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The personality profiles of early adopters of energy-efficient technology

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The personality profiles of early adopters of energy-efficient technology

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Abstract

This study investigates whether energy efficiency investments are driven by differences in personality traits among homeowners. Using data on nearly 3,000 households in Germany, we estimate that compared to the median level, homeowners in the lowest quartile of Openness to Experience have 5.0%-23.4% lower propensity to invest in capital-intensive energy efficiency measures, while homeowners in the highest quartile of Agreeableness are 7.7%-18.0% less likely to do so. Splitting the energy efficiency investments into two groups yields stronger effects of the same two personality traits for window modernisations and thermal insulation installations, whereas no impact of the personality traits is observed for solar energy and other alternative energy systems, possibly because subsidies for the latter were introduced much earlier in Germany, overriding any effects of personality traits in the investment decisions. These findings may also suggest that personality traits are of greater significance for marginal investors.

Keywords: Energy efficiency; Personality traits; Technology; Diffusion; Residential sector

1 Introduction

The importance of energy efficiency investments for the reduction of energy usage in residential buildings is well established, and yet, the uptake of energy-efficient technologies remains moderate (Ramos et al., 2015). While existing research has recognised the critical role of market barriers for the observed reluctance, such as informational and capital constraints (Gerarden et al., 2015; Jaffe & Stavins, 1994), possible behavioural explanations are still relatively unexplored (Stern et al., 2016).

The standard model that describes the diffusion of technologies throughout time is the Diffusion of Innovation (DoI) framework proposed by Rogers (2003). It suggests that along with socio-economic status and communication behaviour, the innovativeness of decision-makers is influenced by their personalities, which in turn affects the adoption speed of a technology. While personality is identified as an important factor in the DoI model, there is a paucity of empirical research focusing on the effects of personality on the diffusion speed of technology, partly due to difficulties in defining and measuring individuals' personalities.

This study attempts to establish if personality is a key driver behind the decision to be an early adopter of a costly energy-efficient technology. To do so, we extend the DoI model with the Big Five, a widely used taxonomy for measuring personality (Costa & MacCrae, 1992), and test the extended model empirically. We observe that homeowners with high levels of Openness to Experience invest earlier in energy efficiency, whereas agreeable homeowners tend to postpone such investments.

The findings illustrate that personality traits can pose a barrier for the deployment of energy efficiency measures in the domestic sector. At the same time, they represent an opportunity for cost-effective policy-making: instead of using heavy financial subsidies to promote energy efficiency, policy-makers can try to adjust their policy initiatives to groups

with predominant personality traits and nudge households toward the desired outcomes. We suggest how this could be achieved.

2 Literature review

There is a growing number of studies highlighting the importance of domestic energy efficiency improvements to mitigate climate change (IEA, 2013, 2015). Despite their potential to contribute to energy security, environmental sustainability and higher economic productivity without increasing energy input, the widespread adoption of energy efficiency measures in the residential building sector is lagging (Bardhan et al., 2014; Karlin et al., 2014).

A large body of literature has focused on identifying economic market barriers to explain this commonly called “energy efficiency gap”. Several lines of evidence suggest that households tend to underinvest in energy efficiency because the negative externalities of energy use (i.e. environmental pollution and health costs) are not sufficiently internalised in energy prices, keeping energy prices too low (Allcott & Greenstone, 2012; Gerarden et al., 2015; Ramos et al., 2015). It has been further argued that the lack of information about energy-efficient technology and the own energy consumption might detain households of investing in energy efficiency (Allcott & Rogers, 2014; Group, 2013). Other explanations include households’ liquidity constraints (De T’Serclaes, 2010), capital market imperfections (Ryan et al., 2012) and hidden costs (Allcott & Greenstone, 2012).

A number of studies have reported links between pro-environmental behaviour (e.g. indoor temperature reductions, recycling) and personal values and social norms. People who make decisions by evaluating the consequences for the ecosystem and biosphere as a whole (biospheric values) and have altruistic values tend to engage more in pro-environmental habits than egoistic people (Poortinga et al., 2004; Steg et al., 2014). Allcott (2011) found that social norms can direct households to mimic the energy saving behaviour of their peers.

Some researchers have examined the impact of personality traits on environmentally related decisions. In contrast to attitudes and norms, which are characteristic adaptations that result from a nexus of individual attributes and contextual factors such as political, social and cultural settings, personality traits define core and relatively fixed personal characteristics that affect how individuals react to stimuli that they encounter (McCrae & Costa Jr, 1999). Based on the Big Five, an established framework for measuring personality with five traits (Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism) (Costa & MacCrae, 1992; Goldberg, 1992), several studies have shown links between personality and environmental engagement. Milfont & Sibley (2012) found that Conscientiousness, Agreeableness, and Neuroticism are positively associated with home electricity conservation (e.g. turning off electric equipment when not in use, using energy-efficient appliances, air-drying clothes instead using clothes drier). Markowitz et al. (2012) showed a positive impact of Openness to Experience on environmental habits, such as using public transportation, carpooling and composting food scraps. Similarly, Brick & Lewis (2016) demonstrated that Openness to Experience, Conscientiousness and Extraversion are positively related to environmental attitudes, which in turn have an impact on pro-environmental activities (e.g. recycling, conserving water, using public transportation). In a study of choice preferences of different power generation programmes for wind farms in Spain, Khashe et al. (2016) reported that the choices correlated with individuals' Big Five personality facets.

Thus far, previous studies on personality traits and environmentally related decisions have predominantly addressed low-cost pro-environmental habits. However, the literature remains narrow in focus dealing with personality traits and energy efficiency investments. Unlike pro-environmental habits, costly energy efficiency improvements are rare decisions that allow to decrease energy usage without necessarily reducing the output service (Karlin et al., 2014; Pérez-Lombard et al., 2013). To fill this knowledge gap, this study centres on

the role of personality traits in energy efficiency investments in the domestic building sector, which may reveal fresh insights for the relatively slow diffusion of energy-efficient technologies in this realm. In line with the definition of energy efficiency by Pérez-Lombard et al. (2013), we consider passive energy-efficient technology (e.g. thermal insulation) and energy systems that generate energy from renewable resources “on-site” (i.e. the energy does not have to be delivered to the consumer) and that simultaneously reduce purchased energy, to be energy-efficient (e.g. solar electricity, geothermal heating).

3 A duration model for domestic energy efficiency investments

This paper uses the Diffusion of innovation (DoI) theory proposed by Rogers (2003) to understand why personality traits may influence the length of time until households decide to adopt energy-efficient technology. According to the five adoption stages of the DoI, an adoption process is triggered by some prior conditions, either being a perceived need to solve a problem, a social norm to follow or previous or existing practices. In the Knowledge and Persuasion stage, the decision-maker familiarises himself/herself with the new technology and forms attitudes towards it, followed by the Decision (rejection or adoption) and Implementation of the decision. In the last stage, the Confirmation, the decision-maker seeks to reinforce the decision that was made. Importantly, the adoption speed depends on the decision-maker’s characteristics and the perceived attributes of the technology, resulting in five categories of adopters: Innovators, Early Adopters, Early Majority, Late Majority and Laggards (Rogers, 2003, pp. 247-251).

Formally, the length of time until a decision-maker adopts an energy-efficient technology (i.e. duration) can be therefore expressed as:

$$t_{i,j} = f(I_i(SES_i, P_i, CB_i), A_j) \quad (1)$$

$t_{i,j}$ = Duration until adoption of energy-efficient technology j for decision-maker i

$f(\cdot)$ = Function f

I_i = Innovativeness of decision-maker i , depending on socio-economic status (SES_i), personality variables (P_i) and communication behaviour (CB_i)

A_j = Attractiveness of energy-efficient technology j , depending on its compatibility, complexity, trialability, observability and relative advantage to conventional technology

Besides socio-economic status (SES_i) and communication behaviour (CB_i), personality-related variables (P_i) are an important component influencing the innovativeness of an individual (I_i). Although Rogers (2003) devotes a separate section in his book that lists individual characteristics that can speed up or delay technology adoptions, he does not specify a coherent framework that allows to capture the whole personality profile of an individual. Meanwhile, the Big Five framework has been widely accepted as a model for conceptualising the structure of personality (Costa & MacCrae, 1992; Goldberg, 1992). Studies have further found strong links between the Big Five and typical characteristics of entrepreneurs, such as the desire to strive for new products and services, the capability to increase productivity or efficiency and to introduce new technologies (Obschonka et al., 2010; Zhao & Seibert, 2006). These attributes may also well facilitate adoption of energy-efficient technology which requires change-oriented and innovative behaviour. We therefore extend the DoI framework by modelling the individual innovativeness I_i as a function of the Big Five personality traits: $I_i = I_i(SES_i, Big5_i, CB_i)$.

The following paragraphs introduce each of the Big Five traits and elaborate on their link to entrepreneurial characteristics and how they are expected to influence the length of time until energy-efficient technology is adopted.

Openness to Experience. Individuals with a high score in Openness to Experience tend to explore new ideas, seek for new experiences and are creative. These are typical characteristics of entrepreneurs, who place their focus on innovation (Schumpeter, 1942),

which entails exploring novel ideas, approaches and technologies. Not surprisingly, empirical studies found a positive relationship between entrepreneurial activities and Openness to Experience (Shane et al., 2010; Zhao & Seibert, 2006; Zhao et al., 2010). We therefore expect Openness to Experience to facilitate early adoption of energy-efficient technology and a negative association with length of time to adoption should apply.

Conscientiousness. Individuals who score highly in Conscientiousness show a tendency of high organisational capability, goal-orientation and working motivation. Entrepreneurship might be a better fit for conscientious individuals because it requires deliberateness and a high degree of organisation to handle the usually vast number of issues during the initial phase of a start-up and to achieve set goals (Baum & Locke, 2004; Shane et al., 2010). Empirical research supports a positive relationship between Conscientiousness and the likelihood of being an entrepreneur (Schmitt-Rodermund & Vondracek, 2002; Zhao & Seibert, 2006; Zhao et al., 2010). Hence, Conscientiousness is expected to shorten the time until an individual invests in energy-efficient technology.

Extraversion. Extraversion describes how energetic, dominant, enthusiastic and assertive individuals are. Entrepreneurs often interact with a diverse range of parties such as partners, capital providers, customers and employees. Extraversion under these settings helps to communicate and assert ideas successfully (Zhao & Seibert, 2006). The majority of studies observed a positive association between Extraversion and entrepreneurship (Schmitt-Rodermund & Vondracek, 2002; Shane et al., 2010), except for the study of Zhao & Seibert (2006) that found no effect. We therefore expect a negative or no impact of Extraversion on the duration until adoption of energy-efficient technology.

Agreeableness. Individuals who score highly in Agreeableness tend to be trusting, cooperative, modest and are concerned for the well-being of others. The low self-interest may make it hard for agreeable individuals to persuade parties of their ideas, to lead tough negotiations (Zhao & Seibert, 2006) or to “swim against the stream”. In the context of

energy efficiency investments, this suggests that agreeable individuals might rather adopt when the majority does. Based on empirical evidence suggesting a negative association between Agreeableness and entrepreneurial activities (Schmitt-Rodermund & Vondracek, 2002; Zhao & Seibert, 2006), – except for the study of Zhao et al. (2010) that found no relationship – we expect a positive or no link between Agreeableness and the duration until investing in energy efficiency.

Neuroticism. Neuroticism describes individuals with low emotional stability, vulnerability to stress and low self-esteem. Entrepreneurs work in a relatively unstructured environment, often have a substantial financial stake in their venture and might not have secure regular income (Zhao & Seibert, 2006), which might cause psychological stress. Individuals with a low score in Neuroticism are more prone to stay resilient in phases of setbacks and, therefore, tend to be more likely entrepreneurs than others (Schmitt-Rodermund, 2004; Zhao & Seibert, 2006; Zhao et al., 2010). Thus, more neurotic individuals are expected to exhibit a relatively longer length of time until they invest in energy-efficient technology.

In the context of the DoI theory, individuals with favourable personality traits for entrepreneurship might therefore be rather classified as members of the Innovators, Early Adopters or Early Majority group. Differences in the durations until adoption may also exist within each of these categories, including the Late Majority and Laggards group. In the case of Laggards, for example, a person with an energy-efficiency-prone personality profile may invest sooner in energy efficiency than other Laggards. Table 1 summarises the hypotheses.

(Insert Table 1 here)

4 Data

The empirical data for the analysis were drawn from the German Socio-Economic Panel (SOEP), which is a longitudinal study that collects information from a representative sample of approximately 23,000 individuals and 12,000 households across Germany [dataset](SOEP, 2014; Wagner et al., 2007).

Ideally, our empirical data would indicate the precise date of the commercial launch date of the energy-efficient products and provide details on each individual's decision-making timeline from initial exposure to deliberation, decision and implementation. While the lack of such information may be seen as a limitation for identifying absolute early and late adopters, the data still allow us to compare the timing of the investment decisions relative to other households: we have access to data from 2009 to 2013 on whether households have replaced their windows or installed thermal insulation, or whether they have a solar energy or any other alternative energy system (e.g. solar photovoltaic (PV) system for electricity generation, solar thermal collectors, wind turbine, geothermal heating). We restrict the analysis to owner-occupied dwellings since such major upgrading decisions are rarely made by renters.

The survey measured the household members' Big Five personality traits on a 7-item Likert scale in 2009 and 2013. Comparing the personality traits between the two years suggests that the changes are relatively small: for 95% of the personality trait differences, the change is not above 2 levels in absolute terms ($N = 5,265$ for each personality trait). This finding is supported by previous studies which similarly showed that personality traits tend to stay relatively stable throughout time (Brown & Taylor, 2014; Cobb-Clark & Schurer, 2012). This allows us to use the personality traits from 2009 to fill the missing years in between.

To map the personality traits and other individual-level attributes (see control variables below) to the household outcomes, we use information on who has the last word when making financial decisions. If the respondent (partner) has the last word, we take the

respondent's (partner's) characteristics. If the partners have equal say, we consider their average attributes. In a second scenario, we assume joint decision-making by the partners for all households to test for honesty of the answers and for comparison purposes.

In line with previous literature, we control for several individual- and household-level characteristics that can influence energy efficiency adoptions, including age, education and building type among others (Chen et al., 2011; Hamilton et al., 2014; Mills & Schleich, 2012; Nair et al., 2010; Poortinga et al., 2003). A summary and description of the variables is presented in Table 2.

(Insert Table 2 here)

5 Research design

The energy efficiency improvements under review are long-term and capital intensive investments that are in most cases one-time events and irreversible. The adoption time for some households might be unknown because the event occurred before or after the observation period (left censored vs right censored). Due to the characteristics of the data and since we elaborate on the elapsed time until households invest in energy efficiency, we draw on the tools of survival analysis to test our hypotheses (Allison, 2014; Wooldridge, 2002). The advantage of survival analysis over traditional panel data regressions, such as random or fixed effects regressions, is (i) that irreversible outcomes can be assessed and (ii) its strength to handle censored data.

We specify four survival models: a discrete, two parametric (Weibull and Gompertz) and the Cox's semi-parametric model. If the discrete hazard rate $P(t)$ is the conditional probability that a household i invests in energy efficiency in a particular year t , given that it has not adopted any energy efficiency measures before, straightforward logistic regression can be applied and the survival model can be specified as follows (Allison, 2014; Sueyoshi,

1995):

$$\log \left(\frac{P(t)}{1 - P(t)} \right) = a + \mathbf{x}'_{it} \mathbf{B} + tC + u_{it} \quad (2)$$

where a denotes the constant, \mathbf{x}_{it} is the vector of the explanatory variables, including the Big Five traits and the control variables, \mathbf{B} is the coefficient vector with $i = 1, \dots, N$ and time interval $t = 1, \dots, T$, and u_{it} is the error term. C is the coefficient for a time variable t which accounts for any variation of the hazard rate with time: next to policy incentives, increased information spillovers from peers (Gerarden et al., 2015) can accelerate (or curb in case of negative feedback from peers) investments throughout time. Note that left censored adoptions are included in the first time interval since the estimation bias is lower than excluding them from the analysis (Cain et al., 2011).

For the parametric models, we assume that the durations follow a Weibull or Gompertz distribution since they both account for variations of the hazard function with time¹. For illustration purposes, we present a testable regression equation for the Weibull model²:

$$\log \lambda(t) = a + \mathbf{x}'_{it} \mathbf{B} + (\alpha - 1) \log t \quad (3)$$

where $\lambda(t)$ is the continuous-time hazard function³ that decreases or increases linearly by the coefficient $\alpha - 1$ with the *log* of time.

A drawback of the parametric models is that the distribution of durations needs to be specified, which increases the risk of model misspecification. The Cox's semi-parametric model overcomes this issue by allowing any duration distribution. In Equation (3), the term assuming linear changes of the hazard function with the *log* of time is replaced with the

¹For details on the choice of parametric models, see Appendix A.1.

²Further details for the inclusion of explanatory variables in parametric duration analysis can be found in Wooldridge (2002).

³For the definition of the continuous-time hazard function $\lambda(t)$, see Appendix A.2.

function $d(t)$, which can be any function of time:

$$\log \lambda(t) = a + \mathbf{x}'_t \mathbf{B} + d(t) \quad (4)$$

The duration models are fitted by maximum likelihood estimation and partial likelihood estimation in the case of Cox's semi-parametric model (Wooldridge, 2002).

Finally, the energy efficiency improvements under review might be triggered by different causal mechanisms. Increased comfort, for example, might be the reason for considering a window modernisation or thermal insulation installation, whereas environmental concern could rather motivate investments in solar PV panels and other alternative energy systems. In the baseline model, we treat the energy efficiency upgrades the same (single kinds of events). In the second model, we distinguish between traditional passive energy efficiency measures and investments in renewable energy systems (multiple kinds of events).

6 Results

The first part of the results reports the estimations of the baseline model, followed by the estimations of the multiple kinds of events model. We use the personality traits and other individual attributes of the household member who has the last word when making financial decisions (respondent or partner), or the average of these attributes of the respondent and partner if they both have equal word in such decisions.

6.1 The baseline model: single kinds of events

Treating the energy efficiency adoptions as single kinds of events generates 7,072 observations from 2,948 households, out of which 1,103 (37.4%) had an energy efficiency improvement before and from 2009 to 2013. Table 3 presents the results of the corresponding duration analyses for the different estimation models.

(Insert Table 3 here)

In all four duration models, Openness to Experience has a significantly positive impact on the probability to invest in energy efficiency measures, which is equivalent to a shorter length of time until a household invests in energy efficiency. All four models further indicate that agreeable homeowners tend to delay energy efficiency investments. Regarding the control variables, a shorter length of time until adoption is observed for higher environmental concern and education, whereas age and dwellings with more households are associated with longer durations until adoption.

Based on the 7-item Likert scale used in the survey, the top half of Figure 1 illustrates the optimal personality profile for an early energy efficiency adoption and compares it with the average scores of homeowners in Germany.

(Insert Figure 1 here)

The data show that German homeowners are in general closely aligned with the optimum position for improving energy efficiency in respect to Openness to Experience, but less so in respect to Agreeableness since it shows a relatively large deviation from the optimal inverted level of 7 (a higher score on the inverted scale of Agreeableness indicates a higher likelihood to invest early). Comparing the personality traits for different socio-economic groups in the bottom half of Figure 1 shows that for all income groups, highly educated and female homeowners (H/H/F, M/H/F, L/H/F) tend to be closest to the optimal profile in respect to Openness to Experience. The high-income, low-education, male (H/L/M) and the medium-income, high-education, male (M/H/M) group with an inverted score of 3.0 deviate the least from the optimal profile in regards to Agreeableness.

6.2 Multiple kinds of events

Table 4 summarises the duration models for window modernisations and thermal insulation installations. Before and during the observation period, 711 households (24.1%) either replaced their windows or adopted thermal insulation for their dwellings.

(Insert Table 4 here)

Similar to the baseline model, the results in Table 4 show that homeowners who score highly in Openness to Experience replace their windows and/or insulate their dwelling earlier and that agreeable homeowners tend to wait longer. The coefficients of the personality traits, however, are stronger and statistically significant at the $p < 0.01$ level in all four duration models.

The results of the duration analysis for solar and other alternative energy investments are presented in Table 5. What is striking in this table is that none of the Big Five traits are statistically significant.

(Insert Table 5 here)

It is further apparent that different to window modernisations and thermal insulation installations, households with higher environmental concern, income, education and male financial decision-makers invest sooner in solar and other alternative energy system. Also, the number of children and the solar irradiance level show a significantly positive impact, whereas their effects are negative for window modernisations and thermal insulation installations.

The findings of the scenario assuming joint decision-making for all households (collective model) can be found in the Appendix B. Overall, the results resemble those of the initial approach since most of the partner households (88.2%) indicate that both partners have equal word when making financial decisions.

7 Model summary and discussion

Table 6 summarises the significant effects of the Big Five personality traits and the goodness of fit measures for the different models. The top half of the table shows the results of the single kinds of events and the bottom half those of the multiple kinds of events approach for the initial model (“last word”) and the collective model.

(Insert Table 6 here)

To assess the goodness of fit of the models, we compare the Bayesian Information Criterion (*BIC*) between the initial and collective model in pairs for each outcome variable (i.e. single kinds of events, window modernisations and thermal installations, solar and other alternative energy systems) and for each kind of duration model (i.e. logistic, parametric (Weibull/Gompertz), Cox’s semi-parametric) separately since the measurements of the events differ, disabling a comparison of the *BIC* across the duration model groups. In order to avoid a penalty for households that stay longer in the risk set (i.e. households with longer durations or no adoptions), we calculate the *BIC* using the number of households instead the total number of observations N^4 .

For each type of duration model, the *BIC* is consistently lower in the initial than in the collective model, supporting the validity of respondents’ answers on who has the last word when making financial decisions (Table 6). We therefore conclude that our initial model does a better fit of the data and refer to it for the subsequent discussion of the personality trait effects.

We illustrate the effect of Openness to Experience on the probability to invest in energy efficiency for the single kinds of events approach by applying the Weibull duration model. The coefficient of 0.076 (see upper part in Table 6) indicates that a one unit increase in Openness to Experience translates into a 7.9% ($100(\exp(0.076) - 1)$) higher likelihood to

⁴With $BIC = -2 \times (\text{likelihood}) + \ln(N) \times k$, it can be easily seen that a higher N increases the *BIC* (weakens the goodness of fit, all else being equal). For multirecord data, the *BIC* should not be penalised for households that drop out late out of the risk set, but only if fewer households are recorded.

invest in energy efficiency. It follows that compared to the median level of Openness to Experience ($x_{med} = 4.50$), being in the lowest quartile of Openness to Experience ($x_{Q1} = 3.83$, $x_{min} = 1$) can reduce the chance to adopt major energy efficiency installations for a building from 5.0%⁵ to 23.4%⁶, all else being equal. Since the effect for Agreeableness is negative, we compare the median score to the highest quartile instead. The figures suggest that being in the highest quartile of Agreeableness can reduce the chance for energy efficiency investments from 7.7% to 18.0%.

Figure 2 compares the hazard function for an individual scoring lowest in Openness to Experience and Agreeableness (1) and for an individual scoring highest (7), together with the quartile indicators and remaining independent variables at their mean values.

(Insert Figure 2 here)

In both graphs, the curves increase over the 5-year period, indicating a higher probability of energy efficiency investments as time passes. During the observation period, the hazard of the max-Openness-to-experience individual is clearly above the min-Openness-to-experience individual, demonstrating the shorter expected length of time until an investment for individuals scoring highly in Openness to Experience, whereas the opposite is the case for Agreeableness. The concave shape evident in both graphs might be a consequence of diminishing prices of energy-efficient technologies (positive slope) along with reductions in financial subsidies, such as the decreasing Feed-in Tariffs for electricity (decreasing slope) (EEG, 2000).

Why is the impact of the personality traits evident for window modernisations and thermal insulations installations, but not for solar and other alternative energy systems? To elaborate on this question, it might be worth looking at the Germany's policy landscape for renewable energy technologies. In 1991, Germany introduced as one of the first countries a Feed-in tariff (FIT) scheme for green electricity (Bundesgesetzblatt, 1990), and continued

⁵ $100(\exp((x_{med} - x_{Q1})0.076) - 1)$

⁶ $100(\exp((x_{med} - x_{min})0.076) - 1)$

promoting investments into alternative energy resources with a series of Renewable Energy Source Acts in the year 2000 (EEG, 2000). Among others, the state guarantees the payments of the FITs for a period of up to 20 years. The long-term and massive subsidies have not only considerably reduced the risks of such investments but also the prices of renewable energy technologies, as observed for solar panels (ClimateDesk, 2013). This possibly made individual differences in personality traits (compared to the subsidies) less important in renewable energy system investment decisions.

On the other hand, policy programmes for energy efficiency refurbishments and newly constructed energy-efficient buildings were much later introduced. Although Germany established action plans to follow the European directive 2006/32/EC on energy end-use efficiency and energy services shortly after its implementation (BMW, 2006; EU, 2006), the base for effective national implementation was set only after the establishment of the “Bundesstelle für Energieeffizienz” in 2009 which is Germany’s central institution aiming to comply with the EU directive 2006/32/EC. Therefore, subsidies for passive energy efficiency measures have existed for a shorter period compared to programmes for renewable energy systems, so that heterogeneous reactions to the investment risks caused by personality traits are still evident in decision related to window modernisations and thermal insulation installations. This may suggest that differences in personality traits are of greater significance in marginal investment decisions where judgement, individual value systems and beliefs play a relatively larger role than objective profitability calculations.

8 Conclusions

The main goal of this study was to determine whether personality traits influence major energy efficiency investments in domestic buildings. Investigating the impact of the Big Five personality traits on the length of time until households improve the energy efficiency of their buildings shows that homeowners who score highly in respect to Openness to

Experience invest in energy efficiency measures earlier, whereas agreeable homeowners rather delay such measures. These findings implicate that low levels of Openness to Experience and high levels of Agreeableness can slow down the diffusion of energy-efficient technology in the domestic sector. For illustration purposes, it has been shown that compared to the median levels, scoring in the lowest quartile of Openness to Experience and highest quartile for Agreeableness can reduce the chances for energy efficiency improvements down to 23.4% and 18.0%, respectively.

Such barriers may pose a challenge for policy-makers since personality traits are fixed psychological constructs that can be hardly changed. We therefore propose to engage with the personality traits through marketing channels by the tools of personality marketing. It is known, for example, that agreeable individuals tend to care more about the environment than others (Czap & Czap, 2010; Milfont & Sibley, 2012; Passafaro et al., 2015). Advertisements for new windows or wall insulations could therefore highlight the ecological benefits of better insulated buildings. Persons with a low score in Openness to Experience, on the other hand, were found to show higher risk aversions (Brown & Taylor, 2014; Lee et al., 2008; Nicholson et al., 2005), so that the attention for these individuals might be better laid to less volatile energy bills: with a better insulated home, the energy consumption is less influenced by temperature changes and, therefore, the dependence of energy costs on the highly volatile prices of fossil fuels could be reduced. Some studies have found geographical concentrations of personality traits (Rentfrow et al., 2013; Rentfrow & Jokela, 2016), so that such marketing strategies could be also leveraged to local or regional large-scale levels.

Overall, the findings of this study illustrate that personality traits can play a crucial role in energy efficiency investment decisions, besides the commonly emphasised cost-benefit considerations. They further suggest that activating different information transmission mechanisms could reach a more diverse group of personalities which may motivate additional investments in energy efficiency and would be less costly compared to financial

subsidies. Such an approach, however, might be rather effective for marginal investors, who have not been strongly incentivised by any financial subsidies yet. Therefore, policy-makers might consider targeting the heterogeneity of personality profiles with informational programmes first, before turning to more costly financial subsidies.

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Tables and figures

Table 1 Duration hypotheses

	Duration until energy efficiency investment <i>H₁₋₅</i>
Openness to Experience	-
Conscientiousness	-
Extraversion	0/-
Agreeableness	0/+
Neuroticism	+

+/-/0: positive/negative/neutral relationship

Table 2 Variable description

Variables	Description
<i>Dependent variable</i>	
Energy efficiency measure	Window modernisation, thermal insulation installation, solar or other alternative energy systems (1 if any of the measures is adopted, otherwise 0)
<i>Independent variables</i>	
<i>Big 5 personality traits</i>	
Openness to Experience	Measured with three item questions based on a 7-item Likert scale
Conscientiousness	Measured with three item questions based on a 7-item Likert scale
Extraversion	Measured with three item questions based on a 7-item Likert scale
Agreeableness	Measured with three item questions based on a 7-item Likert scale
Neuroticism	Measured with three item questions based on a 7-item Likert scale
<i>Control variables</i>	
Risk preference	Readiness to take risks measured on a 11-item Likert scale (0-10)
Environmental concern	Environmental concern measured on a 3-item Likert scale
Income	Logarithm of monthly net household income per household member in EUR
Children	Number of children in household
Age	Age
Gender	Male (1), Female (0)
Education	Highest education according to ISCED-1997-classification
Solar irradiance	Annual sunshine duration for each state averaged from 1980 to 2013 (Deutscher Wetterdienst)
Dwelling type	Farm house (1), 1-2 family house (2), 1-2 family rowhouse, (3), apartment in 3-4 unit building (4), apartment in 5-8 unit building (5), apartment in 9+ unit building (6), high-rise (7)

Table 3 Estimates of four different duration models for the baseline model in Germany

	Logistic ^a	Weibull ^b	Gompertz ^b	Cox's semi-parametric ^b
Openness to Experience	0.093 ***	0.076 **	0.073 **	0.071 **
Conscientiousness	-0.005	-0.007	-0.006	-0.001
Extraversion	-0.017	-0.015	-0.016	-0.012
Agreeableness	-0.105 **	-0.119 ***	-0.112 ***	-0.089 **
Neuroticism	0.001	-0.008	-0.006	0.001
Risk preference	0	-0.041 **	-0.031*	0.001
Environmental concern	0.160 ***	0.179 ***	0.172 ***	0.135 **
Income ^c	0.124*	0.071	0.076	0.102
Children	0.055	0.039	0.038	0.037
Age	-0.021 ***	-0.021 ***	-0.020 ***	-0.017 ***
Gender	0.065	0.109	0.097	0.056
Education	0.074 **	0.079 ***	0.076 ***	0.062 **
Solar irradiance	0.014*	0.012*	0.012	0.011
Dwelling type	-0.340 ***	-0.312 ***	-0.307 ***	-0.285 ***
Year	-0.129 ***			
χ^2	308.07 ***	271.20 ***	256.99 ***	209.86 ***
<i>BIC</i>	5,943.00	4,361.02	4,421.06	16,012.49
<i>N</i>			7,072	
Households			2,948	
Number of adoptions			1,103 (37.4%)	
Observation period			2009-2013	

Notes: The dependent variable represents any of the following energy efficiency improvements: window modernisation, installation of thermal insulation, solar or other alternative energy system.

^a Log-odds ratios

^b Log of the hazard ratios

^c ln(household income per household member)

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 Estimates of four different duration models for window modernisations and thermal insulation installations in Germany

	Logistic ^a	Weibull ^b	Gompertz ^b	Cox's semi-parametric ^b
Openness to Experience	0.160 ***	0.147 ***	0.143 ***	0.143 ***
Conscientiousness	-0.001	-0.003	-0.003	0
Extraversion	-0.006	-0.006	-0.006	-0.005
Agreeableness	-0.146 ***	-0.159 ***	-0.154 ***	-0.132 ***
Neuroticism	0.019	0.01	0.012	0.017
Risk preference	-0.004	-0.042 **	-0.033	-0.004
Environmental concern	0.066	0.1	0.096	0.06
Income ^c	-0.023	-0.061	-0.053	-0.022
Children	-0.150 **	-0.151 **	-0.148 **	-0.133 **
Age	-0.019 ***	-0.020 ***	-0.019 ***	-0.017 ***
Gender	-0.137	-0.069	-0.08	-0.12
Education	0.044	0.052	0.051	0.041
Solar irradiance	-0.019 **	-0.017*	-0.017*	-0.017*
Dwelling type	-0.159 ***	-0.156 ***	-0.154 ***	-0.145 ***
Year	-0.089 ***			
χ^2	105.28 ***	100.56 ***	96.07 ***	81.39 ***
<i>BIC</i>	4,780.78	3,560.10	3,596.91	10,497.11
<i>N</i>			7,785	
Households			2,948	
Number of adoptions			711 (24.1%)	
Observation period			2009-2013	

^a Log-odds ratios

^b Log of the hazard ratios

^c ln(household income per household member)

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Estimates of four different duration models for solar and other alternative energy systems in Germany

	Logistic ^a	Weibull ^b	Gompertz ^b	Cox's semi-parametric ^b
Openness to Experience	0.014	0.009	0.009	0.008
Conscientiousness	0.009	0.006	0.007	0.013
Extraversion	-0.009	-0.007	-0.007	-0.007
Agreeableness	-0.053	-0.08	-0.073	-0.053
Neuroticism	-0.032	-0.041	-0.038	-0.03
Risk preference	0.01	-0.033	-0.023	0.012
Environmental concern	0.206 **	0.231 ***	0.222 ***	0.195 **
Income ^c	0.220 **	0.165*	0.172*	0.201 **
Children	0.181 ***	0.157 ***	0.156 ***	0.145 **
Age	-0.020 ***	-0.021 ***	-0.020 ***	-0.018 ***
Gender	0.394 **	0.411 ***	0.398 ***	0.350 **
Education	0.077 **	0.086 **	0.082 **	0.067*
Solar irradiance	0.051 ***	0.047 ***	0.047 ***	0.045 ***
Dwelling type	-0.558 ***	-0.532 ***	-0.528 ***	-0.510 ***
Year	-0.219 ***			
χ^2	336.91 ***	277.86 ***	268.63 ***	240.40 ***
<i>BIC</i>	3,874.84	3,128.02	3,146.27	8,315.39
<i>N</i>			7,794	
Households			2,939	
Number of adoptions			571 (19.4%)	
Observation period			2009-2013	

^a Log-odds ratios

^b Log of the hazard ratios

^c ln(household income per household member)

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Goodness of fit of duration models

	Single kinds of events							
	Logistic ^a		Weibull ^b		Gompertz ^b		Cox ^b	
	LW	C	LW	C	LW	C	LW	C
Big5 O	0.093***	0.107***	0.076**	0.083***	0.073**	0.083***	0.071**	0.084***
Big5 C								
Big5 E								
Big5 A	-0.105**	-0.078*	-0.119***	-0.101***	-0.112***	-0.093**	-0.089**	-0.068*
Big5 N								
<i>BIC</i>	5,943.00	5,945.01	4,361.02	4,363.02	4,421.06	4,423.06	16,012.49	16,014.24
<i>N</i>	7,072	8,353	7,072	8,353	7,072	8,353	7,072	8,353
#HHs	2,948	3,342	2,948	3,342	2,948	3,342	2,948	3,342
Multiple kinds of events: window modernisation or thermal insulation installation								
	Logistic ^a		Weibull ^b		Gompertz ^b		Cox ^b	
	LW	C	LW	C	LW	C	LW	C
	Big5 O	0.160***	0.151***	0.147***	0.133***	0.143***	0.132***	0.143***
Big5 C								
Big5 E								
Big5 A	-0.146***	-0.119**	-0.159***	-0.137***	-0.154***	-0.131***	-0.132***	-0.109**
Big5 N								
<i>BIC</i>	4,780.78	4,782.79	3,560.10	3,562.10	3,596.91	3,598.92	10,497.11	10,498.87
<i>N</i>	7,785	9,230	7,785	9,230	7,785	9,230	7,785	9,230
#HHs	2,948	3,342	2,948	3,342	2,948	3,342	2,948	3,342
Multiple kinds of events: solar or other alternative energy system								
	Logistic ^a		Weibull ^b		Gompertz ^b		Cox ^b	
	LW	C	LW	C	LW	C	LW	C
	Big5 O							
Big5 C								
Big5 E								
Big5 A								
Big5 N								
<i>BIC</i>	3,874.84	3,876.86	3,128.02	3,130.04	3,146.27	3,148.28	8,315.39	8,317.15
<i>N</i>	7,794	9,251	7,794	9,251	7,794	9,251	7,794	9,251
#HHs	2,939	3,334	2,939	3,334	2,939	3,334	2,939	3,334

^a Log-odds ratios

^b Log of the hazard ratios

LW/C: "Last word"/collective model

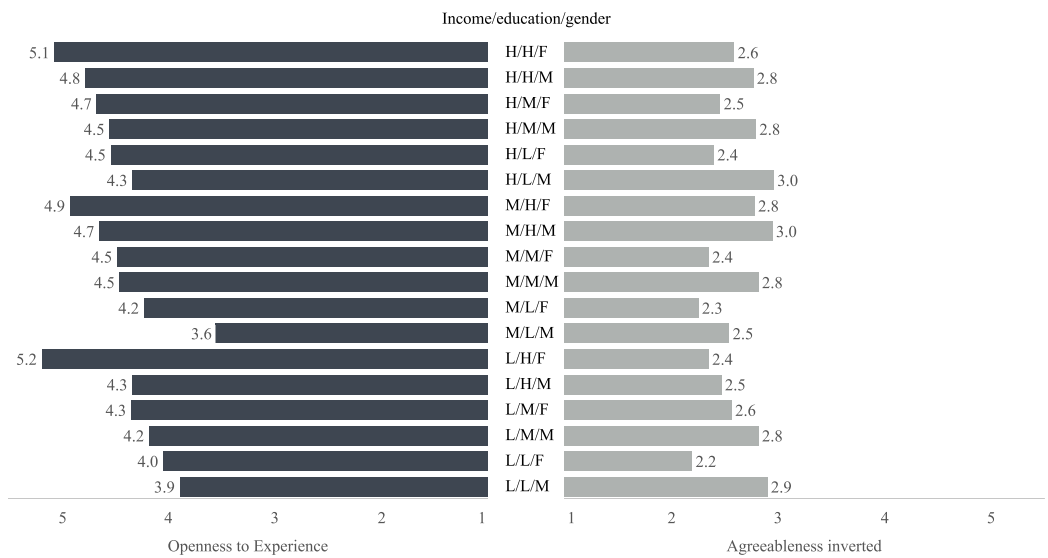
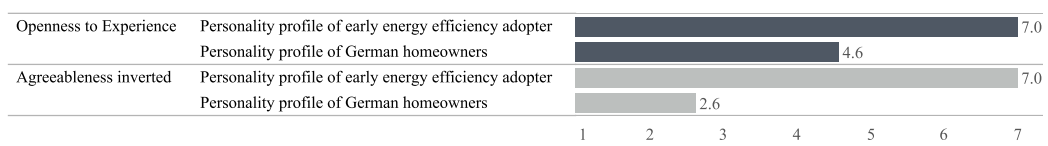
Big5 O/C/E/A/N: The Big Five personality traits of Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

#HHs: Number of households

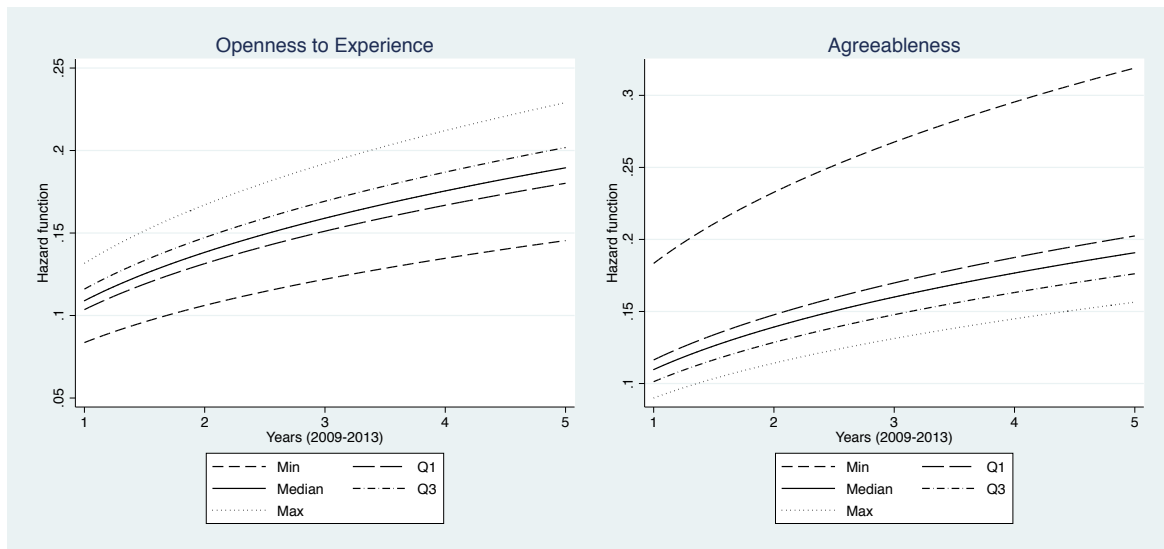
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1 Personality profile of early energy efficiency adopters



Notes: For the bar chart in the bottom half, three different groups are calculated with approximately the same number of households per group for income per household member and education with L/M/H denoting the low/medium/high group for each variable. For gender, F and M denotes female and male homeowners.

Figure 2 Hazard function of Weibull duration model for Openness to Experience and Agreeableness (single kinds of events model)



Appendix A

A.1 Parametric proportional duration models

The key tool to specify a parametric model is the hazard function $\lambda(t)$ (see also Appendix A.2), which defines the probability distribution of the durations until an event happens in the continuous-time context. The main difference between parametric duration models is how the probability for an event to happen changes throughout time. Three models are identified that differ in how time has an impact (Table A). The exponential model assumes that the

Table A Parametric hazard models

	Exponential	Weibull	Gompertz
$f(t)$	$\gamma e^{-\lambda t}$	$\gamma \alpha t^{\alpha-1} e^{-\lambda t^\alpha}$	$\gamma e^{\alpha t} e^{-\frac{\gamma}{\alpha}(e^{\alpha t}-1)}$
$F(t)$	$1 - e^{-\gamma t}$	$1 - e^{-\gamma t^\alpha}$	$1 - e^{-\frac{\gamma}{\alpha}(e^{\alpha t}-1)}$
$\lambda(t) = \frac{f(t)}{1-F(t)}$	γ	$\gamma \alpha t^{\alpha-1}$	$\gamma e^{\alpha t}$

$f(t)$: Probability density function

$F(t)$: Cumulative distribution function

$\lambda(t)$: Hazard function

probability of an event does not depend on the time elapsed. i.e. that the hazard function is constant over time ($\lambda(t) = \lambda$). This is rather an unrealistic assumption for energy efficiency investments since spillover effects, changes in the political landscapes and other time-varying unobservables can influence the adoption speed. Different to the exponential model, the Gompertz and Weibull model account for these impacts. The exponential model is in fact a special case of the Weibull model for $\alpha = 1$. If $\alpha > 1$, the hazard rate is monotonically increasing with time; and monotonically decreasing for $0 \leq \alpha < 1$. Similar to the Weibull model, the Gompertz model allows time to have a constant, positive or negative

impact of time on the hazard rate. In practice, the two latter yield often similar results and therefore, deciding for one or the other should not be crucial.

A.2 Continuous-time hazard function

If $T \geq 0$ denotes the continuous duration with t being a particular value of T , the probability that the duration is less than T is defined as

$$F(t) = P(T \leq t), t \geq 0$$

The probability of “surviving” is defined with the **survivor function**

$S(t) \equiv 1 - F(t) = P(T > t)$. For $h > 0$,

$$P(t \leq T < t+h | T \geq t)$$

is the probability of an event occurrence in the time interval $[t, t+h)$, given that no event has occurred until time t . The hazard function is defined as

$$\lambda(t) = \lim_{h \rightarrow 0} \frac{P(t \leq T < t+h | T \geq t)}{S(t)}$$

Because

$$P(t \leq T < t+h | T \geq t) = P(t \leq T < t+h) / P(T \geq t) = \frac{F(t+h) - F(t)}{1 - F(t)}$$

and with $f(t) = \frac{dF}{dt}$ denoting the density of T , the hazard function can be written as

$$\lambda(t) = \lim_{h \rightarrow 0} \frac{F(t+h) - F(t)}{h} \frac{1}{1 - F(t)} = \frac{f(t)}{S(t)}$$

The hazard function $\lambda(t)$ is not a real probability but more accurately, the unobserved rate at which events occur. For example, if $\lambda(3) = 0.8$, 0.8 is the number of expected events in the infinitesimally small time interval after $t = 3$. Intuitively it can be roughly considered as the probability of an event in a one-unit time interval, given that no event has occurred until time t .

Appendix B

Table B.1 Estimates for four different duration models of the collective baseline model in Germany

	Logistic ^a	Weibull ^b	Gompertz ^b	Cox's semi-parametric ^b
Openness to Experience	0.107 ***	0.083 ***	0.083 ***	0.084 ***
Conscientiousness	-0.006	-0.003	-0.003	-0.002
Extraversion	-0.045	-0.044	-0.044	-0.039
Agreeableness	-0.078*	-0.101 ***	-0.093 **	-0.068*
Neuroticism	-0.006	-0.012	-0.01	-0.004
Risk preference	0.015	-0.030*	-0.02	0.014
Environmental concern	0.148 **	0.165 ***	0.157 ***	0.122 **
Income ^c	0.171 **	0.1	0.107*	0.139 **
Children	0.117 **	0.081 **	0.082 **	0.086 **
Age	-0.014 ***	-0.016 ***	-0.015 ***	-0.012 ***
Gender	0.077	0.095	0.087	0.06
Education	0.043	0.061 **	0.056 **	0.037
Solar irradiance	0.008	0.007	0.007	0.006
Dwelling type	-0.318 ***	-0.294 ***	-0.289 ***	-0.270 ***
Year	-0.168 ***			
χ^2	316.26 ***	252.91 ***	238.22 ***	194.83 ***
<i>BIC</i>	5,945.01	4,363.02	4,423.06	16,014.24
<i>N</i>			8,353	
Households			3,342	
Number of adoptions			1,294 (38.7%)	
Observation period			2009-2013	

Notes: The dependent variable represents any of the following energy efficiency improvements: window modernisation, installation of thermal insulation, solar energy or other alternative energy system.

^a Log-odds ratios

^b Log of the hazard ratios

^c ln(household income per household member)

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

p* < 0.10, *p* < 0.05, ****p* < 0.01

Table B.2 Estimates for four different duration models of the collective model for window modernisations and thermal insulation installations in Germany

	Logistic ^a	Weibull ^b	Gompertz ^b	Cox's semi-parametric ^b
Openness to Experience	0.151 ***	0.133 ***	0.132 ***	0.135 ***
Conscientiousness	0.014	0.016	0.016	0.014
Extraversion	-0.021	-0.023	-0.022	-0.019
Agreeableness	-0.119 **	-0.137 ***	-0.131 ***	-0.109 **
Neuroticism	0.031	0.023	0.024	0.028
Risk preference	0.01	-0.029	-0.021	0.008
Environmental concern	0.071	0.098	0.094	0.064
Income ^c	0.016	-0.035	-0.029	0.016
Children	-0.120 **	-0.129 **	-0.126 **	-0.108*
Age	-0.014 ***	-0.016 ***	-0.015 ***	-0.012 ***
Gender	-0.091	-0.053	-0.06	-0.082
Education	0.021	0.039	0.037	0.02
Solar irradiance	-0.026 ***	-0.024 ***	-0.024 ***	-0.023 ***
Dwelling type	-0.142 ***	-0.138 ***	-0.137 ***	-0.130 ***
Year	-0.107 ***			
χ^2	98.55 ***	86.75 ***	82.93 ***	70.34 ***
<i>BIC</i>	4,782.79	3,562.10	3,598.92	10,498.87
<i>N</i>			9,230	
Households			3,342	
Number of adoptions			831 (24.9%)	
Observation period			2009-2013	

^a Log-odds ratios

^b Log of the hazard ratios

^c ln(household income per household member)

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3 Estimates for four different duration models of the collective model for solar and other alternative energy systems in Germany

	Logistic ^a	Weibull ^b	Gompertz ^b	Cox's semi-parametric ^b
Openness to Experience	0.044	0.032	0.033	0.036
Conscientiousness	-0.011	-0.007	-0.007	-0.008
Extraversion	-0.026	-0.028	-0.027	-0.026
Agreeableness	-0.069	-0.098*	-0.090*	-0.071
Neuroticism	-0.052	-0.056	-0.054	-0.045
Risk preference	0.032	-0.016	-0.005	0.032
Environmental concern	0.173 **	0.199 ***	0.189 **	0.157 **
Income ^c	0.260 ***	0.190 **	0.199 **	0.227 ***
Children	0.248 ***	0.205 ***	0.205 ***	0.200 ***
Age	-0.013 ***	-0.016 ***	-0.015 ***	-0.012 ***
Gender	0.344*	0.340 **	0.332*	0.300*
Education	0.053	0.072 **	0.066*	0.047
Solar irradiance	0.047 ***	0.043 ***	0.043 ***	0.041 ***
Dwelling type	-0.548 ***	-0.528 ***	-0.522 ***	-0.504 ***
Year	-0.263 ***			
χ^2	387.22 ***	294.49 ***	283.67 ***	257.37 ***
<i>BIC</i>	3,876.86	3,130.04	3,148.28	8,317.15
<i>N</i>			9,251	
Households			3,334	
Number of adoptions			679 (20.4%)	
Observation period			2009-2013	

^a Log-odds ratios

^b Log of the hazard ratios

^c ln(household income per household member)

BIC: Bayesian Information Criterion with *N* = number of households (a lower value indicates a better fit)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$