\geqslant 0 \\ A'_T &= 0 \end{aligned}$$

Given the finite time horizon, the model can be solved backward. Starting at period T, it is optimal for the household not to accumulate any further savings ($A'_T = 0$). Thus, conditional on the realization of the income and the random utility shock, as well as the other states, the household choses optimally A'. The optimal choice for electricity can be found using the first order condition of utility with respect to electricity, $\frac{\partial u(c,x)}{\partial x} = 0$, which implies:

$$\frac{c}{x} = \frac{\nu[p_e(1 - \alpha(1 - I_a))]}{(1 - \nu)}$$

In the standard version of this model, the ratio of consumption to electricity is equal to the ratio of the coefficient $\frac{\nu}{(1-\nu)}$, however given the fact that electricity enters the utility function both directly and indirectly through the budget constraint, the nominator depends additionally on the price of electricity p_e and the age of the solar PV plant (receiving FIT or not). The optimal saving-consumption path as well as electricity choice can be obtained by iterating backward until period $t = 1$. The backward solution also provides me with the investment decision of the household in the solar PV plant.

3.5 Estimation

A first set of parameters describing the income process as well as the learning model are estimated using ordinary least square (OLS) regression before solving the model numerically. In order to estimate the income process, I first linearly detrend the income variable as the model does not allow for a trend. Furthermore I estimate a linear version of the learning model (equation 1), as derived in the appendix. The estimated coefficient b is the learning curve parameter and relates directly to the learning rate in a given industry. The learning rate, defined as $(1-2^b)$ expresses hence the cost decrease of producing one unit due a a doubling of aggregate output. Using data for the sample period 1990-2011, I find $b = -0.23$, which implies a learning rate of around 14.7%[28]. Wand and Leuthold (2011) provide an overview of estimated learning rates for solar PV and shows that at global level learning rates are between 18% and 22%. Estimation results for both the income regression and learning rate can be found in the appendix.

Moreover, given the interest rate r, I set the discount rate $\beta = \frac{1}{1+r}$. The parameters to be estimated structurally are summarized by $\Theta = (\gamma, \nu, \pi, \lambda_z)$, where both γ and ν are utility parameter describing risk aversion and share of income spent on electricity and consumption good. The remaining structural parameters relate to the additional "cost" that a household experiences when investing in a solar plant, π, and the scaling factor for the standard deviation of the random utility shock λ_z.

I estimate the set of structural parameters using simulated method of moments (SMM)[29]: For a given set of parameters, I solve the model and simulate the life of 10,000 agents in order to calculate the investment share in solar as well as the correlation, mean and standard deviation of key variables such as electricity consumption, savings and saving to income ratio. I furthermore verify that the predicated and realized investment paths

[28] Lobel and Perakis (2011) find a learning curve parameter of -.12 for German solar PV, which is lower due to the fact that they limit their sample to the period prior to 2007 as well as the choice to include all PV installations up to 30kwp.

[29] Alternatively, it would be possible to infer the utility parameters from the first order condition of $V^I(\cdot)$, a continuous function, and estimate the Euler Equation by Generalized Method of Moments. This procedure would have the advantage that the model can be estimated without solving it numerically. However the small number of investors in the GSOEP data and the short time dimension make this approach unfeasible.

are consistent [30]. The detailed set of micro moments can be found in the appendix.

Following Adda and Cooper (2000), I minimize a joint criteria consisting of the aggregate sales path, expressed as the squared distance between predicted and observed sales of solar PV, weighted by α, the empirical inverse of the variance

$$L^1(\Theta) = \alpha[F_t - F_t(\Theta)]^2$$

and the squared distance of the simulated and observed micro level moments, weighted by W, the optimal weighting matrix obtained from the empirical data.[31]

$$L^2(\Theta) = (\Psi^D - \Psi^S(\Theta))' W (\Psi^D - \Psi^S(\Theta))$$

Thus, the joint criterium that is minimized in order to obtain the structural parameters is

$$\min_{\Theta} L(\Theta) = L^1 + L^2 \tag{3.1}$$

I find a parameter of risk aversion $\gamma = 4.696$, which seems to be of reasonable magnitude. Even though the economic literature is far from agreeing on the exact size of the risk aversion parameter for CRRA type utility functions, as pointed out in Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2005) who investigate individual risk attitudes for Germany, a CRRA coefficients in the interval [0,5] can fit most of the empirical observations.[32] The utility parameter $\nu = 0.951$ on the other hand determines the share of consumption good and electricity for each unit of income. Looking at the average electricity expenditure share of income in the empirical data, I find it around 2.8%. In fact the model fits almost perfectly the mean electricity consumption and standard deviation of the data.[33]. The estimated "cost" parameter $\pi = -2.837$ shows a negative

[30]This implies consistent believes of households regarding the cost of solar PV, given the learning-by-doing model.

[31]While estimating with unit weights would lead to consistent estimates, it would not be efficient. The appendix describes in detail the estimation algorithm and how the weighting matrix has been obtained from the empirical data.

[32] Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2005) also show that the distribution of CRRA coefficients is heavily skewed towards the right and that there is an important number of individuals found to have risk aversion coefficients of 10 or larger.

[33]The complete set of moments can be found in the appendix.

	Paramter value
γ	4.696
ν	0.951
π	-2.837
λ_z	0.482

Table 3.1: SMM parameter estimates

sign.[34] Hence, the 'perceived' cost of a solar plant lies almost 3000 Euros below the actual cost.[35] Considering the average cost of a plant of 43,000 EUR for the period 1990-2011 (30,000 EUR for the sub-period 2000-11) this translates into an non-negligible price reduction of around 6% (9%). Finally, the variance of the individual utility shock parameter $\lambda_z = 0.482$ is found to be important too. This parameter estimate translates into a standard deviation of the random utility shock of 0.048.[36]

3.6 Simulation and policy experiments

Before analyzing the impact of distinct policies on solar PV uptake, I show results for the benchmark case. Table 3.2 gives an overview of the complete model parameters, that are used to simulate the model. The FIT policy is modeled as it has been in place since 2000 (see Figure 3.4 in the appendix).

Analyzing the aggregate sales path and comparing the empirical data with the simulated one (Figure 3.2), I find that the model describes well the shape of the data, i.e. the recent rise of solar PV investment; however it highly over predicts investment shares. While in the empirical data, the solar PV market penetration [37] is below 1.5% , in the

[34]For the correct interpretation, the estimate has to be multiplied by 1000.

[35]Note that π could be also interpreted in an alternative way, as it might captures unobserved factors that are not explicitly modeled, but that influence the aggregate uptake in the empirical data.

[36]I acknowledge the importance of adding standard errors to the here presented point estimates. This is currently work-in-progress.

[37]Defined as solar PV installations over market size in a given year; where the market size is based on the total number of households in 1990 minus the households that installed in $t-1$

Interest rate	4.2	Percent
Discount rate	0.959	
Price electricity	0.23	Euro / kwh
Income parameters		
Mean household income	34354	Euro
Autocorellation coeff.	0.857	
Std(income)	8925	Euro
Solar installation		
Avg plant size	6.31	kwp
Avg electricity produced	5521	kwh / year
Share of autoconsumption	30	Percent
FIT Policy Parameters		
Fit (2004)	0.57	Euro / kwh
Degression rate	5	Percent
Horizon	20	years
Learning Parameters		
ln(a)	9.113	
b	-0.232	

Table 3.2: Model parameterization

model economy, the investment share reaches 50%[38].

Using the benchmark scenario, I simulate different FIT policy changes that could be implemented to reduce the cost of FIT policies. Note however that, given the partial equilibrium setup of the model, I cannot make claims regarding overall welfare impacts of policy changes, as this would require specifying an explicit objective function of the policymaker which should include general equilibrium considerations [39]

I study the impact of policy changes in each of the three key elements that jointly determine the FIT schedule (initial level of FIT, annual degression rate and policy horizon) to identify the most effective feature in terms of uptake. The appendix (Figure 3.6-3.9) shows the aggregate uptake path for each of the experiments. In Figure 3.6, the FIT rate is revised downwards by 20% in 2004. Compared to the benchmark simulation, the number of installations remains almost 20% below the original path and only in the final year recovers to aggregate installation numbers comparable with the original path. In case

[38]As suggested by the GSOEP data, the empirical number of households owing solar PV plants would be considerably larger considering only those households that are "owners" of their private houses. One possibility to better match the lower uptake path would be to include additional heterogeneity in the model, for example in terms of household size groups.

[39]In fact, it was a strategic choice of the German government to implement the EEG act, in order to promote "green growth" and the creation of new jobs in the solar industry.

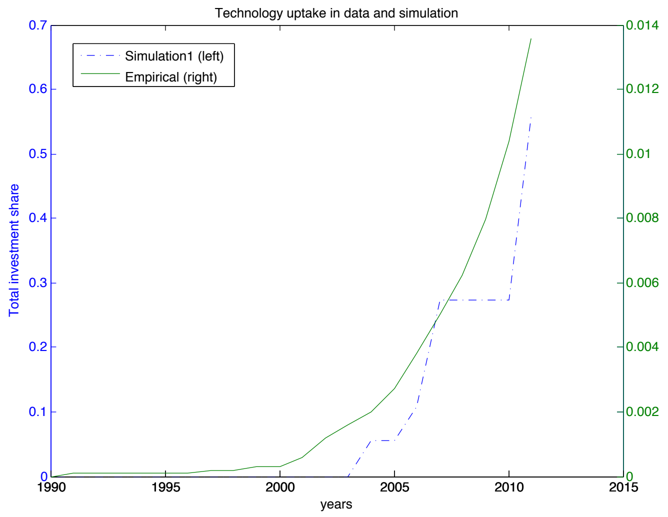

Figure 3.2: Predicted and realized technology uptake

the benchmark level was reached in the last period, this would be clearly a favorable scenario for the policy maker as higher investment at a later point in time are less costly in terms of policy support. Changing the degression rate, on the other hand (Figure 3.7), has quantitatively the biggest impact on aggregate uptake. Also in this case, the initial uptake is unaffected, from year 2007 onwards, nevertheless the number of installations remains around 43% below the benchmark case, and recovers only in 2011.

Figure 3.8 shows the results when the horizon is downward revised to 15 years. Interestingly this policy measure does not lead to an initial drop in the investment compared to the baseline, but at later years it reduces the uptake similarly to the degression rate, with quantitatively smaller impact. Given the FIT schedule, 15 year of policy support are enough to make the investment profitable, as the cost of solar drops heavily once there are sufficient investors. Finally, an interesting implication can be found when looking at the impact of an increase in the price of electricity on the aggregate solar PV uptake. A doubling in the household electricity price leads to a steeper technology uptake path and higher overall adoption. As pointed out in the empirical section, households might decide to invest in solar PV in order to insure against rising electricity prices.[40]

[40]FIT are financed through a surcharge on the cost of electricity. The surcharge for 2012 was 3.59 cent per kWh electricity (considering an average price of 23 cent / kWh for the period 1990-2011 this represents a share of around 15%.

3.7 Conclusion

This paper has the objective to investigate the impact of feed-in tariff policies (FIT) and their design features on the household investment decision in solar PV. For this purpose, I build a dynamic stochastic discrete choice model of household investment to simulate current policies as well as to analyze alternative policy scenarios.

A preliminary empirical analysis reveals that both income and savings are important household variables correlated with the investment decision in a solar PV plant. The model presented in this paper builds on these empirical insights and performs a series of policy experiment in order to assess how changes in key policy parameters (individually) can impact the investment decision of the household and the aggregate uptake path. I find that the different policy parameters have an heterogenous impact on the household incentives and translate to differences in the aggregate technology uptake path. A reduction in the degression rate hence has the biggest negative impact on investment. I also find that an increase in electricity prices is positively correlated with new installations, a feature that is also present in empirical data.

The paper furthermore shows that there are important gains related to modeling the investment decision of the household using a detailed micro founded model. Future work, analyzing the optimal FIT schedule, could hence build on these insights and use the modeling setup together with the generated demand for PV as input for a policy maker's objective function in order to minimize overall cost while targeting a certain level of technology penetration.

3.8 Appendix

3.8.1 Estimation

Income process

In order to maximize the number of observations to estimate the autocorrelation coefficient, I use the full panel time dimension 1984-2011[41]. Given the fact that the GSOEP data only provides monthly net household income, I construct an annual series by multiplying monthly income by 12[42], and clean for outliers by dropping the first and then 99th percentile of the data. After deflating the series by the annual consumer price index, I regress income on a time variable in order to obtain a detrended series. In a second step, I run a pooled regression to estimate the autocorrelation coefficient ρ and the standard deviation of the shock. ε_y. The residual of this regression is the standard error of the income shock, which by construction shows a mean of zero. The standard deviation is 8,925 EUR.

Learning curve

As introduced in the main section, the learning curve model specifies that the cost of solar depends on total cumulative production. To be more precise G, the cost of an installation depends on the total past number of installations at the beginning of the period (Q_{t-1}). The model assumes that the average cost of producing the marginal unit has constant elasticity relative to cumulative output. In order to estimate the learning curve parameters empirically, I take the logarithm yielding

$$\ln G_t = \ln a + b \ln Q_{t-1}$$

The coefficient b is expected to be negative and captures the decrease in average cost when cumulative output increases by 1%. The slope of the learning curve, is defined as the ratio of average cost of production of one unit as output doubles.

$$s = C(2Q)/C(Q) = 2^b$$

[41]I run the regression also only for the time period 1990-2011; results are robust.

[42]This can hence be seen as a lower bound for net annual household income.

Table 3.3: Auxiliary Regression: Income

Dependent variable:	
Income	(1)
	β / SE
l.income	0.857^{***}
	(0.001)
Constant	-79.349^{***}
	(22.629)
Observations	156601
R^2	0.731

* p < 0.1, ** p < 0.05, *** p < 0.01.
Standard errors in parentheses.

Hence when cumulative output doubles, the cost of producing one unit decreases by (1-s)%. This concept is widely referred to as learning rate.

Figure 3.3 shows the relationship in logs between the cost of solar PV and total household installations. Table 3.4 reports the estimation results. I find a point estimate for $b = -.23$, which corresponds to a learning rate of 14.87%.

Structural Estimation

In order to estimate the set of structural parameters $\Theta = (\nu, \gamma, \pi, \lambda_z)$, I use two set of moments. Firstly, I match aggregate investment shares in solar PV. For this purpose I aggregate individual installations by year and form investment shares dividing them by the total number of households in 1990.[43] The second set of moments is related to the micro data obtained from GSOEP. I calculate a total of seven data moments, which are the correlation between savings and income, the mean and standard deviation of elec-

[43]When calculating investment shares, I take into account the decreasing market size each year, given that investment is an absorbing state.

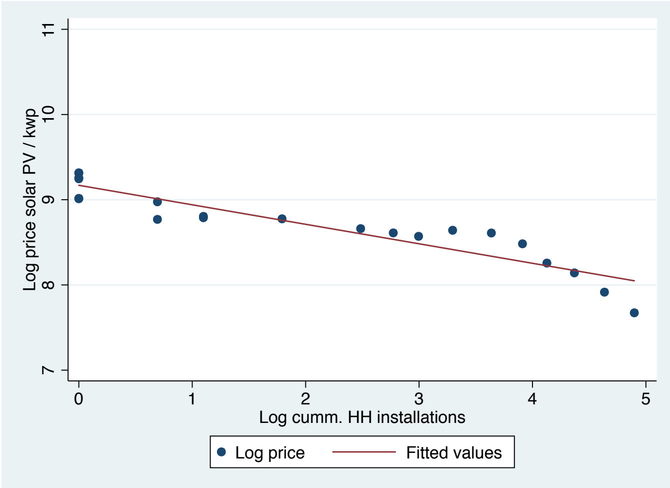

Figure 3.3: Estimated learning curve for household solar PV installations.

tricity consumption, of savings as well as of the saving-to-income ratio.

The optimal weighting matrix for the micro moments is obtained using the variance-covariance matrix of the empirical moments Ω^D by bootstrapping:

$$W = \left(\frac{1}{(1+S)}\Omega^D\right)^{-1}$$

where S is the length of the bootstrap sample. In order to calculate W, I draw 1,000 bootstrap samples from the empirical data and compute the moments for each sample. The vector of moments are then used to determine the variance-covariance matrix Ω^D[44].

For the structural estimation, I solve the minimization problem, described in (2) in two stages. First I run a simulated annealing algorithm[45] and use the obtained estimates in a second stage with `fminsearch`, in order to refine the results.[46] This procedure is likely to overcome the issue of local minima in which the `fminsearch` algorithm might get trapped.

[44] See Gourieroux, Monfort, and Renault (1993)

[45] Matlab global optimization toolbox `simulannealbnd`

[46] For robustness, I experiment using the simulated annealing algorithm with different set of starting values.

Table 3.4: Auxiliary Regression: Learning rate

Dependent variable: Log price	(1) β / SE
L.Log cumm. HH installations	−0.232***
	(0.023)
Constant	9.113***
	(0.058)
Observations	20
R^2	0.849

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Moments	**Empirical (GSOEP)**	**Simulated (n=10000)**
corr(inc,sav)	0.377	0.124
mean(ele)	3135.639	3203.300
sd(ele)	1654.496	1672.500
mean(saving)	5366.443	3202.000
sd(saving)	6730.842	1090.100
mean(sav/inc)	0.137	0.104
sd(sav/inc)	0.112	0.036

Table 3.5: Micro Moments in the empirical data and from model simulation

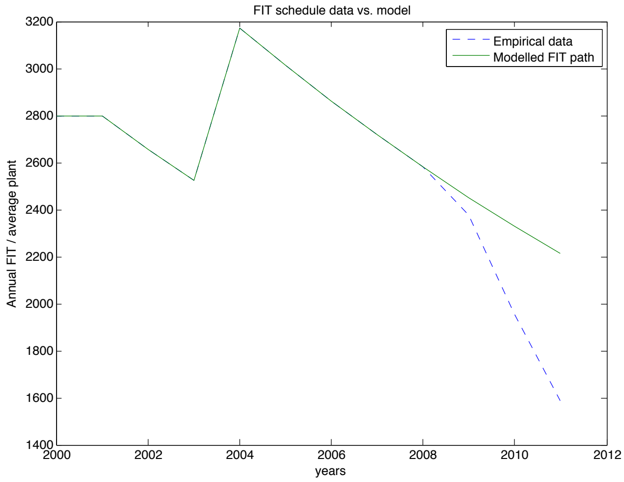

Figure 3.4: FIT policy data and model

3.8.2 Simulation

Averaging over 10,000 individuals, the mean income profile is practically flat (see Figure 3.5). However stochastic income and the random utility shock translate into variation in consumption, given the household's precautionary savings motive.

Figure 3.5: Simulation for the average household, 1990-2011, n=10000

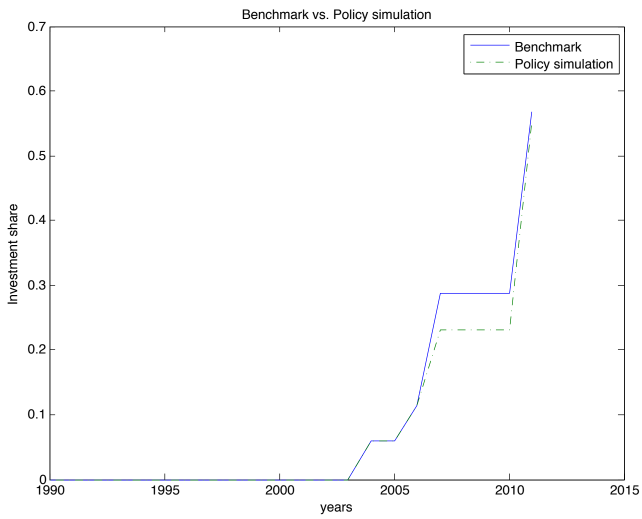

Figure 3.6: Policy simulation: Initial FIT level -20%

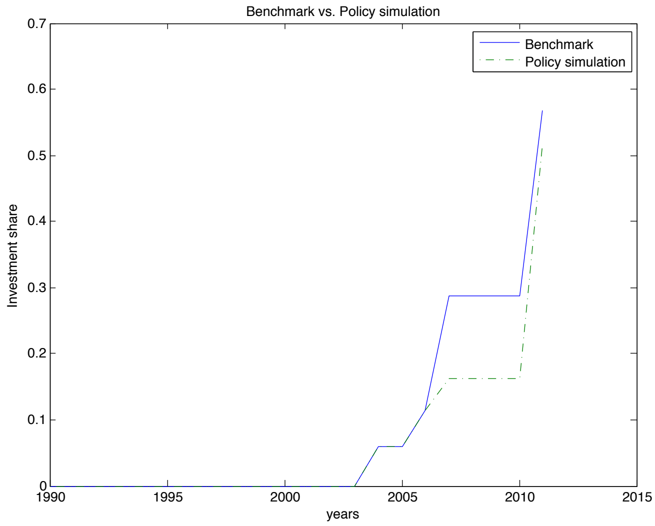

Figure 3.7: Policy simulation: Degression rate 9%

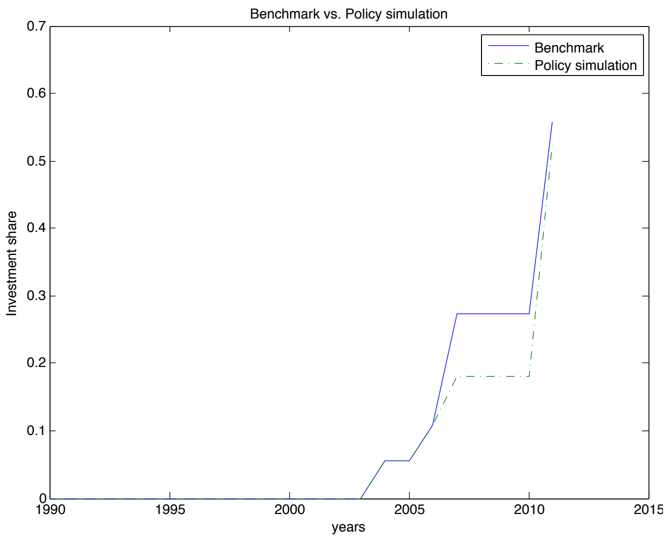

Figure 3.8: Policy simulation: 15 years FIT horizon

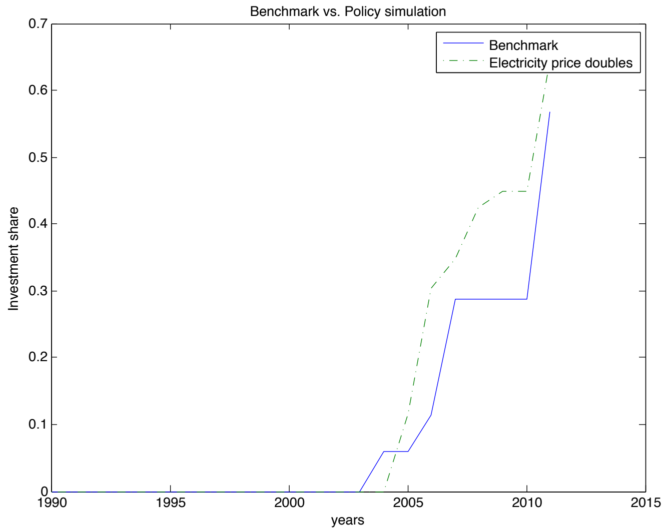

Figure 3.9: Policy simulation: Price of electricity doubles

3.8.3 Empirical evidence

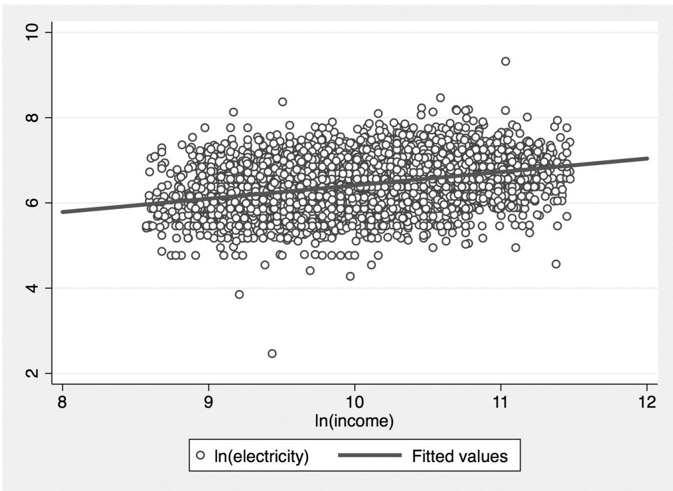

Figure 3.10: Relationship between log income and log electricity

Table 3.6: Summary statistics: balanced panel 1990-2011

	all	solar	no solar
HH net income	29524	36145	29036
	(15211)	(16667)	(14983)
HH annual savings	4983	6034	4894
	(7184)	(7851)	(7118)
Observations	12539	880	11659
Solar PV	0.07	1.00	0.00
	(0.25)	(0.00)	(0.00)
Education			
< highschool	0.17	0.11	0.17
	(0.37)	(0.31)	(0.38)
highschool	0.60	0.52	0.61
	(0.49)	(0.50)	(0.49)
> highschool	0.23	0.36	0.22
	(0.42)	(0.48)	(0.41)
Age head of HH	58.83	57.32	58.94
	(15.52)	(13.52)	(15.65)
Size of HH	1.84	2.05	1.82
	(0.64)	(0.59)	(0.64)
Owner	0.49	0.74	0.47
	(0.50)	(0.44)	(0.50)
Construction year	2.00	2.14	1.99
	(0.88)	(0.94)	(0.87)
Distance to city	3.20	3.47	3.18
	(1.50)	(1.44)	(1.50)
Complain noise	1.89	1.91	1.89
	(0.92)	(0.97)	(0.92)
Complain air	1.79	1.83	1.79
	(0.85)	(0.87)	(0.85)
Complain green	1.40	1.29	1.41
	(0.73)	(0.63)	(0.74)
Electricity	2781.36	2771.91	2781.91
	(1604.41)	(1439.24)	(1613.74)
Observations	13220	921	12299

Table 3.7: Summary statistics: All observations 1990-2011

	all	solar	no solar
HH annual savings	32444	41557	31727
	(18576)	(19938)	(18273)
HH annual savings	5934	8704	5681
	(12013)	(26133)	(9713)
Observations	42749	3184	39565
Solar PV	0.07	1.00	0.00
	(0.26)	(0.00)	(0.00)
Education			
< highschool	0.13	0.08	0.13
	(0.33)	(0.27)	(0.34)
highschool	0.61	0.55	0.62
	(0.49)	(0.50)	(0.49)
> highschool	0.26	0.37	0.25
	(0.44)	(0.48)	(0.43)
Age head of HH	57.73	55.54	57.90
	(15.50)	(13.16)	(15.66)
Size of HH	1.87	2.15	1.85
	(0.66)	(0.63)	(0.66)
Owner	0.53	0.82	0.51
	(0.50)	(0.38)	(0.50)
Construction year	2.12	2.32	2.11
	(0.96)	(1.01)	(0.95)
Distance to city	3.22	3.59	3.19
	(1.48)	(1.46)	(1.48)
Complain noise	1.86	1.81	1.86
	(0.94)	(0.93)	(0.94)
Complain air	1.71	1.67	1.71
	(0.83)	(0.83)	(0.83)
Complain green	1.34	1.25	1.35
	(0.68)	(0.57)	(0.69)
Electricity	2800.64	2874.43	2797.84
	(1707.18)	(1737.51)	(1706.07)
Observations	48459	3520	44939

Table 3.8: Probit: balanced panel

Dependent variable: Solar PV	(1)	(2)	(3)	(4)	(5)
	β / SE	β / SE	β / SE	β / SE	β / SE
ln(income)	0.431***	0.173***	0.169***	0.194***	0.078
	(0.036)	(0.048)	(0.049)	(0.050)	(0.069)
L. ln(saving)					0.020
					(0.028)
< Highschool		−0.249***	−0.253***	−0.258***	−0.133
		(0.065)	(0.066)	(0.066)	(0.085)
Highschool		−0.222***	−0.226***	−0.230***	−0.224***
		(0.043)	(0.043)	(0.044)	(0.052)
Age head of HH		−0.002	−0.003*	−0.002*	−0.005***
		(0.001)	(0.001)	(0.001)	(0.002)
Size of HH:2-3		0.195***	0.208***	0.196***	0.264***
		(0.055)	(0.055)	(0.055)	(0.070)
Size of HH: >3		0.205***	0.225***	0.203***	0.383***
		(0.075)	(0.076)	(0.076)	(0.098)
Owner		0.421***	0.433***	0.409***	0.382***
		(0.042)	(0.042)	(0.043)	(0.054)
Constr. yr >1949, <=1980		0.105**	0.111**	0.120***	0.068
		(0.044)	(0.044)	(0.045)	(0.055)
Constr. yr >1980, <=2000		0.029	0.030	0.039	−0.054
		(0.054)	(0.054)	(0.055)	(0.067)
Constr. yr > 2000		0.238***	0.226**	0.254***	0.143
		(0.090)	(0.091)	(0.091)	(0.111)
Distance to city				0.057***	0.047***
				(0.013)	(0.016)
Complain noise				−0.010	−0.026
				(0.028)	(0.036)
Complain air				0.067**	0.076**
				(0.029)	(0.038)
Observations	12240	11442	11442	11442	6929
Pseudo R^2	0.026	0.057	0.068	0.072	0.063
Aggregate controls	N	N	Y	Y	Y

The regression results are robust to the inclusion of linear and quadratic time trends.

Table 3.9: Probit: unbalanced panel

Dependent variable: Solar PV	(1) β / SE	(2) β / SE	(3) β / SE	(4) β / SE	(5) β / SE
ln(income)	0.481***	0.166***	0.170***	0.206***	0.121***
	(0.018)	(0.025)	(0.025)	(0.027)	(0.039)
L. ln(saving)					0.059***
					(0.016)
< Highschool		−0.089**	−0.094**	−0.089**	0.023
		(0.039)	(0.040)	(0.042)	(0.056)
Highschool		−0.089***	−0.091***	−0.108***	−0.085***
		(0.023)	(0.024)	(0.025)	(0.031)
Age head of HH		−0.004***	−0.004***	−0.005***	−0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
Size of HH: 2-3		0.142***	0.149***	0.114***	0.183***
		(0.030)	(0.031)	(0.033)	(0.043)
Size of HH: >3		0.290***	0.304***	0.257***	0.360***
		(0.039)	(0.039)	(0.042)	(0.055)
Owner		0.592***	0.604***	0.570***	0.520***
		(0.024)	(0.024)	(0.026)	(0.033)
Constr. yr >1949, <=1980		0.097***	0.101***	0.120***	0.120***
		(0.025)	(0.025)	(0.027)	(0.033)
Constr. yr >1980, <=2000		0.088***	0.089***	0.093***	0.051
		(0.028)	(0.028)	(0.030)	(0.038)
Constr. yr > 2000		0.476***	0.462***	0.475***	0.477***
		(0.041)	(0.041)	(0.044)	(0.054)
Distance to city				0.081***	0.078***
				(0.007)	(0.009)
Complain noise				−0.015	−0.033
				(0.016)	(0.021)
Complain air				0.039**	0.056**
				(0.018)	(0.022)
Observations	41083	39667	39667	34636	20490
Pseudo R^2	0.038	0.085	0.095	0.102	0.094
Aggregate controls	N	N	Y	Y	Y

The regression results are robust to the inclusion of linear and quadratic time trends.

Table 3.10: Random effects Probit: unbalanced panel

Dependent variable: Solar PV	β / SE
ln(income)	0.371***
	(0.108)
Education: < Highschool	−0.088
	(0.198)
Education: Highschool	−0.248**
	(0.113)
Age head of HH	−0.017***
	(0.004)
Size of HH: 2-3	0.288**
	(0.134)
Size of HH: >3	0.710***
	(0.176)
Owner	1.213***
	(0.112)
Constr. yr >1949, <=1980	0.163
	(0.113)
Constr. yr >1980, <=2000	0.107
	(0.130)
Constr. yr > 2000	1.289***
	(0.192)
Distance to city	0.132***
	(0.031)
Complain noise	−0.073
	(0.063)
Complain air	0.079
	(0.070)
Cost solar PV	0.000
	(0.000)
FIT policy	10.210***
	(2.346)
Price electricity	104.319***
	(16.694)
Constant	−43.454***
	(5.584)
$\ln(\sigma^2(u))$	3.405
Rho	0.967
Observations	34636

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

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