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Evidence from Germany

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Universität Duisburg-Essen, Department of Economics
Universitätsstraße 12, 45117 Essen, Germany

Rheinisch-Westfälisches Institut für Wirtschaftsforschung (RWI Essen)
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Peter Grösche and Colin Vance*

Willingness-to-Pay for Energy Conservation and Free-Ridership on Subsidization – Evidence from Germany

Abstract
Understanding the determinants of home-efficiency improvements is significant to a range of energy policy issues, including the reduction of fossil fuel use and environmental protection. This paper analyzes retrofit choices by assembling a unique data set merging a nationwide household survey from Germany with regional data on wages and construction costs. To explore the influence of both heterogeneous preferences and correlation among the utility of alternatives, conditional-, random parameters-, and error components logit models are estimated that parameterize the influence of costs, energy savings, and household-level socioeconomic attributes on the likelihood of undertaking one of 16 renovation options. We use the model coefficients to derive household-specific marginal willingness-to-pay estimates, and with these assess the extent to which free-ridership may undermine the effectiveness of recently implemented programs that subsidize the costs of retrofits.

JEL Classification: C25, D12, Q4

Keywords: Heterogenous preferences, residential sector, revealed-preference data

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1 Introduction

Home renovation is generally asserted to be a highly effective means for households to lower expenditures on energy through increased efficiency. From a public policy perspective, energy efficiency in the residential sector confers the additional benefit of reducing reliance on fossil fuels, thereby contributing to both energy security and environmental stewardship. In Germany, as in other industrialized countries, the residential sector accounts for upwards of 30% of energy end use, the overwhelming share of which is consumed for space heating and hot water preparation. Consequently, the improvement of home insulation and heating equipment in the existing building stock, which directly impacts the energy required for heating services, is seen to afford considerable scope for reducing the country's energy consumption.

Over the past decade, the German government has implemented several financial support programs to encourage such retrofitting activities. Homeowners have received access to low-interest loans and – in a recently launched program initiated in 2007 – can alternatively apply for grants. An important question in gauging the policy merits of such measures concerns the homeowner's willingness-to-pay (WTP) for the energy savings that accrue through renovations. Given this information, one can analyze whether and to what extent the subsidization program suffers from free rider effects. Free ridership occurs if the subsidized household would have undertaken the energy-conserving activity even in the absence of the subsidy, that is, if the household's WTP exceeds cost (Train 1994). Despite its relevance to the assessment of publicly-financed programs, WTP estimates for energy-savings and the associated implications for free-ridership have received scant scrutiny to date.

The purpose of the present study is twofold. First, we estimate the determinants of home retrofits and derive therefrom estimates of the marginal WTP for energy savings. Second, we assess the extent to which free rider effects threaten

to undermine the social benefits of the subsidization program. These objectives are pursued using a unique data set of some 2530 owners of German single-family homes, which combines real investment cost for 16 retrofit measures, engineering estimates of the respective energy savings, and information on wage and material costs along with the sociodemographic characteristics of the sampled households.

Our work builds on a handful of earlier studies of household energy consumption behavior, most of which draw on data obtained from surveys in the U.S. With respect to home retrofits, Cameron (1985) was among the first to analyze household choice behavior using a nested logit model. She finds that income, relative energy prices, and retrofit prices are the key determinants of demand for conservation retrofits. Subsequent studies using U.S. household survey data have extended this line of inquiry in a number of directions, including analyses that address the effectiveness of energy conservation programs (Hartman 1988), the effects of changes in energy prices on the consumption of housing, residential energy, and other goods (Quigley and Rubinfeld 1989), and the extent to which homeowners apply high discount rates to home-improvement opportunities (Metcalf and Hassett 1999). Among the few studies of this issue from the European context, Banfi et al. (2008) estimate household's marginal willingness-to-pay using an innovative stated choice experiment conducted among a sample of Swiss apartment tenants and homeowners. Their estimates, obtained from a multinominal logit model, suggest the importance of both energy savings as well as comfort benefits as determinants of retrofit choices.

Although publicly financed programs to encourage energy conservation are increasingly common in industrialized countries, only a few studies have investigated the magnitude of free rider effects. Joskow and Marron (1992) and Eto et al. (1995) conduct a meta-analysis of free ridership by surveying evaluations of demand-side management (DSM) programs conducted by U.S. utilities. With respect to residential programs, the authors uncover a wide range of estimates, varying from zero to up to 50% of free riders. However, most of the reviewed eval-

uations are based on simple survey questions that ask the respondents whether they would have hypothetically reached the same decision in absence of the DSM program. Due to the nature of these questions, the calculated free rider share may therefore be susceptible to a hypothetical- or response bias.[1] Malm (1996) circumvents these difficulties by analyzing the revealed choice of high efficiency heating system purchases among different clusters of consumers. He derives an impressive share of 89% of households that would have bought the efficient equipment even in the absence of a subsidy.

The present paper illustrates an alternative approach for quantifying free-riding by combining revealed preference data with cost estimates derived from engineering calculations. Our method is similar to Cameron's (1985) in that nests are imposed to capture correlation of the utility across alternatives, but, rather than using the nested logit model, we employ an analog thereof that involves the specification of an error-components structure (Brownstone and Train 1999). We additionally allow for heterogeneous preferences by specifying household specific random parameters, closely following Revelt and Train's (1998) analysis of the willingness-to-pay for lower operating costs of household appliances. Our investigation uncovers a potential free-rider share of up to 50% of the sampled households, substantially lower than Malm's (1996) estimates but still sufficiently high to warrant scrutiny of financial support for renovations.

The paper is outlined as follows. After a brief description of the data, Section 2 discusses the challenges of accommodating unobserved heterogenity in a discrete choice framework and describes alternative models derived from random utility theory for addressing them. Section 3 catalogues the empirical results and uses these to derive household-specific estimates of marginal willingness-to-pay. These results are used to draw policy implications with respect to free-rider problems in the context of Germany's current grants scheme. Section 4 concludes.

[1] To the extent that program participants feel committed to justify the existence of the DSM program the bias would yield an underestimation of the true free-rider share.

2 Methodology

Our data are drawn from a sample of 2530 single-family home owners, surveyed in 2005 as part of the German Residential Energy Consumption Survey. Four different retrofit measures (and their combinations) are surveyed: roof insulation, façade insulation, windows replacement, and heating-equipment replacement. These measures, along with the option not to undertake a retrofit, yield a total of 16 different combinations from which the household chooses. In total, 64% of the households retrofitted their homes between 1995 and 2004.

While the decision concerning renovation is essentially driven by two determinants, investment cost and the savings from reduced energy usage, the household's choice is difficult to anticipate because of several uncertainties. First, varying expectations of future energy prices will result in varying expectations of the profitability of renovation options. Further, a household may face information deficits as well as high costs of information acquisition about existing retrofitting alternatives. Even when the alternatives are known, the calculation of energy savings is likely to be beyond the capabilities of the layperson. Finally, there might exist other hidden costs and benefits that determine the household's decision process. Examples of costs include the noise and dirt that accompany some retrofit measures, while benefits may include higher social standing from spill-over effects within a neighborhood (Ioannides 2002). As a consequence of these considerations, there might exist preference heterogeneity concerning the attributes of a retrofit, leading in turn to heteroegeneity with respect to the household's expected net benefits and hence WTP for energy-saving measures. We accommodate such heterogeneity by employing econometric models that afford broad coverage of the determinants – both observable and unobservable – of the individual household's utility from alternative retrofitting options.

2.1 Discrete Choice Models

Random utility theory provides a suitable framework for our analysis, as it predicts choices by comparing the utility associated with distinct retrofitting alternatives. Each household faces a choice set $\mathcal{C}$ with K elements. The utility U_{ij} of household i for alternative $j \in \mathcal{C}$ comprises a deterministic and a stochastic component:

$$U_{ij} = V_{ij} + \epsilon_{ij}, \tag{1}$$

with $V_{ij} = \alpha_j + X_{ij}\beta$ as representative utility, determined by the alternative specific constant α_j and the matrix X_{ij}, which captures alternative-specific attributes (e.g. costs) as well as characteristics of the household (e.g. income). The portion of utility that is unobservable to the researcher is represented by ϵ_{ij}.

Household i chooses alternative j if and only if $U_{ij} > U_{ik}$ for all $k \neq j$, with $j, k \in \mathcal{C}$. The probability $P_i(j)$ of selecting j from the set of alternatives is thus dependent on ϵ_{ij} and is equal to:

$$\begin{aligned} P_i(j) &= Pr\left(V_{ij} + \epsilon_{ij} > V_{ik} + \epsilon_{ik}\right) \\ &= Pr\left(\epsilon_{ik} - \epsilon_{ij} < V_{ij} - V_{ik}\right), \forall k \neq j. \end{aligned} \tag{2}$$

Assuming the error terms to be identically and independently (iid) distributed as Gumbel (or Type I extreme value), the resulting probability model is logistic, giving rise to the well-known conditional logit model (see e.g. Ben-Akiva and Lerman 1985), with choice probabilities equal to:

$$P_i(j) = \frac{e^{V_{ij}}}{\sum_k e^{V_{ik}}}. \tag{3}$$

One drawback of this model is its imposition of the independence of irrelevant alternatives (IIA) assumption, requiring that when one alternative is removed from the choice set $\mathcal{C}$, the choice probabilities of the remaining alternatives rise by the same proportion. This assumption is, in particular, violated when the error

terms are not independent, as is the case when there are subsets of alternatives for which unobserved shocks have concomitant effects. For example, those renovation alternatives involving roof and façade insulation may be associated with high levels of noise and dirt, thereby having a common adverse effect on utility. On the other hand, these same alternatives and possibly others may positively affect utility by contributing to social standing. Hence, each retrofit option may belong to several sets of alternatives that have a common effect on utility. Following Brownstone and Train (1998), one can account for such groupings of similar sets of alternatives – and thereby relax the IIA assumption – by imposing a particular correlation structure on the utility of the alternatives via the addition of an error component:

$$U_{ij} = V_{ij} + \psi\mu_j + \epsilon_{ij} = V_{ij} + \eta_{ij}, \tag{4}$$

where ψ is a normally distributed random parameter with zero mean, and μ_j is a dummy variable which equals one if a certain latent effect is present in the utility of alternative j. Hence, the random quantity ψ only enters the utility of alternatives that share this effect.[2] Although the iid assumption for the ϵ's still holds, the utility of the respective alternatives are correlated via the unobserved portion of utility η :

$$E(\eta_{ij}, \eta_{ik}) = E(\psi\mu_j + \epsilon_{ij}, \psi\mu_k + \epsilon_{ik}) = E(\psi, \psi) = \sigma^2_\psi, \quad j \neq k. \tag{5}$$

Incorporating this latent effect into Equation (3) yields the error-component logit model:

$$P_i(j) = \frac{e^{V_{ij}+\psi\mu_j}}{\sum_k e^{V_{ik}+\psi\mu_k}}, \tag{6}$$

[2]For the sake of simplicity, we restrict our attention here only to the case where one such effect is present, although much more complex correlation structures can be imposed with additional error components.

exhibiting a covariance matrix $\Sigma = \boldsymbol{\mu}\sigma_{\psi}^2\boldsymbol{\mu}' + \sigma_{\epsilon}^2\boldsymbol{I}$, with $\boldsymbol{\mu}$ as $K \times 1$ vector of zeros and ones that create the correlation structure.

Another drawback of the conditional logit model (3) is that it does not allow for taste variation, meaning that any household specific deviation from the mean-sample taste would enter into the unobserved part of utility ϵ_{ij}. In the present application, this would preclude the possibility that households exhibit different responses to the determinants of retrofitting alternatives. An appropriate method to deal with such heterogeneity in adoption behavior is to allow for household specific coefficients $\beta_i = (\bar{\beta} + u_i)$, with u_i as a household specific deviation from the sample mean $\bar{\beta}$, such that β exhibits a distribution across the sample of households. This gives rise to the random-parameter logit model:

$$P_i(j) = \int \left(\frac{e^{V_{ij}(\beta_i)}}{\sum_k e^{V_{ik}(\beta_i)}} \right) f(\beta) d\beta. \tag{7}$$

Equation (7) is a generalization of Equation (3) as it estimates not only the mean coefficient but the parameters of the underlying distribution for those coefficients that are specified as random (Train 2003). For example, if a random parameter β is assumed be normally distributed in the population, the random-parameter logit model estimates the mean and standard deviation of β. The coefficients can thus vary across observations, thereby accounting for taste variations with respect to the attributes of the available retrofitting alternatives. In this way, some parts of the unobserved heterogeneity inherent in the conditional logit model can be removed (Hensher and Greene 2003).

The random-parameter logit fully relaxes the IIA property and additionally allows for any correlation structure between the utility of different alternatives. If the representation of a particular correlation pattern is deemed important, the random-parameter logit can also be specified using the error components described above. As discussed by Koppelman and Bhat (2006), this more flexible approach captures both heterogeneous preferences and complex correlation pat-

terns by layering the error components on top of the random-parameter logit model.

2.2 Specification of Utility

Recognizing the preceding discussion about heterogeneous adoption behavior, we assume that the household's utility V_{ij} is negatively effected by the investment cost C_{ij}, and positively effected by the decline of the building's annual primary energy demand ΔQ_{ij}, measured in megawatt hours (MWh), both of which are associated with a specific retrofitting alternative j. We control for the economic background of the households by including annual disposable income into the analysis.[3] Further, we expect that the level of the household's energy consumption influences the decision of whether to renovate, either positively because a household with a high energy consumption level is more inclined to lower its energy cost, or negatively because a high level reflects low energy awareness. Moreover, because there is a quality differential between the building stocks in western and eastern Germany, a binary variable indicates whether the household lives in the eastern part of Germany. Finally, we include a measure of the accessibility of information on home retrofits within the immediate vicinity of the household. This variable is intended to proxy for the transaction costs of information acquisition, and is defined as the relative availability of certified home auditors within a 20 kilometer radius of the household's location.[4]

[3]As is typical for survey data, information on income is missing for a large share of the households - roughly 20%. To impute these missing values, we employ the expectation-maximization algorithm recommended by King et al. (2001). The employed algorithm can be implemented using a program compatible with the statistical software R, and is downloadable from http://gking.harvard.edu.

[4]To derive this measure we drew upon a list of certified home auditors and their addresses published by the German government. We read the data as a map-layer into a Geographical Information System and overlaid this with a layer of household locations. We then created a circular buffer around each household having a radius of 20 kilometers and generated a count

We choose the conditional logit model as empirical point of departure, and explore the implications of re-estimating the model using three alternative discrete choice models: the conditional logit model with error components, the random parameters logit model, and error components layered over the random parameters logit model, our most flexible model. The specification of utility in the most general form is:

$$
\begin{aligned}
U_{ij} = \alpha_j &+ (\bar{\beta}_1 + u_{i1})C_{ij} + (\bar{\beta}_2 + u_{i2})\Delta Q_{ij} \\
&+ \sum_{l \in \boldsymbol{z}} \beta_l C_{ij} z_{il} + \sum_{m \in \boldsymbol{z}} \beta_m \Delta Q_{ij} z_{im} \\
&+ \sum_{h \in \{1,2\}} \psi_h \mu_{jh} + \epsilon_{ij},
\end{aligned} \tag{8}
$$

where α is a constant that is specific to alternative j, C_{ij} is the investment cost of household i for alternative j, and ΔQ_{ij} is the respective energy-savings variable, computed as the difference in the building's annual primary energy demand in response to retrofit j.[5] The vector $\boldsymbol{z}_{i\cdot} = \{$income, energy consumption, information access, east$\}$ contains the household-specific characteristics that enter utility via interaction effects with investment cost and energy savings. Details on data assembly for cost and energy savings are given in the appendix. Table 1 presents an overview of the data, including a listing of the 16 options and the corresponding average costs and energy savings. The random parameters $\beta_{i1} = (\bar{\beta}_1 + u_{i1})$ for investment cost and $\beta_{i2} = (\bar{\beta}_2 + u_{i2})$ for energy savings, as well as the error components $\psi_h \sim N(0, \sigma^2_{\psi_h}), h \in \{1, 2\}$, are only present in the random-parameters and error components logit models, respectively. For

of auditors within this buffer. As a final step, we divided this count by the number of homes (excluding apartment complexes) within the buffer. The variable thus created serves to capture the relative availability of expert guidance on retrofits within the vicinity of the household.

[5]It is important to emphasize that because such savings accumulate over the lifetime of the retrofit, the value of ΔQ_{ij} is not equivalent to the energy spot price of a MWh, but rather will depend on several household-specific attributes, including time preference and expectations about future energy prices.

Table 1: Mean Investment Cost and Mean Energy Savings

	Number of households chosen	Cost in 1000 €	ΔQ in MWh	Error Comp. 1	Error Comp. 2
No renovation	904			✓	
Roof	82	11.9	6.7		✓
Window	116	6.3	2.8		
Façade	26	10.5	7.2		✓
Heating	313	2.3	3.3		
Roof, Window	102	18.1	9.5		✓
Roof, Façade	17	20.1	13.9		✓
Roof, Heating	90	14.2	9.3		✓
Window, Façade	31	16.7	10.1		✓
Window, Heating	244	8.5	5.8		
Façade, Heating	23	12.7	9.8		✓
Roof, Window, Façade	56	26.3	16.8		✓
Roof, Window, Heating	226	20.4	11.8		✓
Roof, Façade, Heating	22	22.3	15.7		✓
Window, Façade, Heating	70	19.0	12.3		✓
Roof, Window, Façade, Heating	208	28.6	18.3		✓

example, if $u_{i1} = u_{i2} = 0$ for all households i, and $\sigma^2_{\psi_1} = \sigma^2_{\psi_2} = 0$, then Equation (8) collapses to the conditional logit specification.

In specifying the error components ψ_h, the aim was to capture latent effects specific to an outcome or a set of outcomes. We explored several alternatives, guided by the considerations noted above concerning both the hidden costs and benefits of, respectively, grime and prestige associated with particular retrofit options. The presented specification follows closely Cameron's (1985) nested logit analysis by incorporating two error components, the first of which distinguishes the binary decision concerning whether to retrofit, and the second of which groups 13 of the remaining retrofit combinations that tend to produce annoying levels of dirt and disarray (indicated in the final column of Table 1). We also explored models with additional error components for alternatives conferring prestige, but

found these to yield no significant improvements to the model fit.[6]

In the random parameters logit model, we allow for taste heterogeneity – even after controlling for the effects of the interaction variables contained in $\boldsymbol{z}$ – by treating the coefficients of cost and ΔQ as random. Alternative distributions can be availed for capturing heterogeneity, the most common of which are the normal and log-normal. The latter, being bounded on the left by zero, is particularly useful when theory suggests that the coefficient has the same sign for every decision-maker, as is the case here for the expected negative and positive coefficients of cost and ΔQ. The drawback of the lognormal – shared with the normal – is that its long tail can produce unreasonably large coefficients for some share of the observations. We consequently follow Revelt and Train (2000) and Hensher and Greene (2003) in specifying β_1 and β_2 as triangular distributed. The triangular distribution has the form of a tent, peaking in the center at the mean and dropping off linearly on both sides of the center to form a density. It is possible to restrict the triangular distribution to yield coefficients of the same sign for all observations, but this restriction was found to be unnecessary with the present data.

As conditional and error component logit both have closed form solutions, they can be estimated using maximum likelihood. The random parameters logit, by contrast, requires that the integral in equation (7) be approximated by means of simulation using random draws from the mixing distribution (Train 2003). To this end, we employ a Halton sequence to draw realizations from the population triangular distribution. We tested the sensitivity of the parameter estimates with different numbers of Halton draws per observation and found the results to be stable with as few as 100 draws.

[6] As noted by Hensher, Jones, and Greene (2007), specific alternatives can appear with different subsets of alternatives, making it possible to build overlapping error components that, in the present case, include both grimy and prestigious alternatives.

Table 2: Estimation Results of Logit Models

$\times 10^{-2}$	CLogit	RP. Logit	CLogit with EC.	RP. Logit with EC.
Cost (C_{ij})	-12.667^{**}	-12.873^{**}	-18.469^{**}	-18.410^{**}
Energy Savings (ΔQ_{ij})	22.700^{**}	23.296^{**}	32.806^{**}	32.843^{**}
Interaction of Cost with				
Energy Consumption	0.101^{**}	0.102^{**}	0.157^{**}	0.157^{**}
Income	-0.124^{*}	-0.129^{*}	-0.177^{**}	-0.182^{**}
Information Access	0.116	0.121	0.157^{*}	0.157^{*}
East	4.783^{**}	4.946^{**}	7.723^{**}	7.724^{**}
Interaction of Energy Savings with				
Energy Consumption	-0.162^{**}	-0.167^{**}	-0.239^{**}	-0.241^{**}
Income	0.100	0.105	0.152^{*}	0.158^{*}
Information Access	-0.020	-0.022	-0.020	-0.020
East	-0.980	-1.073	-2.817	-2.770
Standard deviation for random parameters distribution				
Cost		4.732		0.110
Energy Savings		1.289		0.318
Standard deviation for error components				
No renovation			0.365	0.501
Annoying renovation			210.741^{**}	211.819^{**}
Log-Likelihood	-5054	-5054	-5035	-5034

**significant at the 1% level, *significant at the 5% level. Alternative specific constants not presented.

3 Results

In this section we present the results of the discrete choice models. The section begins with a cataloging of the coefficient estimates followed by a comparison of model fit. Thereafter we derive the marginal WTP and present its distribution over households. The section closes with a discussion of free-ridership and policy implications.

3.1 Coefficient Estimates and Model Fit

Table 2 presents the results of a conditional-, random parameters-, error components, and error components with random parameters logit model. All four models tell a consistent story. The signs of the significant coefficients are the

same across models and are of similar magnitude, depending on whether error components are present. The key effects pertaining to investment cost and energy savings have the expected positive and negative effect on utility, respectively, and are highly significant. Because the standard deviations for the parameter distributions of these two coefficients are statistically insignificant (i.e. $u_{i1} = u_{i2} = 0 \; \forall i$), there is no empirical evidence for taste heterogeneity beyond the variation that is captured by the interaction effects.

The results of these interaction terms must be interpreted with respect to the coefficients of C_{ij} and ΔQ_{ij}. For example, increasing energy consumption is seen to attenuate both the negative effect of cost and the positive effect of energy savings, which is consistent with the intuition that high energy-consuming households are less responsive to changes in energy expenditures. Likewise, the error components variants of the model indicate that access to information, as measured by the relative availability of certified auditors within a 20 kilometer radius of the household, has a dampening effect on the negative influence of cost that is of roughly the same magnitude as energy consumption. Income, on the other hand, exacerbates the negative influence of costs. An explanation for this finding is not immediately forthcoming, other than to speculate that wealthier households may be more aware of other, more profitable investment opportunities than housing. Finally, households living in the eastern part of Germany experience less disutility from the investment cost than their western counterparts. This result is expected, since the East-German building sector was in dire need of rehabilitation before reunification. This led in the 1990s to an extensive wave of refurbishment on the territory of the former German Democratic Republic.

Regarding the question of model fit, a comparison of the log-likelihoods suggests that little is gained from the incorporation of heterogeneous preferences using the random parameters logit, an unsurprising finding given the insignifi-

cance of the parameter distributions.[7] By contrast, the partitioning of the choice set using the error components appears to be an essential model specification. Not only is the standard deviation on "annoying" alternatives highly significant, indicating that the utilities of the respective retrofit alternatives are correlated, but there is also clear-cut evidence of a significant improvement in the fit of the model compared to the models that omit the error components.[8] We thus conclude that the error components logit model is the superior choice for these data, and we proceed by calculating the respondent's marginal willingness-to-pay for energy savings using the coefficient estimates from this model.

3.2 Marginal willingness-to-pay and its Distribution

The household's WTP for decreasing the building's primary energy demand by one kWh can be derived as the marginal rate of substitution between investment cost and energy savings. For the calculation of the respondent's marginal WTP ($MWTP$), we thus fix the representative utility V_{ij} and take the total derivative of Equation (8):

$$\begin{aligned} dV_{ij} &= dC_{ij}(\beta_1 + \sum_l \beta_l z_{il}) + d\Delta Q_{ij}(\beta_2 + \sum_m \beta_m z_{im}) = 0, \\ MWTP_i &= \frac{dC_{ij}}{d\Delta Q_{ij}} = -\frac{(\beta_1 + \sum_l \beta_l z_{im})}{(\beta_2 + \sum_m \beta_m z_{il})}. \end{aligned} \tag{9}$$

Hence, individual $MWTP$ can be expressed as the ratio of the cost and energy-saving coefficients, including their interaction effects.

[7] A likelihood ratio (LR) test of the conditional logit model without error components against the random parameter logit without error components and two degrees of freedom yields a LR statistic of 0 (p=0.5). The corresponding LR statistic from the models with error components is 2 (p=0.184).

[8] A likelihood ratio (LR) test of the conditional logit model without random parameters against the error components logit without random parameters and two degrees of freedom yields a LR statistic of 38 (p less than 0.0001). The corresponding LR statistic from the models with random parameters is 40 (p less than 0.001).

Figure 1: Marginal WTP Estimates

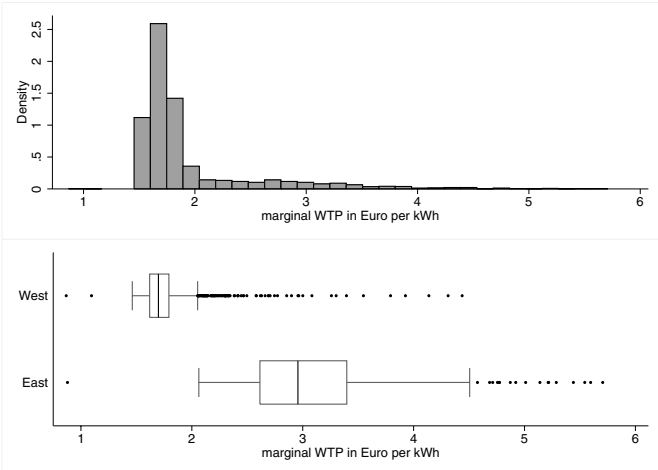


Figure 1 shows the distribution of households' $MWTP$ per kWh change in the building's primary energy demand. An interesting insight into the valuation of energy savings in Germany can be gleaned from the lower panel of Figure 1, which shows the distributions of $MWTP$ estimates according to whether households live in the eastern or western part of the country. Eastern households are seen to reveal a much higher $MWTP$ and a larger variability in their estimates, determining almost the entire right tail of the distribution in the upper panel. Table 3 reports summary statistics of $MWTP$ estimates obtained from the error components logit model. Eastern households exhibit a mean $MWTP$ of €3.28 per kWh, while the mean western $MWTP$ is considerably less at €1.72.[9] The much lower standard deviation indicates that the evaluation of energy savings among western households is fairly homogenous. Given that the immense discrepancy in

[9]Using a Mann-Whitney test we checked whether the east and the west $MWTP$ stems from the same population. We reject this hypotheses at a significance level of $p < 0.0001$.

Table 3: Marginal WTP in East- and West-Germany

	Observations	Mean	Std.Dev.	Median
East	402	3.28	1.76	2.99
West	2128	1.72	0.65	1.69
Total	2530	1.97	1.08	1.73

$MWTP$ is depicted in €/kWh, measured in prices of 2000.

$MWTP$ within Germany is essentially a result of the special situation of Eastern Germany's building stock, we consider the estimates obtained for western households to better reflect the prevailing $MWTP$ in the post-unification period.

3.3 Policy Implications

The most recent financial support program of the German government to encourage retrofits allows households to not only apply for loans, but also provides grants for covering renovation expenses. Up to 10% of the investment cost are awarded, reaching a maximum of €5000 per dwelling. With individual $MWTP$ estimates for energy savings and the associated investment cost in hand, we can approximate the share of households that would undertake the retrofit irrespectively of the financial support. Given that these households cannot be identified by the program authority in advance, they have an incentive to free ride on the grant.

An immediate challenge in gauging the extent of free-ridership returns us to the issue of how to account for hidden costs. We define a free-rider as a household whose individual WTP, calculated as the product of $MWTP_i \times \Delta Q_{ij}$, is greater than the sum of the observed plus hidden costs incurred from a particular retrofit:

$$\text{WTP}_{ij} > \underbrace{\text{observed costs}_{ij} + \text{ hidden costs}_{ij}}_{\text{total cost}_{ij}}.$$

Although our WTP estimates account for hidden costs via the inclusion of both latent effects and information cost, drawing definitive conclusions from the above

equation is obviously complicated by the fact that we still cannot be sure what share of the total costs is accounted for by hidden costs. If this share is large but ignored in the calculation of total costs, our estimate of free-ridership would be inflated. Although we are unable to assign a monetary value to the hidden costs, we can rearrange the equation as (subscripts omitted):

$$\text{WTP} - \text{observed costs} > \text{hidden costs}. \tag{10}$$

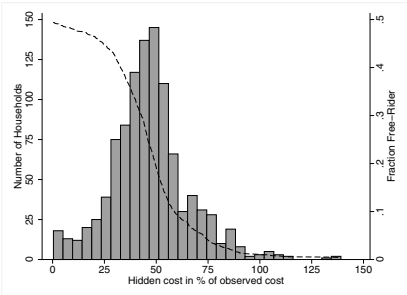
Starting with the special case of zero hidden cost, we designate the household as a free-rider if the inequality in Equation (10) holds. If we subsequently allow for increasingly higher hidden costs, a point will eventually be reached at which the inequality in Equation (10) becomes an equality. From this point on, the household would no longer be a free-rider, as its hidden costs are large enough such that the total cost exceed its WTP.

With these mechanics in hand, we can explore the sensitivity of the estimated free-rider share to different hypothetical levels of hidden costs for all alternatives. Note that because the WTP estimates of households from eastern Germany are likely to be inflated due to the urgency of renovation following reunification, we consider in the following only the 2128 households located in western Germany. We further restrict our attention to the western households that have a WTP that exceed the observed cost, since this this is a necessary condition for potential free-ridership.[10] Depending on the respective retrofit option, roughly 50% of the western households have a WTP $\geq$ observed cost, validating a similar result that was observed by Banfi et al. (2008).

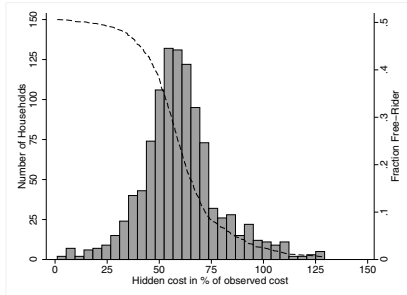
The abscissas of Figure 2 shows the hidden cost as a percent of the observed cost for two commonly chosen retrofit combinations. To facilitate interpretation, the hidden cost is expressed as a share of the observed cost, which for simplification of the exposition is assumed to be equal across households. For each level of

[10]The remaining western households exhibit a WTP $<$ observed cost, and hence can be excluded as free-riders at the outset.

Figure 2: Share of Free-Rider for Selected Retrofit Options



(a) Roof, Window, Heating



(b) Roof, Window, Façade, Heating

this share, the histogram depicts the count of households for which the inequality sign in Equation (10) inflects, and the dashed line traces the corresponding fraction of households that are designated as free-riders over different shares of hidden cost.

Figure 3(a) displays the roof-window-heating option, for which 1054 of the 2128 western households have a WTP $\geq$ observed cost. Starting again with the special case of zero hidden cost, the histogram indicates zero observations, implying that in the absence of hidden cost all 1054 households can be treated as free-riders. Correspondingly, the dashed line, which references the right ordinate, indicates a fraction of just under 50% free-riders for this level of hidden cost. Moving to the right along the abscissa and increasing the hypothetical share of hidden cost increases the number of households for which the inequality in Equation (10) inflects, meaning that these households can no longer be classified as free-riders. For example, the most left bar of the histogram suggests that there are some 20 households for which their total cost exceed their WTP for a share of hidden cost between 0% and 5% of observed cost. Excluding these 20 households from the set of free-riders, the dashed line drops only slightly

to 49% free-rider fraction. Moving further along the abscissa yields a further exclusion of households that are marked by the histogram. At its peak, which corresponds to a share of 50% hidden cost, the estimated fraction of free-riders is still non-negligible, reaching roughly 20% of the sample of western households. This fraction approaches zero only when the hidden cost comprises up to 100% of observed cost.

A similar pattern for a different retrofit alternative is seen in Figure 3(b), which shows the roof-window-facade-heating option. Even when hidden costs comprise the sizeable share of 50% of observed costs, the corresponding share of free-riders is substantial at roughly 38%.

We thus conclude that our results call into question the logic of providing renovation grants to households. Nearly half of the households show a WTP larger than the required observed investment cost, a result that is reduced only marginally when hidden costs are taken into account. As such households cannot be identified in advance, the awarded grants are likely to be exposed to extensive free riding.

4 Conclusions

This paper has estimated willingness-to-pay for energy savings that accompany a building's retrofit. Using revealed choice data from a survey among German homeowners, we rely on the random-utility framework to capture individual and choice alternative attributes that determine the decision process. Starting with the standard conditional logit model, we augment the model's flexibility by first allowing for preference heterogeneity using the random parameters logit model, and second imposing a structure to capture correlation among the utility of the alternatives with the error components logit model. We find that the conditional and the random parameters logit model yield almost identical results, while the error components logit model gives the best fit to the data at hand. Thus, we

conclude that the augmented flexibility of the random parameters logit model does not justify its higher computational costs with these data.

We completed the analysis by using the obtained marginal willingness-to-pay estimates and investment cost to generate insights into the extent to which free-rider effects may undermine the social benefits of a financial support program. We found that for some 50% of the households, the willingness-to-pay exceeds the observed cost, a share that drops only slightly when allowing for the possibility that households incur additional hidden costs.

Our findings are of special interest in Europe, given that a recent directive of the European Union requires that member states introduce political measures to decrease energy end-use by 9%. To the extent that measures such as Germany's grants program suffer from extensive free-riding – and our results suggest that they do – an immediate issue arises as to whether these political targets should recognize free-rider effects, and make corresponding adjustments. The analysis presented in this paper provides the first step in articulating such an adjustment by quantifying the magnitude of the problem. Having done so, two useful endeavors for future research emerge. The first would involve devising methodological approaches for quantifying the level of hidden costs associated with renovation activities, perhaps by drawing on experimental techniques. The second extension would estimate the determinants of free-riding, with the ultimate aim of identifying options for excluding free-riders from program participation by means such as market discrimination.

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Appendix: Data assembly

Our data is drawn from a sample of 2530 single-family home owners, surveyed in 2005 as part of the German Residential Energy Consumption Survey. The data contain a location identifier for each household, which is measured at the municipal level. The data additionally contain socioeconomic and dwelling characteristics, including whether the household received an energy audit and which retrofit measure was implemented within the last 10 years, if any. Four different retrofit measures (and their combinations) are surveyed: roof insulation, façade insulation, windows replacement, and heating-equipment replacement.

4.1 Energy Savings

The computation of energy savings are based on engineering relationships and are measured as the decline of the building's annual primary energy demand following a retrofit. We first reconstruct the size of the building shell using computer aided design. This reconstruction, which combines information on the area of living space, the number of stories, and simplifying assumptions concerning the building form, allows us to derive the extent of the heat-transmitting surface and the required heating power. Following the relationships provided by the respective technical standards set by the German Institute for Standardization, the demand for primary energy can be expressed as:

$$Q = (Q_H (H_T) + Q_W) * e_p, \tag{11}$$

where Q is the building's primary energy demand, Q_H is the demand for space heating, and Q_W is the energy demand for hot water, all under standardized

conditions. The term $e_p \geq 1$ is the efficiency factor of the heating equipment and converts final energy demand (such as energy for space heating) into primary energy demand. Q_H is determined by dwelling size and the insulation quality of the building's envelope. The better the insulation, the less heat is lossed due to transmission through the building's envelope. The total heat loss H_T of a building, measured in Watts per year, is computed as:

$$H_T = \sum_r (U_r + 0.05) * A_r, \tag{12}$$

with A_r describing the surface in m^2 of a certain component r of the building's envelope. The so-called "U-Value" expresses the heat loss of the component in watts per m^2, given a difference of 1 Kelvin between indoor and outdoor temperature.[11] The smaller the U-Value, the better the insulation, and the smaller the heat loss and the energy demand for space heating.

Roof and façade insulation as well as window replacement alter H_T by lowering the U-Value of a specific component, and hence reduce Q_H and Q. An efficiency improvement of the heating equipment lowers e_p. Thus, energy savings ΔQ are computed as the difference in the building's annual primary energy demand in response to changes in H_T and e_p:

$$\Delta Q = \frac{\partial Q}{\partial Q_H} \frac{\partial Q_H}{\partial H_T} dH_T + \frac{\partial Q}{\partial e_p} de_p. \tag{13}$$

Because we lack data on exact U-values and efficiency factors e_p of the buildings in our sample, we use typically applicable figures by construction year, reported in Table 4.

4.2 Cost

Turning to the measurement of costs for each retrofit measure, we use a Geographic Information System (GIS) to calculate a cost-variable that draws on two

[11] Thermal bridges in the component are incorporated by adding 0.05 W per m^2.

Table 4: U-values and efficiency factors

	Home Constructed Between				
	< 1975	1975 -1990	1991 -2001	2002 -2005	Required Standard
U(Roof)	1.5	0.5	0.4	0.3	0.3
U(Façade)	1.5	1	0.5	0.35	0.35
U(Window)	3.5	3.5	2	1.7	1.3
Efficiency Factor for Heaters	<1987	1987 -2001	2002 -2005		Required Standard
e_p (Non-Electric)	1.19	1.11	1.05		1.05
e_p (Electricity)	1.05	1.05	1.05		1.05

Note: U-values are measured in W/(m^2*K). Source: Ecofys (2004), IWU (1997).

principle information sources. The first of these is the BKI, or Construction-Cost Information Center of German Architects, which publishes unit-cost figures for various types of retrofit measures based on samples of retrofitted buildings (BKI 2006). Because these figures are national averages that aggregate material and labor costs, we supplement this information with regional wage data for various classes of craftsman obtained from a labor-survey conducted by the FDZ (2006).[12]

We normalize both average-unit cost and wage data so that they are measured in prices of the year 2000. The final step in calculating investment cost involves constructing the ratio of local wages to the national average, which serves as a regional weighting scheme to be multiplied by the average construction cost from the BKI. This figure is in turn multiplied by an additional weight capturing the

[12]This survey contains average wages for various classes of craftsman, and, as with the household data, is measured at the scale of a municipality, of which there are approximately 13,490 in Germany. For a given craftsman class, there is an average of 200 municipalities from across Germany for which wage data is available. To ensure overlapping coverage with the household data, we use GIS to spatially interpolate wages between the centroids of the represented municipality using an inverse-distance weighted algorithm (Childs 2004). In this way, location-specific wage information from the different craftsman classes can be assigned to each household location in the dataset.

share of each craftsman's labor required for a certain retrofit measure. The total cost for one of the 16 retrofit combinations j is given as the sum among the surface A_r of retrofitted components r from household i as follows:

$$C_{ij} = \sum_r \left(\sum_c \zeta_c \frac{\text{local wage}_{ic}}{\text{national aver. wage}_c} \right) * \text{average-unit cost}_r * A_{ir}, \tag{14}$$

with subscript c denoting the category of craftsman and ζ_c representing the share of craftsman c's labor in the retrofit.[13] While households are denoted by the subscript i, the term "local wage$_{ic}$" captures the wage of craftsman c in i's municipality.

[13] We checked our estimates of the average-unit cost against other published estimates (e.g. Jakob (2006) or Finanztest (2007)) and found the figures to be commensurate.