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Big Hassle on the Decarbonization Frontier

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February 11, 2026

Abstract

We introduce the concept of marginal hassle cost (MHC)—the opportunity cost of time required to complete burdensome administrative tasks—as a measure of non-pecuniary transaction costs. We develop an experimental procedure to elicit MHC and validate it using a field experiment on heat pump adoption in Canada. On average, MHCs are comparable in magnitude to respondents' wage rates but display substantial heterogeneity and are only weakly correlated with wages. MHCs are systematically higher for human-assisted than for computer-assisted tasks. These results show that hassle costs are economically significant and can meaningfully deter participation in government programs aimed at decarbonization.

JEL: H20, H31, Q40, Q58

Key Words: Hassle Costs, Government Programs, Decarbonization, Field Experiments

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1 Introduction

Hassle costs encompass several types of non-monetary transaction costs that affect adoption and take-up rates in several economic sectors, including governmental programs (Bertrand et al., 2004; Alatas et al., 2016), product and service purchases (Marshall, 2015), and charitable donations (Hutchinson-Quillian et al., 2021). Although hassle costs are frequently invoked to explain the low take-up of welfare-enhancing technologies and programs, they are typically imprecisely defined and measured. Empirically, they are often a catch-all phenomenon intertwined with informedness, information spillovers, and other unobserved non-monetary barriers to take-up (Fowlie et al., 2015; Currie and Musen, 2025; Alpert et al., 2024).

In this paper, we focus on defining and measuring the hassle costs associated with participation in government programs. Specifically, we define the concept of *marginal hassle cost* (hereafter MHC) of a government program. This is the opportunity cost of time required to plan and deal with the administrative and other time-consuming tasks required to enroll or comply with a program. We then propose an experimental procedure to elicit and empirically identify its distribution in a sample population that can be applied in a wide range of contexts. Finally, we implement and validate our approach in a pre-registered field experiment,[1] exploiting the first step of a randomized encouragement design to study the adoption of heat pumps, a technology critical for decarbonizing energy systems. Our goal is to test three hypotheses about the MHC in a policy-relevant setting.

Our first hypothesis is that the MHC is equal to the opportunity cost of time, which can be proxied by the wage rate (Becker, 1965) as is typically recommended by government agencies (U.S. Environmental Protection Agency, 2020). Our experiment enables us to recover an individual-specific value for the MHC, which can directly be compared to the wage rate of the same individual.

Our second hypothesis is that the MHC depends on the precise nature of the administra-

[1]The study was registered on the AEA RCT Registry on August 16, 2023: AEARCTR-0011873.

tive tasks individuals must deal with. For instance, the opportunity cost of spending one hour discussing with a contractor or an accountant versus learning the same information by browsing online could be different. Our field experiment explicitly tests how the MHC varies across two interventions, one human-assisted and the other computer-assisted, designed to inform individuals about electric heat pump adoption. In particular, we compare the MHC associated with an online training program versus a similar program delivered by a person.[2] Crucially, our experimental design explicitly rules out individual unobserved heterogeneity, such as the perceived degree of informativeness of the different programs, which could confound the estimation of the MHC across the two interventions.

Our third hypothesis is that the MHC translates into perceived hassle costs that are an economically significant barrier to the adoption of technologies crucial to the decarbonization of energy systems. Large-scale adoption of energy efficiency technologies is critical for achieving the electrification of end-use energy systems and meeting decarbonization goals (Davis, 2023). However, despite generous government subsidy programs, adoption rates for low-carbon technologies for space and water heating are currently far below what is needed to meet climate targets (Vérin and Poirier, 2024). Hassle costs may be a driver of this slow adoption. In our setting, which is far from atypical, households can claim no less than four different types of subsidies from separate entities, with different eligibility criteria and application procedures.

Three primary findings emerge. First, the MHC is of the same order of magnitude as two different measures of the marginal wage rate we consider. The average MHC is about 20% larger than the average net wage rate in our sample and exactly equal to the average gross wage rate. However, there is substantial heterogeneity across individuals. The correlation between the MHC and the wage rate varies from -0.03 to 0.08 across specifications. This leads us to conclude that, while it is relevant on average in our surveyed population, the wage rate is an imperfect proxy for the hassle cost perceived by a given individual. The lack of correlation between the MHC

[2] The experiment randomly assigns which program, human- or computer-assisted, each respondent is offered during the elicitation.

and wage rate is especially problematic for targeting interventions using income-based metrics to alleviate the bureaucratic burden of government programs (Nichols and Zeckhauser, 1982).

Second, the MHC varies with the nature of the administrative task to be completed. Specifically, spending one hour assisted by a person tends to be perceived as more costly than completing a computer-assisted program. The fact that the MHC is both malleable across tasks and has a weak correlation with the wage rate suggests that idiosyncratic preferences and/or behavioral and psychological processes are important drivers of the MHC.

Third, prior to adopting a heat pump, individuals perceive total hassle costs as economically significant. Total hassle costs associated with heat pump adoption are on average \$283, but substantial heterogeneity exists.[3] In addition, the distribution of hassle costs shows evidence of adverse selection—individuals with the highest hassle costs also have a better ex-ante return on their investment in heat pumps and in spending time learning about the technology.

Related Literature We make contributions to four distinct but interconnected strands of the literature. Our work is first linked to studies that provide evidence of hassle costs associated with the administrative burden of government programs. Hassle costs have been shown to be economically important in the contexts of health insurance markets (Handel and Kolstad, 2015; Drake et al., 2022; Alpert et al., 2024; Dunn et al., 2024), income tax filing (Benzarti, 2020), and food stamp programs (Homonoff and Somerville, 2021; Finkelstein and Notowidigdo, 2019), among others. We provide a novel way to experimentally quantify the marginal hassle cost, based on the opportunity cost of time, and show that these costs vary with the nature of the task.

Second, our experiment contributes to the literature quantifying the value of time (VOT) using experimental and quasi-experimental approaches. Several recent studies investigate the VOT in the context of transportation and commuting (Goldszmidt et al., 2020; Van Ommeren and Fosgerau, 2009; Small et al., 2005).[4] As in Goldszmidt et al. (2020), our goal is to uncover

[3] All dollar values correspond to Canadian dollars.

[4] Goldszmidt et al. (2020) provides a comprehensive overview of papers in the VOT literature.

heterogeneity in our statistic of interest; the MHC in our case. Our approach, however, enables us to obtain individual-specific estimates rather than group averages. As we show, this more precise quantification is crucial. While our average MHC is about 20% larger than the net wage in our sample, the individual-level correlation between MHC and net wage is close to zero. Using a group-average wage rate to quantify the welfare effects or in targeting strategies to minimize hassle costs could therefore be highly misleading.

Third, our individual-specific quantification also enables us to investigate the correlation between total hassle costs and adoption benefits, which is crucial to studying how hassle costs may induce positive or negative selection into subsidy programs. This relates to studies in development economics that have evaluated the impact of deliberately introducing hassle costs, typically a time-consuming task such as redeeming a voucher, as an alternative to pricing instruments to reduce product waste and avoid regressive program outcomes (Olken, 2016; Dupas et al., 2016; Alatas et al., 2016; Dunn et al., 2024). These studies use hassle costs as targeting or screening mechanisms to ensure poorer populations are not excluded from welfare-enhancing products and programs, and more generally, that products or programs are adopted by groups who most need them. The purposeful use of hassle costs as a screening or self-selection mechanism has also been explored in industrial organization and marketing (Marshall, 2015; Dukes and Zhu, 2019).

Finally, a large body of literature investigates the market failures and barriers that contribute to the low adoption of energy-saving technologies (Jaffe and Stavins, 1994; Allcott and Greenstone, 2012; Gillingham and Palmer, 2014; Gerarden et al., 2017). In this literature, hassle costs are often suspected to play an important role, but their quantification remains elusive. For instance, Fowlie et al. (2015) refer to important non-monetary costs to rationalize the low take-up rate of energy efficiency investments. Survey evidence also suggests that hassle costs are high among the reasons why households do not undertake such investments (Wekhof and Houde, 2023). Our study fills an important gap in this literature by providing the first direct quantification of hassle costs and demonstrating their economic importance in the context of energy demand.

The remainder of the paper is organized as follows. The next Section presents our framework to measure marginal hassle costs. In Section 3, we present our field experiment. In Section 4, we discuss the data and assess the validity of the experimental procedure using a reduced-form analysis. In Section 5, we present the main results. Section 6 follows with a policy analysis and conclusion.

2 Framework: Measuring Marginal Hassle Costs

Our goal is to estimate the individual-specific marginal hassle cost for a hassle-inducing task. We consider the case of an individual deciding whether to invest in a technology supported by government subsidies, though our framework is general and can be applied in many other settings. We define the utility of adopting the technology by $U_j(X_j, \mathcal{P}|\theta)$, where $j = 1$ if the technology is adopted and $j = 0$ otherwise; the vector X_j represents the characteristics of the technology including its cost; $\mathcal{P}$ represents policies, e.g., any available subsidies, that impact the net benefits of adoption; and θ is a vector of preferences. Before the investment, the individual may be uncertain about some components of X_j or $\mathcal{P}$, for instance, some cost components (viz., future operating costs) and the eligibility criteria for the subsidies. In addition, investing in the technology requires completing specific tasks (e.g., contacting contractors, filling out paperwork). We assume that the effort required to resolve the uncertainty and execute the different tasks involves giving up leisure time. Let us denote the amount of leisure allocated to the investment decision by l. When contemplating whether to learn and execute these tasks, the individual has beliefs about the perceived leisure time that needs to be spent, which we denote $\mathcal{B}(l)$. The marginal value an individual places on the welfare loss from giving up this leisure is the marginal hassle cost, which we denote by ω. The perceived total hassle cost incurred by the individual is thus: $\omega \cdot \mathcal{B}(l)$.

In our setting, individuals must decide whether to invest time in a program that will help them learn about the technology and the policy in place, thereby resolving the uncertainty. We use a rational search framework to model this decision. The individual will decide to complete the task and incur the cost $\omega \cdot \mathcal{B}(l)$ if the following inequality holds:

$$\max_{j=(0,1)} E_{X,\mathcal{P}}\left[U_j(X_j,\mathcal{P}|\theta)\right] \leq E_{X,\mathcal{P}}\left[\max_{j=(0,1)} U_j(X_j,\mathcal{P}|\theta)\right] - \omega \cdot \mathcal{B}(l), \tag{1}$$

where the LHS represents the maximization problem for expected utility given ex-ante beliefs about the technology X_j and policies $\mathcal{P}$, and the RHS represents the expected net benefit of making the decision after giving up leisure time to resolve uncertainty about adopting the technology. As it is typical in a search model, the term $E_{X,\mathcal{P}}\left[\max_{j=(0,1)} U_j(X_j,\mathcal{P}|\theta)\right] - \max_{j=(0,1)} E_{X,\mathcal{P}}\left[U_j(X_j,\mathcal{P}|\theta)\right]$, represents the value of information (hereafter referred as VOI). Equation 1 states that an individual will choose to undertake hassle-inducing but informative tasks before making the investment decision if the perceived hassle cost is less than the expected value of information.

2.1 Heterogeneity and Beliefs

In our empirical context, we consider that the marginal value of leisure ω is heterogeneous and varies across individuals and tasks. For example, someone might value the time spent searching the internet for contractors differently from the time required to manage contractors or complete paperwork. In addition, ω could also be influenced by the nature and design of the policy. We denote the different tasks by $\mathcal{A}$. Therefore, $\omega_i(\mathcal{A},\mathcal{P})$ is the marginal hassle cost for individual i specific to a given task and policy context $\mathcal{P}$.

Moreover, the amount of leisure time l needed to accomplish the different tasks is heterogeneous across tasks and is likely not perfectly known ex ante by each individual. We define the belief function $\mathcal{B}_i(l|\mathcal{A})$, to represent individual i's beliefs about the expected time spent on different tasks $\mathcal{A}$.

Finally, beliefs about X_j vary across individuals, leading to an individual-specific value of information, VOI_i. Accounting for the different dimensions of heterogeneity, the decision to perform the hassle-inducing task is defined by:

$$\omega_i(\mathcal{A}, \mathcal{P}) \cdot \mathcal{B}_i(l|\mathcal{A}) \leq VOI_i. \tag{2}$$

Equation 2 defines the full set of factors affecting the decision to undertake the hassle-inducing task.

2.2 Identification: Recovering the Distribution of the MHC

We aim to estimate an individual-specific value of the marginal hassle cost: ω_i. To ease notation, we will thus omit $\mathcal{A}$ and $\mathcal{P}$, which do not vary within-subject in our setting. The challenge is to account for heterogeneity in beliefs $\mathcal{B}_i(l)$ and value of information VOI_i, which confound the identification of ω_i in Equation 2.

Our strategy consists of fixing beliefs about the expected time to complete a task that provides information, and then eliciting the compensation required to perform the task. The task is described as taking varying lengths of time to complete, while maintaining the same informational content. In this way, we hold individuals' expectations about the program's informativeness constant. This is crucial for our identification.

More specifically, the elicitation procedure is deployed as follows. First, we propose a task related to the investment decision with a well defined time duration. We thus fix beliefs about the expected time spent: i.e., $\mathcal{B}_i(l_0) = l_0$ for all i. Then, we elicit, using an incentive-compatible mechanism, the amount each individual needs to be compensated for executing this task, which we denote s_0. Because the task provides information, s_0 can be negative if the perceived hassle cost is less than the perceived value of information, or positive if the opposite is true. This compensation is such that the following equality holds:

$$\omega_i \cdot l_0 - VOI_i = s_0. \tag{3}$$

This follows from equation 2. A priori, even though the amount of time spent on the task is well-defined, we do not know how each individual perceives the usefulness of the task to inform their investment decision. Therefore, both ω_i and VOI_i are unknown. To identify ω_i, we create exogenous variation in the task duration such that $l_0 < l_1$, while maintaining the same information in both tasks. In particular, our procedure ensures that the expected informativeness is not affected by the variation in l. Formally, point identification of ω_i requires that the quantity VOI_i is constant for a small variation in the task duration, denoted Δl (where $\Delta l = l_1 - l_0$).

After completing a second elicitation, the compensation an individual requires for completing the second task corresponds to the following equality:

$$\omega_i \cdot l_1 - VOI_i = s_1. \tag{4}$$

Equations 4 and 3 form a system of two equations and two unknowns. The marginal hassle cost for each household i is therefore given by

$$\omega_i = \frac{s_1 - s_0}{\Delta l}. \tag{5}$$

The value of information, for this specific task, can also be identified using:

$$VOI_i = \frac{s_1 - s_0}{\Delta l} \cdot l_1 - s_1. \tag{6}$$

The above framework is based on decision utility, i.e., how individuals perceive the net benefits of completing an unpleasant task before engaging in it. It is the relevant framework to study hassle costs that act as barriers to program take-up and technology adoption. Equation 2 states that individuals will trade off the cost of performing an unpleasant task with its expected benefits, or simply said, its potential usefulness. How individuals perceive such benefits could be prone to behavioral biases. Our identification strategy does not require us to assume that individuals collect and process information in a rational manner, which is often not the case, notably in the energy context (La Nauze and Myers, 2023). Our focus is on estimating ω_i, which is individual-specific but not specific to the heat pump adoption task. The quantity VOI_i, however, is individual- and task-specific and could vary due to program design. Although we report VOI_i, it is context-specific. Our focus is on the distribution of ω_i.

Up to this point, we have implicitly assumed that the cost function is locally linear for a small variation in task duration. We can relax this assumption and consider a fixed cost to participating in the program, which could be a psychic cost or a truly experienced cost associated with planning the task. Let us denote this cost κ_i. The decision to perform the task then becomes:

$$\omega_i \cdot \mathcal{B}_i(l) + \kappa_i \leq VOI_i. \tag{7}$$

With this type of cost function, we can still point-identify the marginal hassle cost using the above-mentioned strategy. However, we cannot separately identify, without further variation, both the perceived value of information of the intervention and the fixed cost. We can thus refer to the quantity $VOI_i - \kappa_i$ as the *net* value of information (net VOI)—the value of information net of the fixed cost to complete the task. If we assume the fixed cost is constant across the same task but on varying duration, we can identify the net VOI.

3 A Field Experiment to Encourage Heat Pump Adoption

3.1 Overview

We elicit the distribution of marginal hassle costs in the context of heat pump adoption. Our context is typical of households' decision environments in cities across North America and Europe, where governments and energy utilities offer generous subsidy programs to encourage the adoption of technologies needed to decarbonize the energy system. These programs and technologies induce considerable complexity and uncertainty in household decision-making. For instance, in Kelowna, Canada, our focal market, a household interested in adopting a heat pump to heat and cool their home must navigate rebate programs offered by the local utility, the city, the province, and the federal government, with each program having its own requirements and application process, generating a considerable amount of uncertainty about eligibility that requires time to resolve. To add to this uncertainty, heat pumps are a rapidly changing technology with several heterogeneous characteristics and models that households must learn about before installation. These concerns seem particularly acute in Kelowna, where households reported lacking information on cost savings, the technology's performance, and available rebates.[5] To overcome these informational and bureaucratic barriers, the City of Kelowna followed the model of several other cities and designed an energy coach program.[6] Their program aimed to provide a one-stop shop assistance service where households could learn about rebate programs, heat pump technologies, and get help planning their installation.

We worked with the City of Kelowna to randomly offer households access to one of two versions of an energy coach program designed to inform about heat pump adoption and rebate programs. In collaboration with local Kelowna program administrators, we designed a human-assisted energy coach program and an alternative version, similar in spirit, consisting of an online training program that does not require interacting with a person. We then designed an incentive-compatible procedure to elicit each respondent's willingness to accept, in dollars, completing the version of the program to which they were randomized. We followed the approach outlined in Section 2.2 and used within-subject variation in the expected program duration to estimate an individual-specific MHC. Specifically, for each household, we elicited their stated value for a given program duration, revised the duration while maintaining the same information in the new duration, and elicited a second opportunity cost.

[5]These concerns were collected in our endline survey, where we asked households: What crucial questions do you have regarding heat pumps?

[6]In the U.S., an early example of such a program was the Small Town Energy Program (STEP) developed with support of the Department of Energy: `https://www.osti.gov/servlets/purl/1113542`.

3.2 Implementation Details

We implemented the pre-registered field experiment in Kelowna, Canada, between April and August 2024.[7] The target population for the study was approximately 36,000 homeowners living in detached or low-rise attached dwellings in Kelowna. Our municipal partner provided us with all property addresses within the City of Kelowna from their property assessment database, which includes information on property addresses and property type (among other variables), for each dwelling within city boundaries. We excluded apartment buildings and mobile homes from consideration because they were more likely to be non-owner-occupied units. We refer to the list without apartments and mobile homes as "single-family" properties. The experimental procedure is described in detail in the following subsections and summarized in Figure 1.

3.2.1 Mailer Campaign

We randomly selected 11,500 addresses from the single-family properties in Kelowna to receive a mailer about home energy efficiency measures with a link to a survey on heatpumps.[8] Mailers were distributed in two waves, one in April 2024 and a second in June 2024. We used the first wave (N=500) to validate our data collection procedure. The survey could be accessed using either a QR code or a short URL, both of which were included in the mailer. Figure A.2 in the appendix displays the mailer.

The mailer included a statement that a baseline compensation of $25 was available to all respondents who completed an online survey about home energy efficiency measures.

[7] The study was registered on August 16, 2023, on the AEA RCT registry (RCT-ID: AEARCTR-0011873). The Carleton University Research Ethics Board-A (CUREB-A) approved the project on May 2, 2023 (Ethics Clearance ID: 119405).

[8] In a subsequent study, we plan to study the impact of heat pump adoption using a randomized encouragement design where the heat pump mailer and the energy coach program serve as the randomized encouragement. Households that do not receive mailers (N≈26,000) will be the control group for this experiment. For this study, we only focus on the sample of encouraged households.

3.2.2 WTA/WTP for the Energy Coach Program

Once potential participants accessed the online questionnaire, a welcome page stated that the survey aimed to identify barriers to heat-pump adoption and elicit Kelowna homeowners' preferences for electric heat pumps to heat and cool their homes. They were informed that the survey required approximately 10 minutes, and that eligible respondents would receive a \$25 Amazon gift card, with the possibility of an additional reward of up to \$200 determined by a randomized computer draw (total value: \$25–\$225). The \$25 gift card was guaranteed for all homeowners, while the draw for the additional \$200 was implemented as an incentive-compatible mechanism described below. Participants then provided informed consent and completed screening questions on homeownership and prior heat-pump adoption.[9]

We then introduced the Energy Coach program (human- or computer-assisted, depending on the random assignment) to participants. Descriptions of both programs included the same purposes and outcomes: helping households learn about and plan energy-efficiency upgrades (e.g., heat-pump installation), providing information only, with no obligation to act. The human-assisted treatment was described as a consultation by phone or video call with an energy coordinator, while the computer-assisted treatment was presented as an online learning module accessible on computers or smartphones.

After introducing the program, we asked two sequential questions. First, we asked participants if they would be willing to pay for this service. Based on the answer to this first question, we distinguished between individuals who needed to be compensated to complete the program (non-takers) and those who were willing to pay to complete it (takers). Second, we asked follow-up questions, where non-takers had to report their willingness-to-accept (WTA) and takers had to report their willingness-to-pay (WTP) for completing the program. We used Becker et al. (1964)'s second-price auction procedure to elicit the WTA, which allowed us to implement an incentive-

[9]The latter question was important to determine survey eligibility because only homeowners who did not own a heat pump went on to participate in the elicitation.

compatible approach to obtain the true compensation individuals required to participate in a field setting (Cole et al., 2020). We explained the auction procedure in the questionnaire and informed participants that compensation would be paid upon completion of the program. For participants willing to pay for the program (about 20% of the sample), we did not incentivize the WTP elicitation. We were constrained in our ability to collect money from participants. As stated in our pre-analysis plan, our elicitation of the MHC thus focuses on individuals who requested compensation to complete the program (non-takers), which is consistent with the idea that we elicit the MHC for a task perceived as a hassle.

After the initial elicitation of WTA/WTP, each participant was informed that the time to complete the program could be half an hour longer/shorter. Our identification strategy requires this variation in duration, which does not alter the perceived degree of informativeness of the program while not deceiving participants. We exploit the fact that there is natural variation in the time it takes participants to complete such a program, either because the human assistant is slower or because some individuals complete online training more quickly or slowly. We explained this to the survey participants before they completed the second elicitation, emphasizing that the program's informational content would remain the same but could take less or more time to complete (see equation (4)).

3.2.3 Additional Randomization and Stated VOI

To ensure the validity of our design and identification strategy, we added between-subject randomization to test whether the perceived informativeness of the program remained constant after we varied the expected duration. Specifically, we asked all participants how informative they thought the program would be using a ten-point Likert scale. We refer to this question as the stated value of information, which we denote SVOI. We randomized, between subjects, at which point in the elicitation procedure we asked this question: for half the participants, we asked this question after the first WTA/WTP elicitation, and for the other half, we asked the same question after the second elicitation. We also randomized whether we started with the longer or shorter program duration.

Finally, we randomized the order of three questions into four sequences: Sequence 1: 1hr $\rightarrow$ SVOI $\rightarrow$ 1.5hr; Sequence 2: 1.5hr $\rightarrow$ SVOI $\rightarrow$ 1hr; Sequence 3: 1hr $\rightarrow$ 1.5hr $\rightarrow$ SVOI; Sequence 4: 1.5hr $\rightarrow$ 1hr $\rightarrow$ SVOI. The design of (2 arms; human-/computer-assisted) $\times$ (2 valuation types; WTA/WTP) $\times$ (4 question orders) yielded 16 experimental groups.

Our null hypothesis is that the perceived informativeness of the program, as measured by the SVOI, is not influenced by whether we increase or shorten the expected program duration. We thus test whether the perceived informativeness is the same after the first WTA/WTP elicitation and the second elicitation.

3.2.4 Other Questions: Income, Demographics, and Expected Hassle

Additional demographic questions were asked at the end of the survey to elicit income, age, gender, and the highest level of education attained. A key hypothesis to be tested is whether the MHC is equal to the marginal wage rate. To assess this, we added a sub-module to compute the marginal wage rate in this section of the questionnaire.

We asked about total gross income, the number of weeks worked in the prior year, approximate hours worked per week, occupation, and pension income, which we use to estimate each individual's marginal wage rate. The marginal gross wage rate we report is gross income excluding any pension income, divided by the number of hours worked per year, computed from respondents' stated number of weeks and weekly hours worked. We also compute the reported net wage rate by subtracting federal and British Columbia income taxes from the estimated gross income, using the marginal tax schedule and basic personal credits applicable to each respondent's income level.

Finally, we asked respondents a hypothetical question about the estimated time they believed they would spend on specific tasks needed to adopt a heat pump, such as learning about heat pumps, planning and executing the installation, and finding out about and claiming available rebates and incentives. We use this information to determine the belief about the total time spent on specific tasks related to heat pump adoption and to compute the total hassle cost (THC), which is simply the expected time spent on these tasks multiplied by the MHC.[10]

All respondents completing the full questionnaire received an email with a $25 Amazon gift card. Once all the data were collected, we implemented the second-price auction to select respondents who would be compensated if they decided to complete the human-assisted or computer-assisted energy coach program. Selected respondents received a follow-up email with the amount of the compensation offer and further details about how to complete the program. The compensation for participating in the program was paid when respondents completed the program they were assigned to.

In February 2025, approximately six months after the first survey roll-out, we emailed participants who completed the survey and invited them to complete a four-minute endline survey. We offered a lottery for one $500 Amazon gift certificate for participants who completed this survey. Further details on the endline survey follow in the following sections.

4 Data and Validity of the Experiment

4.1 Sample Description

In Table 1, we summarize the attrition along the recruitment process and the characteristics of the final sample. We had a high response rate to the mailers. A total of 1,446 households that received a mailer began the survey, which corresponds to a 13.77% response rate. Our goal was to target homeowners without a heat pump and with a fossil fuel heating system. After excluding individuals who did not meet those conditions (N=364), individuals who did not consent on the first page of the survey (N=33), or dropped out just after the consent page (N=32), we are left

[10]For survey respondents that declared having already installed a heat pump, we also asked about the time they recall actually spending on these tasks. We use this information to determine whether non-heat pump adopters have ex-ante-biased beliefs about their expected time on those tasks.

with 1,082 individuals. This sub-sample corresponds to an attrition of 25.10%. Note that at this stage, participants were unaware of the assignment to the two treatment arms. Therefore, the between-subject treatment could not impact attrition.

Of the individuals who gave consent, 80% (N=864) completed the survey. This 20% attrition rate is balanced between the human-assistant and online training treatment arms (see Panel C of Table 1).

As per our pre-analysis plan, in Panel D, we distinguish between individuals who are not willing to pay for the program and need to be compensated (non-takers), and for which we elicit a willingness-to-accept (WTA) and the other individuals (takers) for which we elicit a willingness-to-pay (WTP). We find that almost 80% of individuals are non-takers for the energy coach program, i.e., require compensation to participate. Once we remove outliers, defined as individuals with WTA or WTP above the 95% percentile, this percentage falls to about 75%. The ratio of non-takers to takers is balanced across treatment arms. In Panel E, we present summary statistics for the sample of individuals used in our primary analysis. We find no statistical differences between the two treatment arms.

4.2 Reduced-Form Analysis

We begin with a reduced-form analysis to investigate how the WTA/WTP amounts we elicit vary across treatments. We compare the mean WTA or WTP amounts within-subject for the shorter versus longer durations and across-subject between the treatment arms corresponding to the two versions of the program. Table 2 presents the results. Panel A presents the results for individuals who must be compensated to participate, i.e., non-takers. The within-subject variation in program duration has the expected effect: on average, individuals require a higher compensation when we inform them that the program could take more time to be completed. This is true for both types of programs, and the increase in duration has about the same marginal impact across treatments. We, however, observe that the average compensation is much higher in the human-assisted program, almost twice that in the computer-assisted program.

Panel B of Table 2 presents the corresponding results for the sample of individuals willing to pay to participate in the program. The within-subject variation in duration now has a minimal effect on the WTP amounts, not distinguishable from zero. We cannot exclude the possibility that this asymmetry relative to non-takers is driven by the absence of an incentive-compatible procedure for eliciting WTP from takers. Interestingly, the average WTP is much higher for the human assistant program than for the online training program. The fact that both the WTA and WTP amounts are higher for the human assistant program suggests potentially large heterogeneity in the perceived net benefits of the program. Both higher hassle costs and the perceived value of information could drive this. As we show in the next section, both components of individuals' decision utility contribute to this result.

In the appendix (Table A.1), we also report the stated value of information. As a reminder, our identification strategy requires that increasing the duration does not impact the perceived informativeness of the program. We find that this is the case, which validates our identification. Whether we asked about how informative the program could be before or after changing its duration has little impact.[11] Across treatments, we also do not find strong evidence that the two types of programs might have been perceived differently in terms of informativeness.

5 MHC Results

We recover the MHC using Equation 5 for each survey participant. Table 3 presents the main results. The statistics reported are for people who are required to be compensated, which we

[11]We observe one difference that is marginally statistically significant at the 5% level with a two-sided test. The two-sided test, however, is conservative, given that the variation in duration was from 1.5h to 1h. It would then be more appropriate to use a one-sided t-test with an alternative hypothesis that the stated value of information (SVOI) decreases due to a revision in duration that shortens program duration. The fact that the average SVOI is larger leads us to strongly reject the null under this one-sided t-test (p-value of 0.96).

labeled as the non-takers.[12] In Panel A, we report the mean and median of the MHC along with the same statistics for the marginal wage rate computed for the corresponding group of individuals. The average MHC is statistically indistinguishable from the gross wage rate, but 8.0$/h larger than the net wage rate. This corresponds to a 18.6% difference, which is statistically significant at the 5% level. Once we distinguish between the MHC associated with the human-assisted versus the computer-assisted program, we find that the MHC for the computer-assisted program is 11.3$/h lower than the average MHC for the human-assisted program (significant at the 5% level). The MHC for the online training program is now, on average, closer to the average net wage rate—a difference of 2.8$/h that is not statistically significant. The MHC for the human-assisted is 13.8$/h larger than the net wage, a 31.1% difference.

Focusing on comparing the mean or median is, however, somewhat misleading. There is substantial heterogeneity in individual-specific MHC values. Whether we pool or distinguish the treatments, the correlation between the MHC and the (net or gross) wage rate is close to zero in all cases. This absence of correlation is depicted in Figure A.3 (Appendix A), which presents binned scatter plots for both treatment groups between the MHC and the net wage rate. For both treatments, there is no clear relationship between the MHC and wage rate.

5.1 Heterogeneity Analysis

Panels a) and b) of Figure 2 show the distributions of the MHC for each treatment group. Again, we focus on observations from non-takers for which the MHC is obtained with the incentive-compatible procedure to infer their WTA. Two insights emerge—not only is there substantial heterogeneity, but there is also a mass of observations at zero. More precisely, about 30% of observations have an MHC of zero. We describe these individuals as *scope-insensitive* as they

[12]As stated in our pre-analysis plan, we focus on the MHC estimated for individuals incentivized to declare the true compensation they requested to complete the program. We also exclude outliers, defined as observations above the 95% percentile. In Table 3, we always apply the 95% percentile for the corresponding outcome variables (Panel A to D) as the threshold to define outliers, which explains why the sample size slightly varies across panels.

did not adjust the amount they wished to be compensated in response to variation in program duration.

Scope insensitivity could be due to several factors. First, the fact that we varied the program duration by half an hour could have been perceived as relatively innocuous by some individuals. Although we made it clear in the elicitation procedure that they could revise their compensation, some individuals might have been indifferent to this marginal variation. This suggests that hassle costs may vary non-linearly with respect to marginal changes in duration, and larger variations are required to identify the shape of the hassle cost function. Second, some behavioral biases pertaining to the perception of unpleasant tasks could also be at play. For instance, we observe that scope insensitivity is more prevalent in the human assistant program. Given how much time individuals spend online daily, spending half an hour more (or less) time online could be perceived as more salient. To gain further insights into the driver of scope insensitivity, we regress the probability of having an MHC of zero or not on the demographic variables we collected. We show the full results in the appendix (Table A.2). Overall, we do not find that observables are strong predictors. However, the dummy for age above 65 years is a robust and statistically significant predictor—the older household group is 17% more likely to be scope insensitive to program duration, which is consistent with the prior that retirees might be less time-constrained.[13]

In Table A.3 we present the MHC results, but excluding scope-insensitive individuals. The mean MHC level is now well above the wage rate in both treatments. This is true for both the gross and the net wage. This is especially true for the MHC estimated for the human assistant program, which is almost twice larger than the average wage rate. Note that this result is not driven by outliers, as the median MHC (100$/h) is also close to the average MHC of 96.0$/h. The difference between the MHC for the human assistant program and the online training program increases to 28.2$/h.

To further explore heterogeneity in the MHC, we regress its value on demographic variables

[13]We also find that house size is positively correlated with scope insensitivity.

and other observables. Table A.4 presents different specifications where we pool the treatment groups and exclude scope-insensitive individuals. With the exception of the dummy for gender, we find no other predictors that are strongly correlated with the MHC.

5.2 Total Hassle Costs

We now compute the total hassle costs for the specific context of heat pump adoption. As part of the questionnaire, we asked respondents about the time they expected to spend on different tasks associated with the adoption process, which we previously denoted $\mathcal{B}_i()$. For each individual, we compute the total hassle costs, denoted THC_i, as the product of their marginal hassle costs, ω_i, and the expected time they reported:

$$THC_i = \omega_i \cdot \sum_a \mathcal{B}_i(l_a), \tag{8}$$

where the subscript a denotes the different tasks for which we elicited beliefs, namely the time spent learning about the heat pump technology, learning about rebates, planning the installation, and contacting contractors. In our context, those are the main tasks households will have to perform to adopt a heat pump. In other jurisdictions, additional tasks might be needed, such as obtaining permits or performing an energy audit. To contextualize the beliefs of our participants, we compare their beliefs with the reported time of Kelowna's homeowners who have already adopted a heat pump, which we surveyed during the same period. Figure 3 compares the distributions of the total time spent for non-heat pump-adopters and adopters. On average, non-adopters believed they would spend 6 hours, with a median of 4 hours, on the various tasks we listed. Whereas heat pump adopters reported spending 11 hours, on average. This high average, however, is driven by individuals who spent substantial time on various tasks. Among heat pump adopters, 25% stated having spent more than 15 hours on the various planning tasks. Overall, these results suggest that non-adopters tend to underestimate the expected time they would spend on heat pump adoption.

This is, in turn, translates into over-optimism about the total hassle costs they might actually encounter.

In Table 3, we report the total hassle costs based on the beliefs of non-adopters on the expected time to complete the various tasks. As we have just documented above, this expected time could be subject to a systematic underestimation. Nonetheless, we argue this is the relevant estimate to compute the total hassle costs. This approach is consistent with a decision utility framework that includes the perception of hassle costs as households contemplate the adoption of the technology. Alternatively, we could increase the total hassle costs to reflect the fact that non-adopters have, compared to adopters, biased beliefs about the expected time to complete the various tasks. However, given that our focus is on the hassle costs perceived prior to adoption, the perceived time spent is the policy-relevant quantity to study barriers to adoption.

The mean total hassle cost is \$283.7. However, there is substantial heterogeneity underlying these values both across treatments and individuals. The average total hassle cost for the human assistant program is \$350.4, which is much larger than for the online training program, which has a mean of \$227.1. These values include scope-insensitive individuals. If we consider individuals with only non-zero marginal hassle costs (Panel C of Table A.3), the mean hassle cost increases to \$470.4. For the human assistant program, it is \$618.6, and \$357.8 for the online training program.

In our context, the total hassle costs of heat pump adoption are likely driven by a combination of human- and computer-related tasks. The mean for each treatment arm we reported above assumes that individuals interact only with humans or computers in performing the administratively burdensome tasks. This is for illustrative purposes as we should expect selection in different types of tasks. To avoid the higher perceived hassle costs of human-assisted tasks, individuals could find ways to spend more time online for some tasks, whenever possible.

In Appendix A, we also show the correlation between the marginal hassle cost, the expected total time spent and total hassle costs (see Figure A.5). We do not observe a strong correlation between the MHC and the expected time spent, suggesting that higher/lower MHCs are not driven by how much time people expect to spend across the total adoption process, which suggests that the MHC might be locally linear in the time duration we elicit.

5.3 The Net Value of Information

Our empirical strategy also allows us to identify what we described in Section 2.2 as the net value of information (net VOI), a revealed-preference measure of the perceived informativeness of the program net of the fixed cost to participate.

In Appendix B, we analyse the estimate of the net value of information and present the joint correlation between the net VOI and the MHC (Figure B.6). We observe a positive but nonlinear relationship between the two quantities: individuals with higher MHC perceive the program as more informative. This suggests that hassle costs could induce adverse selection in an energy coach program. Ideally, we would like to offer the program to individuals with the highest (net) value of information. The fact that these individuals also tend to have the highest MHC means they would be the most difficult to enroll, however.

5.4 Endline Survey

We conducted an online follow-up survey six months after the experiment. We invited all participants who completed the energy coach enrollment survey and provided their email addresses with the goal of identifying heat pump adopters. We also asked about the intention to adopt a heat pump among those who have not yet adopted one.

We received responses from approximately 36% of the invited households (N=308). Among respondents, 26 households reported replacing their heating system during the study period, of whom 21 adopted a heat pump. Appendix C provides detailed results from the endline survey, including an analysis of adoption barriers based on open-ended questions. We also show the correlation between the intention to adopt, for the remaining non-adopters who participated in the endline survey, and the marginal hassle cost, or the total hassle cost. We observe a weak correlation between the two pairs of variables, 0.07 and -0.12, respectively.

6 Policy Analysis

In this section, we use estimates of the magnitude of the total hassle costs to determine how hassle costs may impact the adoption of heat pumps. Our goal is to show the relative economic magnitude of hassle costs in the adoption decision.

We use a simple techno-economic model calibrated with individual-specific values, which calculates the annualized costs of a natural gas furnace (the current heating system for survey participants) and an electric air source heat pump for survey participants. The model determines the optimal heat pump model for each household and calculates the cost-effectiveness of selecting a heat pump instead of a natural gas furnace for each house. Total hassle costs enter the calculations as an additional upfront cost. We compare the levelized cost of reducing greenhouse gas emissions with and without hassle costs. The model is based on Khastar and Rivers (2026) and described briefly in Appendix D.

Figure 4 shows the private (i.e., not including externalities) cost-effectiveness of heat pump adoption for all surveyed individuals based on the techno-economic model. We report the results in dollars per tonne of carbon dioxide avoided. Negative values indicate that households can both reduce emissions and save on heating system expenditures by adopting a heat pump. We compare the simulation results with and without accounting for hassle costs.

We assume a heat pump rebate of $10,000 is available, roughly similar to existing provincial incentives at the time of survey implementation. The figure shows that some households can adopt a heat pump at lower cost than a furnace. Without considering hassle costs, households responsible for 32.3% of greenhouse gas emissions from space heating would experience lower costs using a heat pump compared to a furnace. Accounting for hassle costs, only 14.3% of households would experience lower costs. Findings are similar if we consider households that experience positive costs of heat pump adoption as well. For example, roughly 90% of households can adopt a heat pump at a private cost of less than \$25/t CO_2 without considering hassle costs, but only about 75% of households can do so if hassle costs are considered. The analysis suggests that hassle costs can be a significant barrier and, in part, explain the low adoption of energy-efficient technologies and practices.

7 Conclusion

This study underscores the critical role of hassle costs as barriers to the adoption of government programs and technologies aimed at decarbonization, such as heat pumps. By introducing and validating a novel framework for measuring marginal hassle costs (MHC), we provide evidence that these costs are high and vary widely among individuals. The weak correlation between MHC and wage rates challenges the common assumption that the opportunity cost of time is a valid proxy to estimate individual value-of-time to evaluate government programs. Our findings also reveal that individuals have a higher marginal hassle cost to interact with human-assisted programs compared to computer-assisted alternatives. Finally, we also show that in the context of heat pump adoption, perceived hassle costs are an important barrier to adoption, and higher hassle costs deter individuals with the highest marginal value of public funds of a subsidy program. Hassle costs thus lead to adverse selection, and current subsidy programs to encourage the adoption of clean technologies do not appropriately account for such non-monetary costs.

References

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., Purnamasari, R., and Wai-Poi, M. (2016). Self-targeting: Evidence from a field experiment in indonesia. *Journal of Political Economy*, 124(2).

Allcott, H. and Greenstone, M. (2012). Is there an energy efficiency gap? *Journal of Economic Perspectives*, 26(1):3–28.

Alpert, A., Dykstra, S., and Jacobson, M. (2024). Hassle costs versus information: how do prescription drug monitoring programs reduce opioid prescribing? *American Economic Journal: Economic Policy*, 16(1):87–123.

Becker, G. M., DeGroot, M. H., and Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science*, 9(3):226–232.

Becker, G. S. (1965). A theory of the allocation of time. *The economic journal*, 75(299):493–517.

Benzarti, Y. (2020). How taxing is tax filing? using revealed preferences to estimate compliance costs. *American Economic Journal: Economic Policy*, 12(4):38–57.

Bertrand, M., Mullainathan, S., and Shafir, E. (2004). A behavioral-economics view of poverty. *American Economic Review*, 94(2).

Cole, S., Fernando, A. N., Stein, D., and Tobacman, J. (2020). Field comparisons of incentive-compatible preference elicitation techniques. *Journal of Economic Behavior & Organization*, 172:33–56.

Currie, J. and Musen, K. (2025). Information, spillovers, or hassle costs? effects of medicaid prior authorization on preschool antipsychotic prescribing. NBER Working Paper 34369.

Davis, L. W. (2023). The economic determinants of heat pump adoption. NBER Working Paper 31344.

Drake, C., Ryan, C., and Dowd, B. (2022). Sources of inertia in the individual health insurance market. *Journal of Public Economics*, 208.

Dukes, A. and Zhu, Y. (2019). Why customer service frustrates consumers: Using a tiered organizational structure to exploit hassle costs. *Marketing Science*, 38(3).

Dunn, A., Gottlieb, J. D., Shapiro, A. H., Sonnenstuhl, D. J., and Tebaldi, P. (2024). A denial a day keeps the doctor away. *The Quarterly Journal of Economics*, 139(1).

Dupas, P., Hoffmann, V., Kremer, M., and Zwane, A. P. (2016). Targeting health subsidies through a nonprice mechanism: A randomized controlled trial in Kenya. *Science*, 353(6302).

Ferguson, A. and Sager, J. (2002). Cold-climate air source heat pumps: Assessing cost-effectiveness, energy savings and greenhouse gas emission reductions in canadian homes. Technical report, CANMET.

Finkelstein, A. and Notowidigdo, M. J. (2019). Take-up and targeting: Experimental evidence from snap. *The Quarterly Journal of Economics*, 134(3):1505–1556.

Fowlie, M., Greenstone, M., and Wolfram, C. (2015). Are the non-monetary costs of energy efficiency investments large? understanding low take-up of a free energy efficiency program. *The American Economic Review*, 105(5).

Gerarden, T. D., Newell, R. G., and Stavins, R. N. (2017). Assessing the energy-efficiency gap. *Journal of Economic Literature*, 55(4):1486–1525.

Gillingham, K. and Palmer, K. (2014). Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy*, 8(1):18–38.

Goldszmidt, A., Muir, I., List, J. A., Smith, V. K., Metcalfe, R. D., and Wang, J. (2020). The value of time in the united states: Estimates from nationwide natural field experiments. NBER Working Paper 28208.

Handel, B. and Kolstad, J. T. (2015). Health insurance for "humans": Information frictions, plan choice, and consumer welfare. *American Economic Review*, 105(8).

Homonoff, T. and Somerville, J. (2021). Program recertification costs: Evidence from snap. *American Economic Journal: Economic Policy*, 13(4):271–298.

Hutchinson-Quillian, J., Reiley, D., and Samek, A. (2021). Hassle costs and workplace charitable giving: Field experiments with google employees. *Journal of Economic Behavior & Organization*, 191:679–685.

Jaffe, A. B. and Stavins, R. N. (1994). The energy-efficiency gap: What does it mean? *Energy Policy*, 22(10):804–810.

Khastar, M. and Rivers, N. (2026). The role of backup fuel in residential electrification: Assessing the environmental, economic, and grid impacts of heat pump backup systems in cold-climate residential. *Energy and Buildings*.

La Nauze, A. and Myers, E. (2023). Do consumers acquire information optimally? experimental evidence from energy efficiency. NBER Working Paper 31742, National Bureau of Economic Research.

Marshall, G. (2015). Hassle costs and price discrimination: An empirical welfare analysis. *American Economic Journal: Applied Economics*, 7(3).

Nichols, A. L. and Zeckhauser, R. J. (1982). Targeting transfers through restrictions on recipients. *The American Economic Review*, 72(2).

Olken, B. A. (2016). Hassles versus prices. *Science*, 353(6302):864–865.

Rivers, N. and Shaffer, B. (2020). Stretching the duck: How rising temperatures will change the level and shape of future electricity consumption. *The Energy Journal*, 41(5):55–88.

Small, K., Winston, C., and Yan, J. (2005). Uncovering the distribution of motorists' preferences for travel time and reliability. *Econometrica*, 73(4):1367–1382.

Statistics Canada (2023). Census profile, 2021 census of population: Kelowna, city (cy) [census subdivision], british columbia. Table. Statistics Canada Catalogue no. 98-316-X2021001. Released November 15, 2023.

U.S. Environmental Protection Agency (2020). Handbook on valuing changes in time use induced by regulatory requirements and other epa actions. Technical Report EPA-236-B-15-001, National Center for Environmental Economics, Office of Policy, Washington, DC. Following guidance from the Office of Management and Budget Circular A-4 (The White House, 2003).

Van Ommeren, J. and Fosgerau, M. (2009). Workers' marginal costs of commuting. *Journal of Urban Economics*, 65(1):38–47.

Vérin, A. and Poirier, M. (2024). Pace of progress: Achieving the necessary momentum to meet canada's 2050 climate goals in the residential building sector. Building Decarbonization Alliance.

Wekhof, T. and Houde, S. (2023). Using narratives to infer preferences in understanding the energy efficiency gap. *Nature Energy*, 8(9):965–977.

8 Tables and Figures

Table 1: Attrition and Sample Description

	Total	HA	OT	Diff HA-OT
Panel A				
Number of homes in Kelowna	37842	-	-	-
Number of mailers sent:				
Wave 1	500	-	-	-
Wave 2	10000	-	-	-
Total	10500	-	-	-
Panel B: Attrition based on screening questions				
Number of surveys started by scanning the QR code	1446	-	-	-
Percentage of surveys started by scanning the QR code	13.77	-	-	-
Attrition and exclusions:	(364)	-	-	-
Attrition in the first page	(33)	-	-	-
Non-owners	(97)	-	-	-
HP users	(111)	-	-	-
Non-FF users (eg. oil or wood)	(91)	-	-	-
Attrition after the first page	(32)	-	-	-
Number of respondents continue to randomization	1082	-	-	-
Percentage of respondents continue to randomization	10.3	-	-	-
Panel C: Attrition based on rate of survey completion				
Number of respondents with complete responses	864	415	449	-34
Number of respondents with incomplete responses	218	119	99	20
Panel D: Attrition based on WTA versus WTP for program and outliers				
Individuals with WTA>= 0	688	326	362	-36
Individuals with WTP>= 0	176	89	87	2
Outliers with WTA>= 0	45	18	27	-9
Outliers with WTP>= 0	18	11	7	4
Individuals with WTA>= 0 & No Outliers	643	308	335	-27
Individuals with WTP>= 0 & No Outliers	158	78	80	-2
Panel E: Demographics for final sample: Individuals with WTA>= 0 or WTP>= 0				
Gender (M/F)	0.526	0.54	0.52	0.02
Age Cat.	52.30	52.07	52.51	-0.43
Education Cat.*	2.78	2.75	2.80	-0.05
Income	79534	79776	79310	466
Pension (Y/N)	0.32	0.33	0.32	0.01
Nb Obs.	801	386	415	-

The column HA refers to the Human Assistant treatment, and OT refers to the Online Training.
*Kelowna's median income is $82,000 CAD Statistics Canada (2023).

Table 2: Willingness-to-accept (WTA) and Willingness-to-pay (WTP) for Program Participation

	Human Assistant (HA)	**Online Training (OT)**	**Diff.: HA-OT**
Panel A: Individuals with WTA$>= 0$			
Mean WTA_{1h}	87.22	48.95	-38.30***
Mean $WTA_{\text{1.5h}}$	111.59	69.37	-42.19***
Δ Means: $WTA_{\text{1.5h}} - WTA_{\text{1h}}$	24.36***	20.43***	-
Nb Obs.	308	336	-
Panel B: Individuals with WTP$>= 0$			
Mean WTP_{1h}	35.38	17.58	-17.81***
Mean $WTP_{\text{1.5h}}$	39.04	19.85	-19.19***
Δ Means: $WTP_{\text{1.5h}} - WTP_{\text{1h}}$	3.65	2.28	-
Nb Obs.	78	80	-

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Main Results: Marginal Hassle Cost, Wage Rate, Total Time Spent, Total Hassle Cost, and Net Value of Information

	All Individuals	**Human Assistant (HA)**	**Online Training (OT)**	**Diff: HA-OT**
Panel A: Marginal Hassle Cost (MHC) versus Wage Rate (Wage)				
Mean MHC (\$/h)	52.1	58.0	46.8	11.3*
Mean *Gross Wage* (\$/h)	56.6	57.1	56.2	0.9
Mean *Net Wage* (\$/h)	44.1	44.3	44.0	0.3
Median MHC (\$/h)	50	50	40	10**
Median *Gross Wage* (\$/h)	45.9	43.5	46.1	-2.6
Median *Net Wage* (\$/h)	36.6	35.4	36.9	
Δ Means: *MHC-Gross Wage* (\$/h)	-4.4	1.0	-9.4*	-
Corr: MHC α *Gross Wage*	0.03	0.06	-0.01	-
Δ Means: *MHC-Net Wage* (\$/h)	8.0*	13.8**	2.8	–
Corr: MHC α *Net Wage*	0.04	0.08	-0.03	–
Nb Obs.*	431	205	226	431
Panel B: Expected Time Spent on Heat Pump Adoption Tasks (Time)				
Mean $Time$ (h)	6.0	6.3	5.8	0.58
Median $Time$ (h)	4	4	4	0
Corr: MHC α $Time$	-0.02	-0.01	-0.05	-
Nb Obs.	557	256	301	557
Panel C: Total Hassle Cost (HC)				
Mean HC (\$)	283.7	350.4	227.1	123.3**
Median HC (\$)	80	60	100	-40
Corr: MHC α HC	0.59	0.58	0.60	-
Nb Obs.	557	256	301	557
Panel D: Net Value of Information (netVOI)				
Mean $netVOI$ (\$)	-27.9	-44.6	-13.1	-31.5***
Median $netVOI$ (\$)	0	0	0	0
Corr: MHC α $netVOI$	0.36	0.36	0.50	-
Nb Obs.	602	287	314	602

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

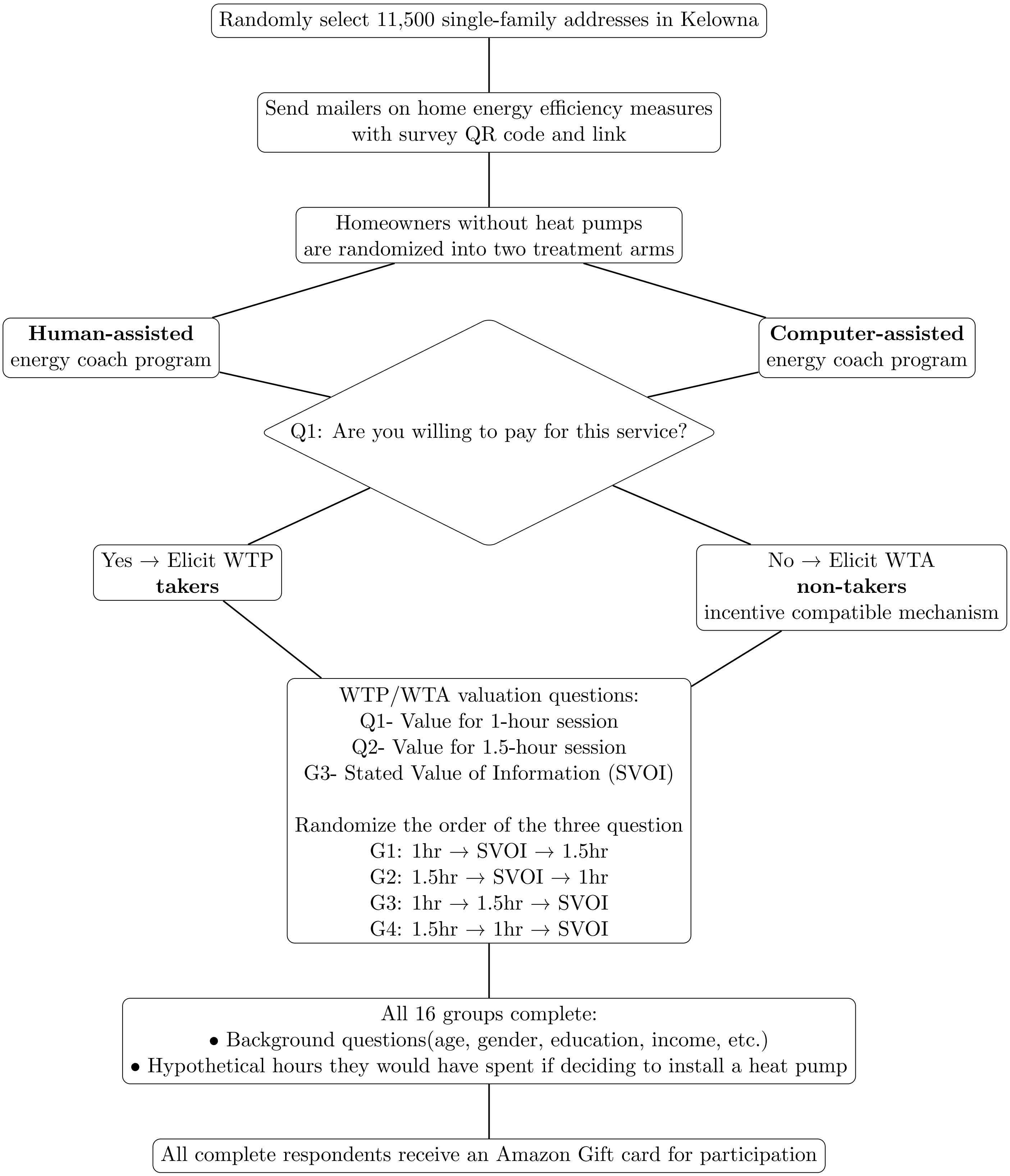
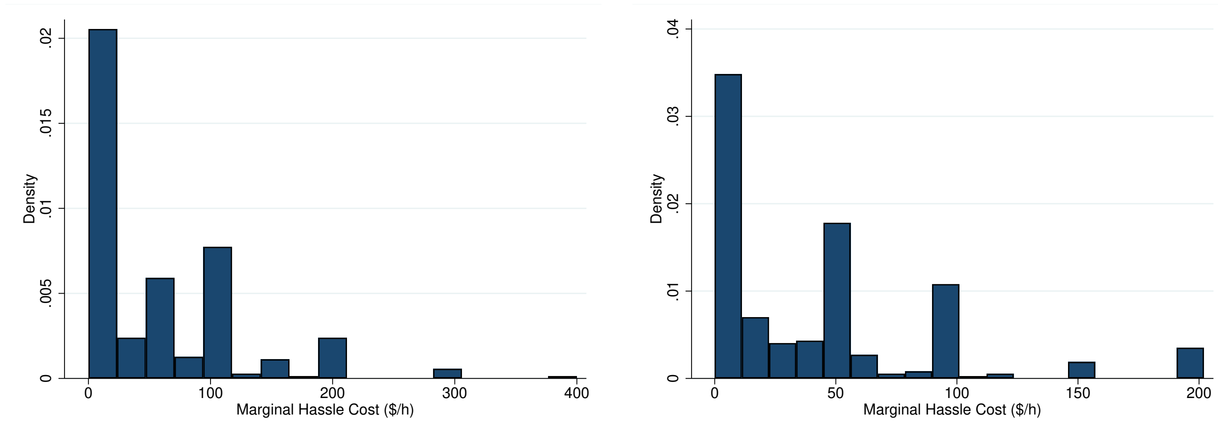


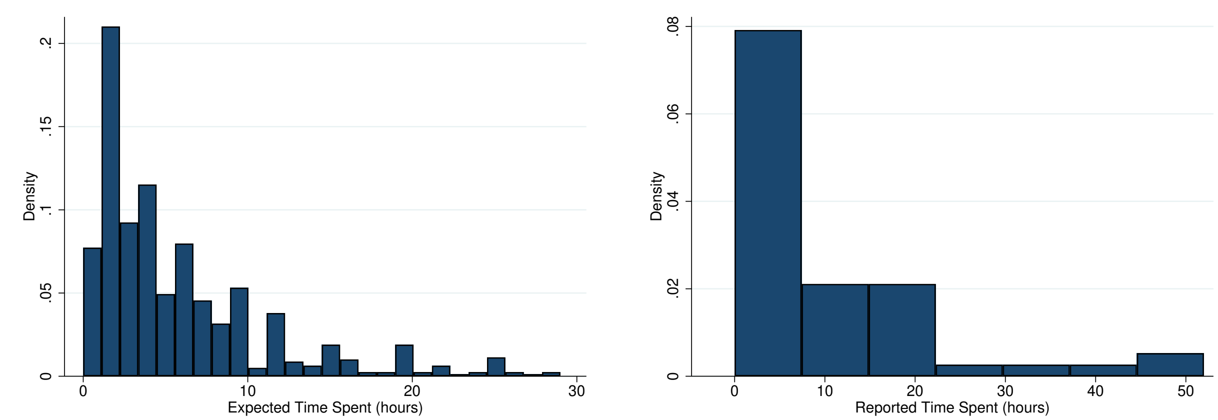
Figure 1: Experiment flow: sampling, treatment assignment, WTP/WTA valuation branches, and survey elicitation.



(a) Human Assistant

(b) Online Training

Figure 2: Distributions of Marginal Hassle Cost by Treatment Groups.



(a) Non Heat Pump Adopters (N=710)

(b) Past Heat Pump Adopters (N=51)

Figure 3: Total time Spent on Heat Pump Adoption Tasks: Non-Adopters vs Adopters

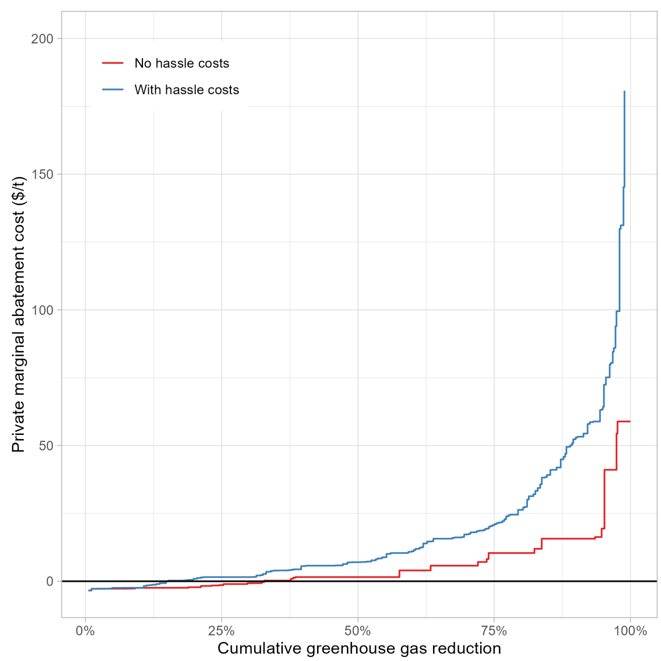


Figure 4: Cost effectiveness of heat pump adoption

A Additional tables and figures

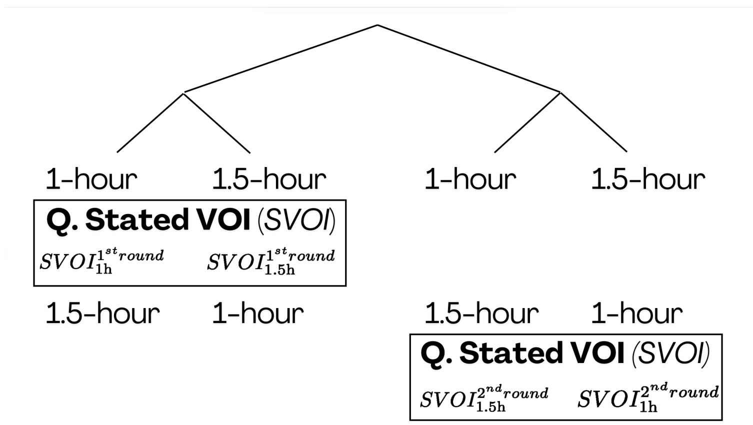


Figure A.1: Additional Between-Subject Randomization within Main Treatment Arms

Figure A.2: Kelowna Energy Efficiency Mailer

Table A.1: Analysis Stated Value of Information (SVOI)

	Human Assistant (HA)	**Online Training (OT)**	**Diff.: HA-OT**
Panel A: Individuals with WTA $>= 0$			
Stated Value of Information (SVOI) for 1h Duration After 1st **versus 2**nd **Elicitation**			
Mean $SVOI_{1h}^{1^{st}round}$	5.73	6.07	0.33
Mean $SVOI_{1h}^{2^{nd}round}$	5.76	6.42	-0.66*
Δ Means: $SVOI_{1h}^{1^{st}round} - SVOI_{1h}^{2^{nd}round}$	0.024	0.34	-
Nb Obs.	129	151	-
Stated Value of Information (SVOI) for 1.5h Duration After 1st **versus 2**nd **Elicitation**			
Mean $SVOI_{1.5h}^{1^{st}round}$	5.73	6.33	0.59
Mean $SVOI_{1.5h}^{2^{nd}round}$	6.56	6.52	-0.039
Δ Means: $SVOI_{1.5h}^{1^{st}round} - SVOI_{1.5h}^{2^{nd}round}$	0.82*	0.19	-
Nb Obs.	131	147	-
Panel B: Individuals with WTP $>= 0$			
Stated Value of Information (SVOI) for 1h Duration After 1st **versus 2**nd **Elicitation**			
Mean $SVOI_{1h}^{1^{st}round}$	6.48	6.71	0.24
Mean $SVOI_{1h}^{2^{nd}round}$	6.49	7.30	0.81
Δ Means: $SVOI_{1h}^{1^{st}round} - SVOI_{1h}^{2^{nd}round}$	0.015	0.58	-
Nb Obs.	36	36	-
Stated Value of Information (SVOI) for 1.5h Duration After 1st **versus 2**nd **Elicitation**			
Mean $SVOI_{1.5h}^{1^{st}round}$	6.39	7.29	0.90
Mean $SVOI_{1.5h}^{2^{nd}round}$	6.66	7.58	0.92
Δ Means: $SVOI_{1.5h}^{1^{st}round} - SVOI_{1.5h}^{2^{nd}round}$	0.27	0.29	-
Nb Obs.	36	32	-

*

$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2: Scope Insensitivity w.r.t. Observables

Linear Probability Model wit 0-1: $D = 1$ **if Scope Insensitive**				
Total Income ($/y)	-0.000204			-0.000469
	(-0.67)			(-1.33)
Pensionner (1-0)	0.132**			0.00212
	(2.78)			(0.03)
Partially Employed (less 52 w/y)	0.143			0.0954
	(1.09)			(0.67)
Full-time Employed (52 w/y)	0.151			0.108
	(1.13)			(0.75)
Par-time (< 40 h/w)	-0.189			-0.0902
	(-1.42)			(-0.62)
Full-time ($\geq$ 40 h/w)	-0.135			-0.0195
	(-1.05)			(-0.14)
35 to 44 years		-0.0172		-0.000196
		(-0.31)		(-0.00)
45 to 54 years		-0.0124		0.0153
		(-0.22)		(0.23)
55 to 64 years		0.0683		0.133*
		(1.21)		(1.98)
65 years and over		0.164**		0.187*
		(3.09)		(2.27)
Female		0.0164		0.0258
		(0.49)		(0.67)
College degree		-0.0315		-0.0585
		(-0.67)		(-1.08)
University degree		-0.0168		-0.00807
		(-0.40)		(-0.17)
House age (y)			0.000411	0.000330
			(0.49)	(0.38)
House size (sq. ft.)			0.00340	0.00275
			(1.74)	(1.40)
Heating system age (6-10 y)			0.0532	0.0669
			(0.98)	(1.22)
Heating system age (11-15 y)			0.0492	0.0418
			(0.77)	(0.65)
Heating system age (16-20 y)			0.0405	0.0414
			(0.82)	(0.83)
Heating system age (> 20 y)			0.139	0.167
			(1.42)	(1.67)
N	790	790	644	644
R^2	0.022	0.025	0.009	0.041
adj. R^2	0.015	0.017	-0.002	0.010

Notes: t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3: Robustness: Marginal Hassle Cost, Wage Rate, Total Time Spent, Total Hassle Cost, and Net Value of Information

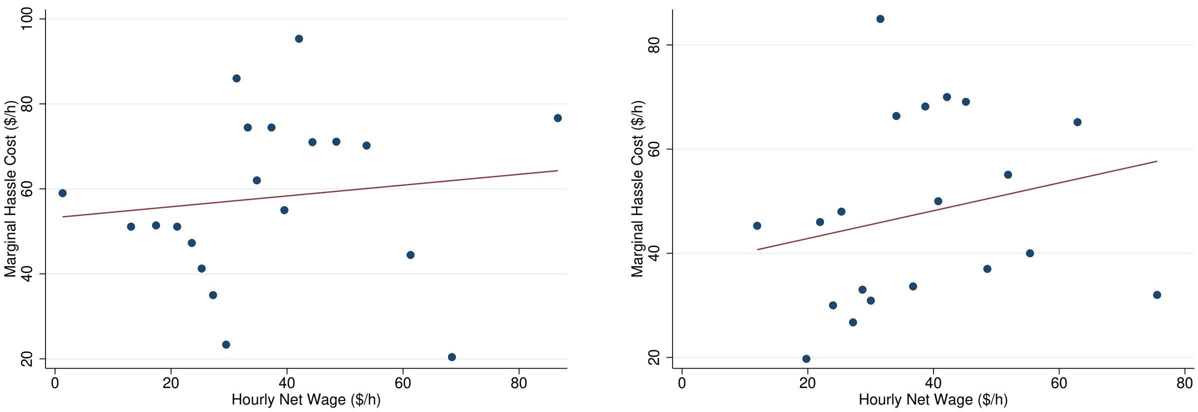
	All Individuals	**Human Assistant (HA)**	**Online Training (OT)**	**Diff: HA-OT**
Panel A: Marginal Hassle Cost (MHC) versus Wage Rate (Wage)				
Mean MHC (\$/h)	80.3	96.0	67.8	28.2***
Mean *Gross Wage* (\$/h)	55.4	57.0	54.1	2.9
Mean *Net Wage* (\$/h)	43.3	44.7	42.2	2.5
Median MHC (\$/h)	58	100	50	50***
Median *Gross Wage* (\$/h)	47.1	46.6	47.8	-1.2
Median *Net Wage* (\$/h)	37.6	36.7	37.8	
Δ Means: *MHC-Gross Wage* (\$/h)	24.9***	39.0***	25.6***	-
Corr: MHC α *Gross Wage*	0.10	0.12	0.07	-
Δ Means: *MHC-Net Wage* (\$/h)	36.9***	51.3***	25.6	–
Corr: MHC α *Net Wage*	0.10	0.13	0.05	–
Nb Obs.*	280	124	156	280
Panel B: Expected Time Spent on Heat Pump Adoption Tasks (Time)				
Mean *Time* (h)	6.1	6.6	5.7	0.91
Median *Time* (h)	4	4	4	0
Corr: MHC α *Time*	-0.05	-0.08	-0.07	-
Nb Obs.	336	145	191	336
Panel C: Total Hassle Cost (HC)				
Mean HC (\$)	470.4	618.6	357.8	260.8***
Median HC (\$)	250	400	200	200**
Corr: MHC α HC	0.45	0.41	0.46	-
Nb Obs.	336	145	191	336
Panel D: Net Value of Information (netVOI)				
Mean $netVOI$ (\$)	-6.3	-14.9	-0.1	-14.8***
Median $netVOI$ (\$)	0	0	0	0
Corr: MHC α $netVOI$	0.16	0.15	0.41	-
Nb Obs.	347	151	195	347

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.4: Marginal Hassle Costs w.r.t. Observables

	Dep. Var.: Marginal Hassle Cost (MHC)	
	All Individuals	**w/o Scope Insensitive**
Total Income ($/y)	0.0977*	0.0814
	(2.03)	(1.30)
Pensionner (1-0)	-5.701	-6.073
	(-0.59)	(-0.45)
Partially Employed (less 52 w/y)	-5.300	-5.644
	(-0.24)	(-0.16)
Full-time Employed (52 w/y)	-0.849	1.589
	(-0.04)	(0.04)
Par-time (< 40 h/w)	-0.0568	6.272
	(-0.00)	(0.18)
Full-time ($\geq$ 40 h/w)	-1.211	14.15
	(-0.06)	(0.42)
35 to 44 years	-2.564	-8.291
	(-0.28)	(-0.76)
45 to 54 years	-2.127	-5.612
	(-0.23)	(-0.50)
55 to 64 years	-11.82	-1.019
	(-1.25)	(-0.08)
65 years and over	-10.57	10.76
	(-0.90)	(0.68)
Female	-11.59*	-18.22**
	(-2.17)	(-2.64)
College degree	-2.280	-12.36
	(-0.30)	(-1.31)
University degree	-5.718	-8.393
	(-0.86)	(-0.97)
House age (y)	-0.0831	-0.0140
	(-0.70)	(-0.09)
House size (sq. ft.)	-0.179	2.191
	(-0.71)	(0.86)
Heating system age (6-10 y)	-2.156	4.229
	(-0.28)	(0.43)
Heating system age (11-15 y)	-6.414	-2.409
	(-0.71)	(-0.20)
Heating system age (16-20 y)	-1.238	3.241
	(-0.18)	(0.37)
Heating system age (> 20 y)	-12.14	-9.537
	(-0.95)	(-0.58)
N	511	304
R^2	0.051	0.077
adj. R^2	0.012	0.012

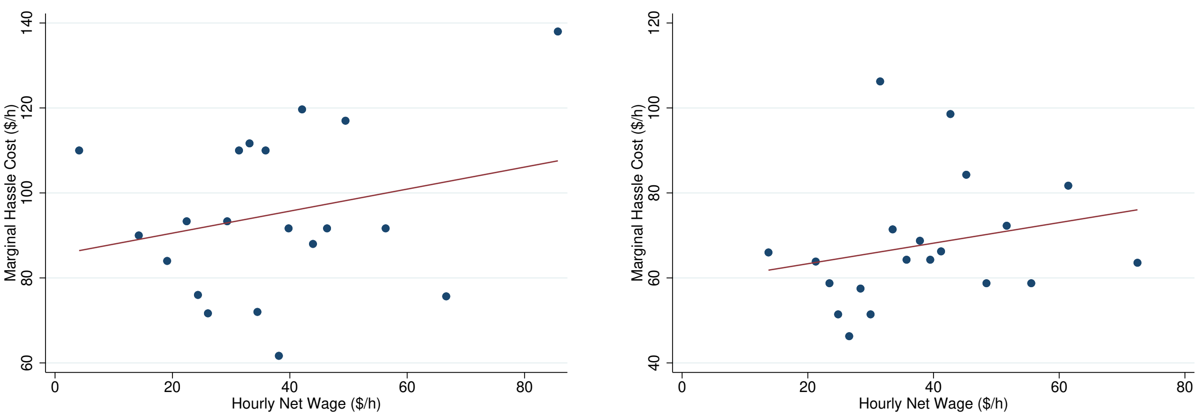
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



(a) Human Assistant

(b) Online Training

Figure A.3: Marginal Hassle Cost vs Net Wage Rate



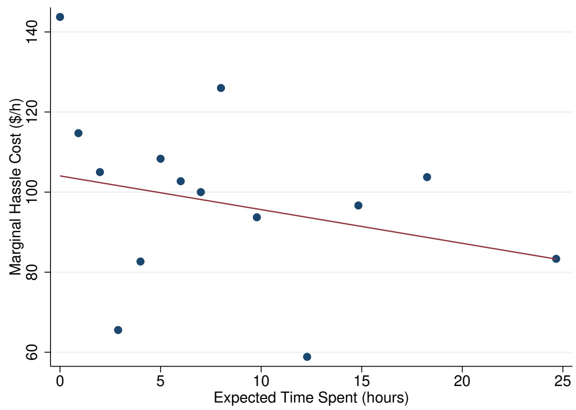
(a) Human Assistant

(b) Online Training

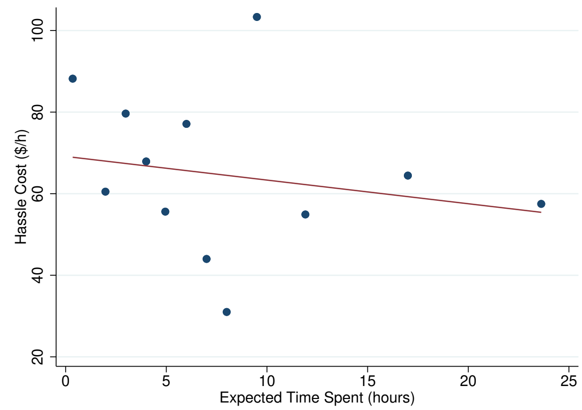
Figure A.4: Marginal Hassle Cost vs Net Wage Rate without Scope-Insensitive Individuals

B Net Value of Information

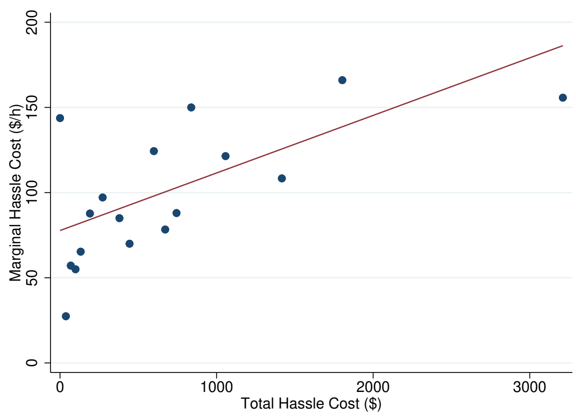
Using Equation 6, we can compute individual-specific values of the Net Value of Information (net VOI). The estimates of the net VOI are specific to our program and how we present it. Our goal was never to estimate the VOI of the program per se. It is a behavioral parameter that



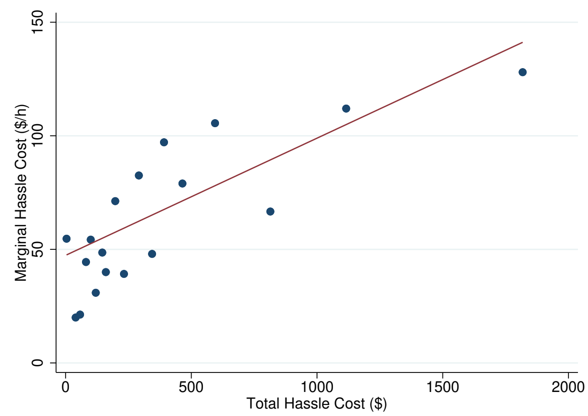
(a) Human Assistant



(b) Online Training



(c) Human Assistant

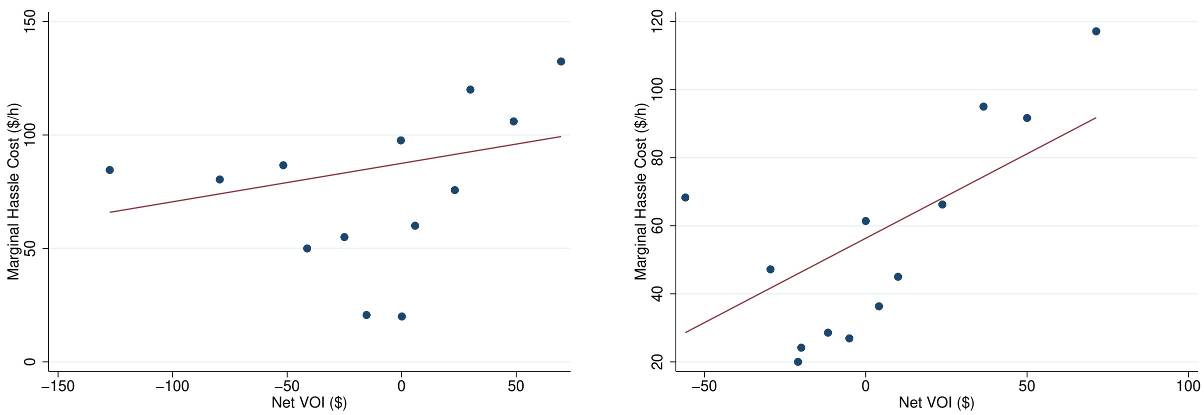


(d) Online Training

Figure A.5: Marginal Hassle Cost vs Time Spent and Total Hassle Costs.

we need to control for. Therefore, our estimates of the (net) VOI should not be generalized to all types of energy coach program. As we show in Table 3, it is, however, noteworthy that a large share of homeowners did not expect positive net benefits from such an intervention—for a large share of individuals, the net VOI is below zero. In fact, the median is exactly zero for both programs. As governments and energy utilities look for ways to increase take-up of heat pumps and low-carbon technologies the energy coach and one-stop-shop approaches are popular programs, the above results suggest that it may be hard to convince households to take advantage of such programs.

Examining the correlation between the marginal hassle cost (MHC) and the net value of information (VOI), we find a positive relationship, especially for the online training program. Individuals who perceive a higher information value from the program also report higher marginal costs of completing it. This pattern is consistent with a form of adverse selection: if the energy coach program were subsidized to compensate for hassle costs, participation would not necessarily come from those who value the information most, because they are also the ones having the largest hassle costs.



(a) Human Assistant

(b) Online Training

Figure B.6: Marginal Hassle Cost vs net VOI.

C Endline Survey

Six months after the initial recruitment, we reached out to all respondents who had completed the baseline survey (N=861) via email and invited them to complete a four-minute online follow-up questionnaire. The survey asked about heat pump adoption in the last six months, intention to adopt a heat pump in the upcoming months/years, barriers to adoption (for adopters and non-adopters), realized and expected time required to complete tasks related to heat pump adoption, and self-assessed knowledge of heat pump technology and functionality.

A total of 320 participants started the survey, and 308 completed it, corresponding to a response rate of approximately 36%. Among those, 25 respondents reported having replaced their heating system during the previous six months, of whom 20 indicated that they replaced it with a heat pump. Among those who did not change their heating system (N=283), about 52% reported an intention to replace their heating system with a heat pump; however, the median expected replacement date is more than 6 years in the future. With respect to knowledge of heat pump technology, about half of non-adopters reported being not knowledgeable at all (17%) or slightly knowledgeable (34%). In contrast, only one respondent out of the 21 heat pump adopters reported not being knowledgeable at all.

The analysis of open-ended questions regarding barriers to adoption in Table C.5 shows that financial considerations were the most frequently cited obstacle (39%), followed by installation and availability constraints (10%). Perceived efficiency (8%) and concerns about heat pump performance in cold Canadian climates (7%) were mentioned less frequently, while system compatibility issues were relatively rare (2%). A residual category of other barriers accounts for 33% of responses.

Table C.5: Main barriers to residential heat-pump adoption (N = 205)

#	**Barrier**	**N**	**%**	**Hassle**	**Keywords**
1	Cost & finance	80	39.0	Low	upfront cost, affordability
2	Install / availability	21	10.2	**High**	installer access, scheduling
3	Efficiency perception	17	8.3	Low	perceived savings, performance
4	Extreme-temp performance	14	6.8	Low	cold climate concerns
5	System compatibility	5	2.4	Medium	home fit, electrical capacity
6	Other	68	33.2	Low	miscellaneous responses

Hassle = extra time/effort households expect beyond the monetary outlay. Percentages are computed using the total number of respondents ($N = 205$).

D Policy Analysis Model

D.1 Home Energy Demand

We obtain data on estimated annual energy consumption for space heating by house from the EnerGuide Rating System (ERS) database, E_{il}, where houses are indexed by i and locations (weather stations) are indexed by l.[14] Figure D.7 shows a histogram of space heating energy consumption for houses that participated in the survey. Heat demand ranges from 25 to nearly 150 GJ per house per year.

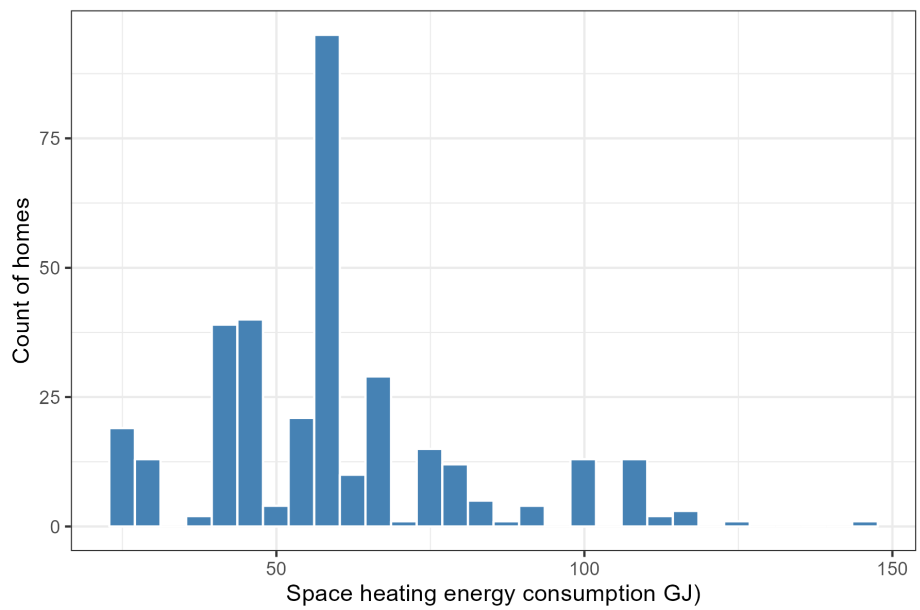


Figure D.7: Histogram of estimated space heating energy requirements

We obtain typical outdoor temperature by hour at location l, t_{hl}, where $h \in 1..8760$ represents hours in a typical year, from the Environment Canada CWEC database. Figure D.9 shows a histogram of hourly temperature for the study site. Temperature in Kelowna ranges from -20 to

[14]The ERS database contains model-predicted data of energy consumption for approximately 1.7 million houses across Canada that completed an energy audit under the auspices of the EnergGuide for Homes program. It is maintained by Natural Resources Canada. The data are available at the Government of Canada Open Data portal, at the following link: https://open.canada.ca/data/en/dataset/0a7619fd-2ffe-44b5-9027-3dfcec0866fd.

nearly 40°Cover the course of the year.

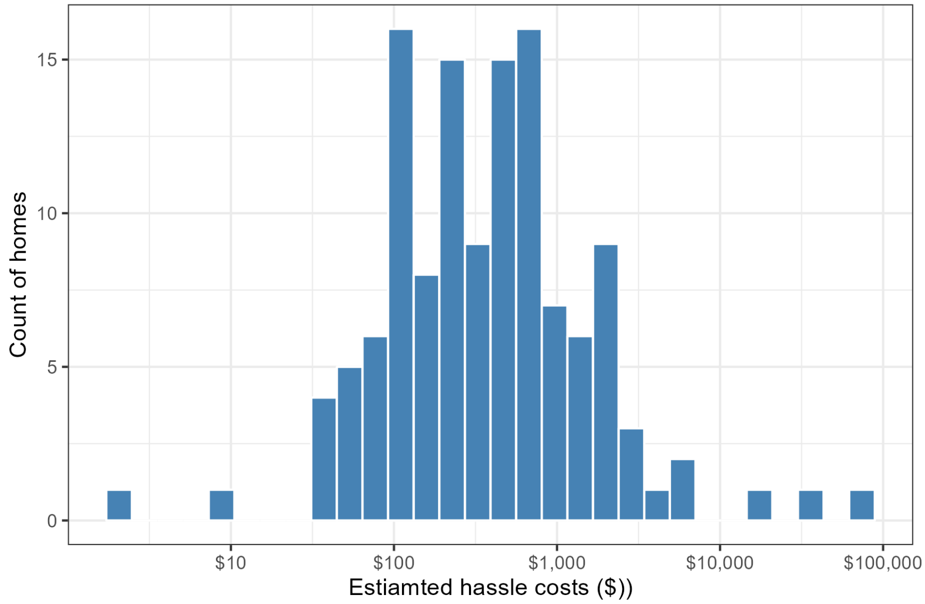


Figure D.8: Histogram of estimated hassle costs associated with heat pump adoption

We define $\hat{t}_i$ as the temperature for house i at which no energy additions from the heating system are required to maintain the indoor temperature at a comfortable level. This is usually taken as 16 to 18°C.

Heating degrees for house i at hour h in location l are defined as the number of degrees below $\hat{t}_i$ in each hour of the year:

$$hd_{ihl} = \begin{cases} \hat{t}_i - t_{hl}, & \text{if } t_{hl} < \hat{t}_i \\ 0, & \text{if } t_{hl} \geq \hat{t}_i. \end{cases}$$

We calculate the annual heating degree hours as the sum of heating degree hours over all hours of the year: $hda_{il} = \sum_h hd_{ihl}$.

We calculate the heating input per heating degree hour as: $x_{il} = E_{il}/hda_{il}$. This variable determines the change in house heat load as the outdoor temperature falls below $\hat{t}_i$ (i.e., each degree below $\hat{t}_i$ requires x more units of additional heat. By definition, no external heat is required at

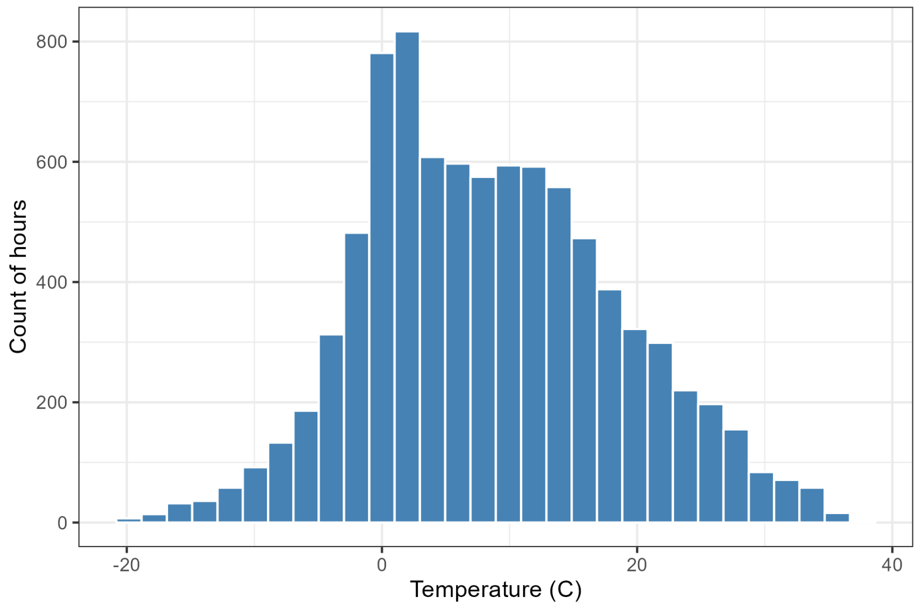


Figure D.9: Histogram of hourly temperature in Kelowna, BC. Data from Environment and Climate Change Canada CWEC databse.

$t_{hl} \geq \hat{t}_i$. We use a value of 16 degrees Celsius for $\hat{t}_i$, consistent with evidence in Rivers and Shaffer (2020). The heating system output required in any hour is now given by $H_{ihl} = hd_{ihl} \times x_{il}$.

D.2 Heating System Parameters

For a house with a natural gas furnace, we assume furnace efficiency η^F is invariant to temperature and load and that the furnace is sized to meet the maximum load. We assume new furnaces have $\eta^F = 0.95$. We assume that the upfront cost of a furnace is \$5,500. While we don't model air conditioning energy costs in this model, we assume that a new central air conditioner costs \$5,000. We assume these costs are invariant to furnace size.[15]

For heat pumps, we index available heat pump models by m. For any given outdoor temperature, we define minimum and maximum heat pump output by $\underline{g}_{mt}$ and $\bar{g}_{mt}$, and minimum and maximum heat pump coefficient of performance by $c\underline{o}p_{mt}$ and $c\bar{o}p_{mt}$, respectively. These parameters are available at discrete temperatures from heat pump manufacturers, and we linearly

[15] See `https://www.furnaceprices.ca/air-conditioners/central-air-conditioner-prices-canada/`.

interpolated between to obtain a continuous relationship between outdoor temperature and coefficient of performance. Values for the heat pump models considered in this paper are drawn from Ferguson and Sager (2002), and interpolated values for the coefficient of performance and heat pump output are given in Figure D.10.

A heat pump can operate at output below $\underline{g}_{mt}$ by cycling. The efficiency penalty during cycling operations is defined as ϕ and is treated as a decrement on heat pump coefficient of performance, such that coefficient of performance during cycling is: $c\underline{o}p_{mt} \times (1 - \phi)$. The actual coefficient of performance is linearly interpolated between the maximum and minimum, depending on heating load, H_{ihl}. Specifically:

$$cop_{mt}(H_{ihl}) = \begin{cases} c\underline{o}p_{mt} \times (1-\phi), & \text{if } H_{ihl} < \underline{g}_{mt} \\ c\underline{o}p_{mt} + \frac{H_{ihl} - \underline{g}_{mt}}{\bar{g}_{mt} - \underline{g}_{mt}} c\bar{o}p_{mt}, & \text{if } H_{ihl} \geq \underline{g}_{mt} \ \ \& \ \ H_{ihl} \leq \bar{g}_{mt} \\ c\bar{o}p_{mt}, & \text{if } H_{ihl} > \bar{g}_{mt} \end{cases}$$

A heat pump can only provide heat at outdoor temperatures above $\tilde{t}_m$. At temperatures below $\tilde{t}_m$, or when the house energy demand exceeds the maximum output of the heat pump, a backup energy source is required. Here, we assume that the backup energy source is electricity, and we assume electric resistance backup is η^E=100% efficient in converting electricity input to thermal output. If the home uses a heat pump with electric resistance backup, we assume the household can disconnect from the natural gas network.

We obtain heat pump costs from on-line sources.[16] There is considerable heterogeneity in heat pump installed costs. We assume heat pump installed costs are \$16,000 plus \$3,000 per ton of capacity, such that, for example, a 3-ton heat pump is \$25,000. In our base simulations, we assume a rebate of \$10,000 is available for all central heat pumps.

[16]For example: `https://1clickheat.com/product/mitsubishi-zuba-central-hyper-heat-ducted-heat-pump/` and `https://bryansfuel.on.ca/wp-content/uploads/2024/03/2024-zuba-central-pricing.pdf`.

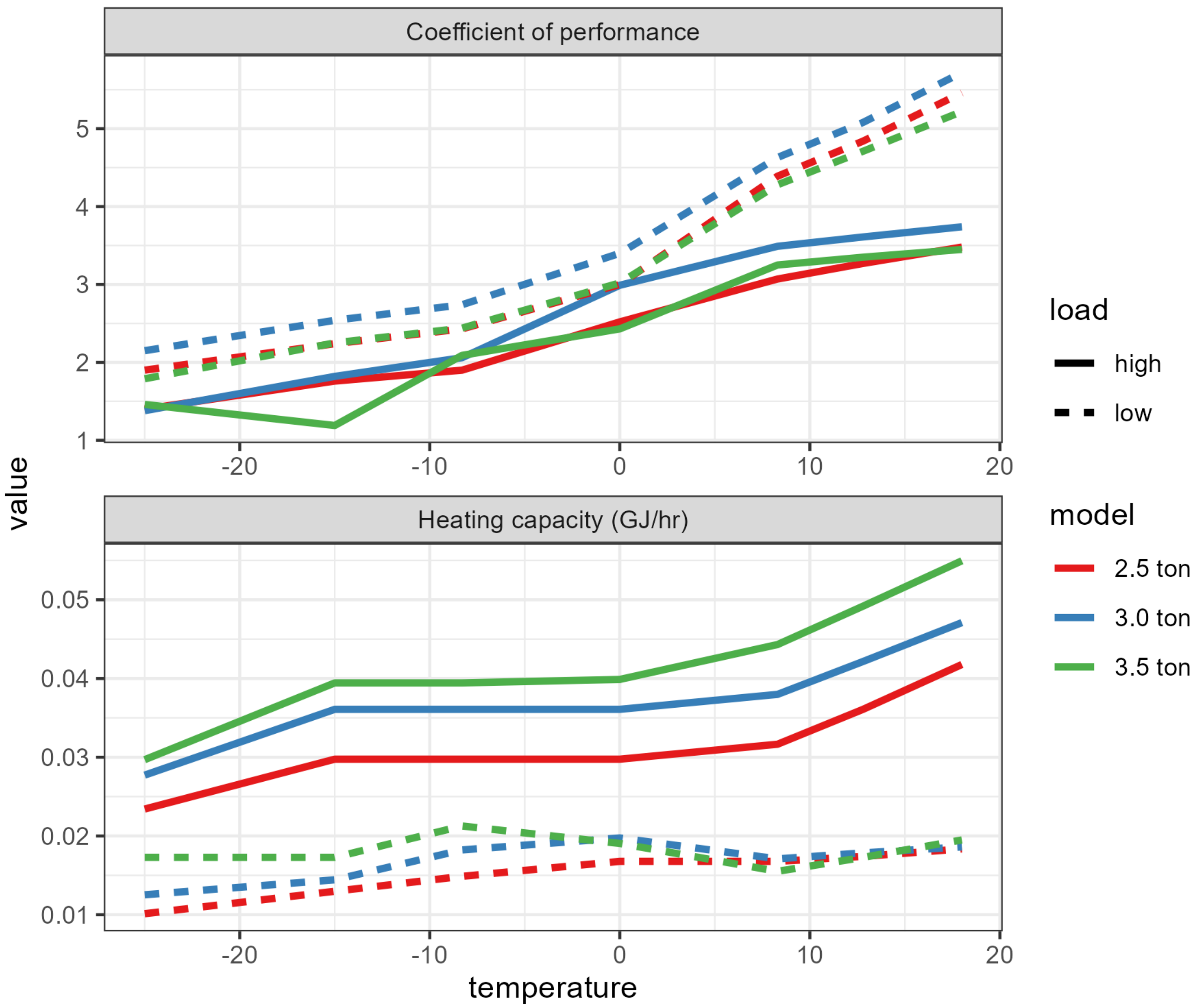


Figure D.10: Heat pump performance

parameter	value	units
p^N	9.28	\$/GJ
p^E	14.16	c/kWh
$\bar{p}^N$	153.89	\$/year
$\bar{p}^E$	275.45	\$/year
z^N	50	kg CO_2/GJ
z^E	0	kg CO_2/kWh
p^C	100	\$/t CO_2

Table D.6: Energy prices and characteristics

D.3 Energy Prices and Characteristics

The *variable* price of natural gas is given by p^N, and the variable price of electricity is given by p^E (both of these prices are *exclusive* of any carbon price). The *fixed* price of natural gas and electricity are given by $\bar{p}^N$ and $\bar{p}^E$, respectively, and are given in dollars per year. The carbon content of natural gas and electricity is given by z^N and z^E. The carbon price is p^C and is expressed in dollars per tonne. Table D.6 shows assumed parameter values. Energy prices are drawn from Fortis Energy residential rates as of 2024.[17] We use a carbon price of $100/t as representative.

D.4 Total cost, emissions, and energy consumption

D.4.1 Furnace

If a natural gas furnace is used as a stand-alone heating system, the required energy (natural gas) each hour is given by: $e^F_{ihl} = \frac{1}{\eta^F} H_{ihl}$. The annual variable cost of energy for space heating is $\sum_h e^F_{ihl}(p^N + z^N p^C)$, and the annual emissions are given by $\sum_h e^F_{ihl} z^N$. The annualized (private) cost of the heating system is the energy cost to operate the furnace, plus the annualized cost of the furnace itself, plus the annual fixed costs of natural gas and electricity: $A^F_{il} = \sum_h e^F_{ihl}(p^N + z^N p^C) + \beta C^F + \bar{p}^N + \bar{p}^E$, where β is a capital recovery factor and C^F is the upfront cost of the furnace. We calculate the capital recovery factor based on the expected lifetime of the furnace, L,

[17] https://www.fortisbc.com/accounts-billing/billing-rates/natural-gas-rates/residential-rates

and the interest rate, i, using $\beta = i + (1+i)^L/((1+i)^L - 1)$. We assume $i = 0.07$ and $L = 15$ for both furnace and heat pumps.

D.4.2 Heat Pump

The energy consumption of heat pump system m (including the backup electricity system) is determined by the outdoor temperature and the heat pump capacity relative to the house energy load, as well as temperature-specific heat pump performance, as follows:

$$e_{ihlm}^{HP} = \begin{cases} 0, & \text{if } t_{hl} \geq \hat{t}_i \\ H_{ihl}/cop_{mt}(H_{ihl}), & \text{if } \tilde{t}_m \leq t_{hl} < \hat{t}_i \;\;\&\;\; g_{ihlm} \geq H_{ihl} \\ \eta^E H_{ihl}, & \text{if } t_{hl} < \tilde{t}_m \\ \eta^E H_{ihl}, & \text{if } g_{ihlm} < H_{ihl} \end{cases}$$

The annual cost of energy, using heat pump model m, is $\sum_h e_{ihlm}^{HP}(p^E + z^E p^C)$, and the annual emissions are given by $\sum_h e_{ihlm}^{HP} z^E$. The annualized (private) cost of the heating system is the energy cost to operate the heat pump, plus the annualized cost of the heat pump itself, plus the annual fixed costs of electricity: $A_{ilm}^{HP} = \sum_h e_{ihlm}^{HP}(p^N + z^N p^C) + \beta C_m^{HP} + \bar{p}^E$, where β is a capital recovery factor and C_m^{HP} is the upfront cost of the heat pump. Depending on the scenario, C_m^{HP} includes the hassle cost associated with heat pump installation as well as any rebate to offset heat pump costs. The optimal heat pump for house i in location l is given by $m_{il}^* = \arg\min A_{ilm}^{HP}$.

D.5 Cost-Effectiveness

For house i in location l, the cost-effectiveness of adopting a heat pump is given by:

$$\frac{(A_{il}^F - (A_{il}^{HP})^*)}{\sum_h e_{ihl}^F z^N - \sum_h (e_{ihl}^{HP})^* z^E},$$

where $*$ indicates the cost and emissions associated with the optimal heat pump for house i at location l.