# Moral Hazard and the Energy Efficiency Gap: Theory and Evidence

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**Abstract:** We investigate how moral hazard problems can cause suboptimal investment in energy efficiency, a phenomenon known as the energy efficiency gap. We focus on contexts where the quality offered by the energy efficiency provider is imperfectly observable. We formalize underprovision of quality and compare two policy solutions: energy-savings insurance and minimum quality standards. We then provide empirical evidence of moral hazard in home energy retrofits in Florida. We find that for those measures, the quality of which is deemed hard to observe, realized energy savings are subject to day-of-the-week effects. Specifically, energy savings are significantly lower when those measures were installed on a Friday—a day particularly prone to negative shocks on workers' productivity—than on any other weekday. We finally specify a model to simulate the Floridian market and find that the deadweight loss from moral hazard is about twice as large as that due to associated carbon dioxide externalities.

**JEL Codes:** D86, Q41

**Keywords:** Credence good, Day-of-the-week effect, Double moral hazard, Energy efficiency gap, Energy-savings insurance, Minimum quality standard

ENERGY EFFICIENCY MEASURES are widely advocated as a means of both saving money and cost-effectively reducing externalities associated with energy use. Yet in practice, they are little adopted. This phenomenon is commonly referred to as the energy efficiency gap. One of its manifestations is the increasingly documented discrepancy be-

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tween realized energy savings and those predicted by engineering models (Metcalf and Hassett 1999; Davis et al. 2014; Fowlie et al. 2015; Graff Zivin and Novan 2016; Maher 2016; Houde and Aldy 2017). Another long studied manifestation is the abnormally high discount rates (typically 10%–30%) implied by energy efficiency sales patterns (Hausman 1979; Train 1985).

A variety of explanations have been investigated to explain the energy efficiency gap (Gillingham et al. 2009; Allcott and Greenstone 2012). Jaffe and Stavins (1994), who first conceptualized the problem, emphasized the difference between market-failure and nonmarket-failure explanations of the gap. Market failures such as information asymmetries, positive externalities from innovation, or negative externalities associated with energy use, may distort incentives for energy efficiency investment. This motivates implementation of corrective policies. Nonmarket failures such as heterogeneity in consumer preferences or hidden costs (e.g., inconvenience caused by insulation installation) may also prevent widespread adoption of energy efficiency. Yet, unlike market failures, these are normal components of markets. As such, they should be accounted for in economic assessments but do not per se warrant any particular intervention. More recently, the dichotomy has been enriched with the concept of behavioral anomalies to account for apparent undervaluation of energy savings by energy users (Allcott et al. 2014; Gillingham and Palmer 2014).

In this paper, we provide a market-failure explanation for the energy efficiency gap: moral hazard in the provision of quality. We empirically find that the problem can explain a large part of the discrepancy between predicted and realized energy savings. This manifestation of the energy efficiency gap has so far been considered to be due to nonmarket failures, especially measurement errors or upward-biased thermal simulations.[1] Our contribution is to show that it can be due to a market failure, namely, systematic undertreatment of quality by energy efficiency providers when the informational context gives them the opportunity to do so. We show that the welfare losses due to moral hazard in home energy retrofits, though potentially important, can be partly mitigated by policy interventions such as minimum quality standards and energy-savings insurance.

Our motivation comes from the credence-good nature of energy efficiency, a little-studied aspect of this technology. Just like taxi rides or auto repairs, many energy effi-

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1. Recent explanations of the gap between predicted and realized savings also include increased intensity of utilization, though with a limited role (Fowlie et al. 2015); replacement of technologies that were not being used in the first place (Davis et al. 2014); upgrade toward oversized technologies (Houde and Aldy 2017); overestimation of pre-retrofit energy use in engineering predictions of energy savings (Sunikka-Blank and Galvin 2012; de Wilde 2014).

ciency measures are subject to verifiability and liability issues which make their performance never completely revealed to the buyer (Sorrell 2004; Dulleck and Kerschbamer 2006). This is especially the case in buildings, where energy use depends on unobservable factors such as weather forecasts, occupants' behaviors, and the quality of energy efficiency equipment. These properties are conducive to a set of information asymmetries, of which two have received most attention. One is adverse selection in housing decisions. The intuition is that the energy efficiency of a dwelling is hard to observe and therefore will not be capitalized into sale prices or lease contracts. The intuition is proving correct in rental housing, as rented dwellings are found to be less energy efficient than owner-occupied ones (Scott 1997; Davis 2012; Gillingham et al. 2012; Myers 2013; Krishnamurthy and Kriström 2015). The effect is less clear in home sales. More energy-efficient homes, as measured by their energy performance certificate, are found to sell with a premium, but no counterfactual situation without certificates is available for comparison (Brounen and Kok 2011; Murphy 2014; Fuerst et al. 2015). Another much-studied information asymmetry associated with energy efficiency is moral hazard in energy demand. It is well established that building occupants use more energy when they face zero marginal cost of usage, for instance, because they signed up a utility-included rent contract (Levinson and Niemann 2004; Maruejols and Young 2011; Gillingham et al. 2012).

The information asymmetry considered here is related but involves different parties. We are interested in underprovision of quality in the installation of energy efficiency measures. We specifically examine home energy retrofits, where a contractor may take advantage of the lack of expertise of the homeowner to perform insulation or duct sealing poorly. This can be interpreted as supply-side moral hazard. As we shall see, full analysis of the problem and solutions thereto require one to also consider the demand-side moral hazard discussed above.

Our contribution is threefold. First, we formalize how supply-side moral hazard can cause an energy efficiency gap and examine two little-discussed policy remedies: energy-savings insurance, a private solution, and minimum quality standards, a public one. The analysis builds on a double-moral-hazard framework borrowed from the literature on warranties (Cooper and Ross 1985). We articulate the mechanism by which asymmetric information induces the contractor to cut quality in equilibrium. This deters adoption of energy efficiency measures. Both policy solutions are found to be second best: energy-savings insurance reduces marginal energy expenditures, which induces demand-side moral hazard and therefore requires incomplete coverage in equilibrium; minimum quality standards incur enforcement costs.

Second, we provide the first empirical evidence of supply-side moral hazard in home energy retrofits. Using a data set of 3,000 retrofits sponsored by Gainesville Regional Utilities (GRU) in Florida, we exploit variation in the type of measures (classified as easy or hard to observe) and the day of the week on which they were installed. We find that realized energy savings underperform predicted ones and, in particular, that the former can vanish for hard-to-observe measures if those were installed on a Friday. The result is robust to a number of robustness checks, including testing for contractors selecting specific measures on Fridays. It suggests that perhaps due to fatigue, retrofit workers are likely to shirk if the informational context gives them the opportunity to do so. Controlling for the Friday effect, the discrepancy between predicted and realized energy savings shrinks by 70%. Incidentally, the exercise contributes to the empirical literature on day-of-the-week effects on workers' productivity (Campolieti and Hyatt 2006; Bryson and Forth 2007) and more generally to the empirical analysis of moral hazard and credence goods (Abbring et al. 2003; Dulleck et al. 2011; Schneider 2012; Balafoutas et al. 2013).

Third, we integrate the theoretical and empirical approaches to assess the welfare consequences of moral hazard in home energy retrofits. The model developed in the theoretical exercise is calibrated to simulate the Floridian market, using data from the GRU program and the US Residential Energy Consumption Survey (RECS). We find that the deadweight loss due to moral hazard could be twice as large as that due to associated carbon dioxide externalities. This result is robust to a range of specifications and can be approximated by a sufficient statistic that abstracts from consumer preferences. Energy-savings contracts with insurance coverage in the 10%–20% range can mitigate losses, while minimum performance standards produce benefits in excess of reasonable enforcement costs. The performance of each instrument is close if carbon dioxide externalities are absent or fully internalized. If externalities remain unpriced, however, the demand-side moral hazard induced by insurance magnifies losses, and standards appear to be a better policy option.

Our analysis is a first step pointing to supply-side moral hazard in home energy retrofits as an important problem, both empirically and economically. Policy instruments already existing in the marketplace could be adjusted to deliver their full potential. Energy performance contracts, which are common in commercial buildings, could be promoted in the residential sector. Certification of professional installers, which is so far mostly voluntary, could evolve toward a mandatory regime. Hybrid instruments combining standards and insurance might also produce substantial benefits.

The outline of the paper is as follows. Section 1 introduces the theoretical model, derives key predictions, and examines policy solutions. Section 2 presents the empirical approach and the results. Section 3 provides a numerical welfare assessment. Section 4 concludes.

## 1. A MODEL OF ENERGY EFFICIENCY INVESTMENT WITH DOUBLE MORAL HAZARD

Our model builds upon the double-moral-hazard model of Cooper and Ross (1985). To fix ideas, we consider the canonical case of home energy retrofits, which involve hidden actions from both the homeowner and the retrofit contractor. Other situations that give rise to one-sided moral hazard, for instance, energy efficiency improvements in the commercial and industrial sectors, can be viewed as special cases of this general model.[2] The exposition here focuses on the key elements and predictions of the model. Formal assumptions, additional propositions, complete proofs and graphical illustrations are provided in an appendix (available online).

## 1.1. Setup

Consider a homeowner using energy for air conditioning (or space heating). The energy service $s$, measured in cooling degree days (alternatively, heating degree days), provides her with increasing comfort $V(s)$, multiplied by a taste parameter $\theta > 0$. For instance, a person living in a hot area would be characterized with a high value of $\theta$ (alternatively, a low one).

The homeowner spends $pE^0(s)$ on energy, where $E^0(\cdot)$ is the energy use and $p$ the price of energy. She sets her energy service $s^0_\theta$ so as to maximize the discounted sum of net utility:

$$U^0(\theta, s) \equiv \big(\theta V(s) - pE^0(s)\big)\Gamma(r, l), \tag{1}$$

where $\Gamma$ is a discount factor function of the discount rate $r$ and the investment horizon $l$. We assume time invariance of energy price, technology, and comfort valuation. The energy service $s$ is therefore constant over time. The discount factor is $\Gamma(r, l) \equiv \sum_{t=1}^{l}(1 + r)^{-t} = (1 - (1 + r)^{-l})/r$.

The homeowner can undertake a retrofit investment supplied by a contractor. Each party can take hidden actions that influence ex post energy use, $E(s,q)$. The homeowner's ex post energy service $s$ is unobserved to the contractor. In turn, the quality $q$ with which the contractor completes the retrofit is unobserved to the homeowner, who as a nonexpert cannot verify insulation installation or duct sealing, for instance. Energy use, which is reported on the homeowner's utility bill, is common knowledge to both parties, who are also aware that it increases with $s$ and decreases with $q$. The framework is deterministic, and linearity of utility with respect to energy expenditures reflects risk neutrality.[3]

Upon investing, the homeowner maximizes utility $U(\theta, s, q)$, net of upfront cost $T > 0$ and includes an idiosyncratic value, $\delta$, capturing, for instance, aesthetic and

2. Moral hazard in the provision of energy efficiency also arises in the car and truck markets. As documented by Reynaert and Sallee (2016), manufacturers may strategically overstate fuel economy values. This gap between stated and realized fuel economy is also an example of supply-side moral hazard.

3. We ignore uncertainties coming from the weather variations determining heating or cooling needs, from measurement errors propagated in the complex engineering models used to predict energy savings, or from the volatility of energy prices. This simplification is equivalent to assuming that the effects of $s$ and $q$ on energy use both satisfy first-order stochastic dominance.

acoustic benefits associated with insulation (if positive) or inconvenience incurred for installation (if negative):

$$U(\theta, s, q) \equiv (\theta V(s) - pE(s, q))\Gamma(r, l) - T + \delta. \tag{2}$$

The contractor maximizes profit formed by the revenue from the sale $T$ minus the cost $C(\cdot)$ of providing quality $q$. We assume zero profit, so that:

$$T = C(q). \tag{3}$$

The assumption is meant to reflect the competitive nature of the industry.[4] We show in the appendix that the equilibrium analysis is nevertheless robust to alternative market structures.

We model the energy efficiency contract as a two-stage game in which the homeowner is the principal and the contractor is the agent. In the first stage, the homeowner of type $\theta$ invests if her net present value $NPV(\theta)$ is positive, given her energy service $s_\theta^*$ and the quality $q_\theta^*$ she expects to be offered in equilibrium:

$$NPV(\theta) \equiv U(\theta, s_\theta^*, q_\theta^*) - U_0\left(\theta, s_\theta^0\right) \geq 0. \tag{4}$$

In the second stage, both agents determine their optimal action given their belief about the other party's action. We solve the game using backward induction.

### 1.2. Supply-Side Moral Hazard

We model the social optimum as a cooperative game with perfect information. We show in the appendix that this game generates strictly increasing reaction functions: a contractor will offer more quality to a homeowner he perceives as demanding more energy service; the homeowner will demand more energy service if she expects to be offered more quality. The intersection of the two reaction functions defines a perfect-information equilibrium that determines the socially optimal level of quality.

If actions $s$ and $q$ are not perfectly observable, the parties each maximize their private surplus, given their beliefs about the other party's action. This does not affect the homeowner's first-order conditions and therefore leaves her reaction function unchanged. In contrast, the contractor does not internalize how quality benefits the homeowner. His reaction function is now flat: whatever behavior he expects from the homeowner, he sets quality at the level that minimizes production cost. The intersection of the two reaction functions defines the asymmetric-information equilibrium.

Equilibrium actions under perfect information (*PI*) and asymmetric information (*AI*) can be unambiguously compared:

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4. The home energy retrofit industry is highly fragmented. For instance, firms operating in the heating, ventilation, and air conditioning (HVAC) industry in California are typically small, offer low wages, face low barriers to entry, and have an annual turnover as high as 25% (Zabin et al. 2011).

**Proposition 1**: Under asymmetric information, an energy efficiency contract is subject to supply-side moral hazard. The contractor offers less quality to any homeowner of type $\theta$ than under perfect information: $q_\theta^{AI} \leq q_\theta^{PI}$. The homeowner responds by using less energy service: $s_\theta^0 < s_\theta^{AI} \leq s_\theta^{PI}$. The two inputs together make investment less profitable: $NPV^{AI}(\theta) \leq NPV^{PI}(\theta)$.

Comparison is ambiguous when it comes to equilibrium energy use. Undoing moral hazard increases both $q$ and $s$, which has an opposite effect on $E(\cdot, \cdot)$. In words, the energy savings induced by improved quality are partly offset by an increase in energy service. This phenomenon is known as the rebound effect. At some point, it can backfire, that is, be such that energy use is higher after investment. While conceptually important in the presence of negative energy-use externalities, as we will see later, backfire rebound effects are empirically limited (Gillingham et al. 2013). In most cases, therefore, the energy savings realized under asymmetric information will be lower than those predicted under perfect information (e.g., by engineering models).

We now extend the above result to the whole market. Consider a continuum of homeowners of mass 1, all living in a similar dwelling and only differing with respect to their preference for thermal comfort $\theta$. We show in the appendix that the higher the value of $\theta$, the higher the demand for energy service, hence the higher the quality offered under perfect information. This shifts the homeowner's reaction function upward. In contrast, the quality offered under asymmetric information remains at minimum. As a result, the moral-hazard effect is increasing in $\theta$. We also show that the net present value of investment is increasing in $\theta$. This means that there exists a unique marginal investor of cutoff type $\theta_0^*$ such that $NPV(\theta_0^*) = 0$. Combining this with proposition 1 leads us to the following proposition:

**Proposition 2**: Asymmetric information creates an energy efficiency gap at the market level. Both the number of investing consumers and social welfare are lower than under perfect information: $N^{AI} \leq N^{PI}$ and $W^{AI} \leq W^{PI}$,

where $N^* \equiv 1 - F(\theta_0^*)$ is the equilibrium number of participants, $F(\cdot)$ is the cumulative distribution function of $\theta$, and $W^*$ is aggregate welfare, calculated under zero-profit condition as the sum of utility before investment for nonparticipants and utility after investment for participants:

$$W^* \equiv \int_0^{\theta_0^*} U^0\left(\theta, s_\theta^0\right) \mathrm{d}F(\theta) + \int_{\theta_0^*}^{+\infty} U(\theta, s_\theta^*, q_\theta^*) \mathrm{d}F(\theta). \tag{5}$$

Anticipation of the quality gap discourages homeowners with low valuations of comfort to invest. As a result, investment is suboptimal on both the intensive and extensive margins. Again, without further specification of the technology $E(\cdot,\cdot)$, we cannot conclude about how aggregate energy use differs in the two equilibria.

### 1.3. Policy Solutions

The textbook remedy to moral hazard is a risk-sharing contract. In the context of home energy retrofits, such a contract can take the form of energy-savings insurance. Alternatively, a regulator may want to address the problem with a verifiable quality standard. A third option, sometimes found in practice, is to combine the two. In this section, we compare the two solutions in their purest form in order to identify their relative strengths and weaknesses. We find that none can achieve the first-best outcome.

#### *1.3.1. Energy-Savings Contracts and Double Moral Hazard*

Energy-savings contracts or insurance, more commonly referred to as energy performance contracts, have been offered for nearly 20 years in the commercial sector (Mills 2003), less frequently in the residential sector.[5] Such contracts typically have the contractor pay the homeowner any shortfall in energy savings below a pre-agreed baseline. In our simple framework with no risk aversion, insurance can be modeled as a contract specifying a share $k$ of energy expenditures borne by the contractor in exchange for an actuarially fair insurance premium $I$:

$$I = k\,pE(s,q)\Gamma(r,l). \tag{6}$$

Such an insurance contract creates an incentive problem that superimposes the one it is meant to address in the first place. The contract can be modeled as a three-stage game, in which the contractor now is the principal and the homeowner is the agent. In the third stage, the parties cooperatively determine optimal insurance coverage $k^*_\theta$; in the second stage, they privately set their own action, given their belief about insurance coverage $k$ and the other party's action; in the first stage, they decide whether or not to participate.

The insurance induces the contractor to offer some quality, otherwise he would have to make excessive payments to the homeowner. In other words, the risk-sharing contract mitigates supply-side moral hazard. At the limit, it could even eliminate it, as complete coverage ($k = 1$) would induce the contractor to offer socially optimal quality. But at the same time, the contract gives rise to demand-side moral hazard: by lowering the homeowner's marginal value of energy service, it induces her to use more energy. At the limit, complete coverage would drive the homeowner's marginal energy expenditure to zero, thereby inducing her to use energy service up to satiation. Complete coverage is therefore not optimal:

**Proposition 3**: Energy-savings contracts create demand-side moral hazard. As a consequence, optimal insurance coverage is incomplete: $0 < k^*_\theta < 1$.

5. GreenHomes America, Inc., NJ-PA Energy Group, LLC. and EcoWatt Energy, LLC. are the few examples we have found of companies offering energy-savings insurance in the US residential sector.

Note that if the building occupant were not adjusting her energy service (e.g., a tenant subscribing to a utility-included rent contract or an employee in a commercial building), then the second moral hazard would not occur. The optimal contract would stipulate complete coverage and bring the parties to the social optimum. This may explain why energy performance contracts are common in the commercial sector but rarely offered to residential consumers.

Note also that by increasing both $q$ and $s$, the energy-savings contract generates a rebound effect. Unlike that induced by the simple energy efficiency contract discussed in section 1.2, this rebound effect can be interpreted as moral hazard. Formally, the rebound effect associated with the energy efficiency contract materializes as the positive slope of the homeowner's reaction function, which is not affected by the informational context. In contrast, the rebound effect associated with the energy-savings contract corresponds to an upward shift of the homeowner's reaction function. This can be interpreted as demand-side moral hazard, just like the downward shift of the contractor's reaction function due to asymmetric information could be interpreted as supply-side moral hazard.

In practice, homeowner types, $\theta$, can be difficult to observe. A uniform contract with undiscriminated coverage is therefore most likely to be offered to all homeowners. Such a contract generates additional deadweight losses, as the coverage might be optimal to one homeowner but is suboptimal to all others.

#### *1.3.2. Minimum Quality Standard*

A number of voluntary certifications exist in the marketplace, most notably those provided by the Building Performance Institute (BPI) and the Residential Energy Services Network (RESNET) in the United States. These programs typically ensure that professional workers and contracting companies are trained to the best practices and that their performance is regularly verified.

We model such standards as a verifiable minimum quality input $\bar{q}$, for instance, prescribing the grade of materials used and the application taken in installation. The instrument generates two types of inefficiencies. First, compliance needs to be verified, which generates enforcement costs $M(\bar{q})$. These costs do not arise with energy-savings insurance, which rely on a commonly observed variable, namely, the energy use reported on utility bills. Second, just like a uniform insurance contract, minimum quality standards do not account for consumer heterogeneity.

We show in the appendix that the value of $\bar{q}$, which minimizes the deadweight loss, is such that the marginal disutilities of those homeowners for whom the standard is too tight and the marginal utilities (net of marginal enforcement costs) of those willing to invest beyond the standard are equalized.

To sum up, both insurance and standards can mitigate moral hazard but none can eliminate it. Leaving aside the deadweight loss arising from consumer heterogeneity, which is equally faced by a uniform insurance contract and a uniform quality standard, the comparison between the two instruments boils down to how the deadweight loss due to demand-side moral hazard induced by insurance compares with enforcement costs incurred with the standard. This is a context-specific question, which we examine numerically in section 3.

#### 1.3.3. *Interaction with Energy-Use Externalities*

As we show earlier, undoing moral hazard has an ambiguous effect on energy use due to the rebound effect. To the extent that it backfires while energy-use externalities remain unpriced, implementing policy remedies to moral hazard can have the unintended consequence of exacerbating deadweight losses. In the appendix, we uncover sufficient conditions for this not to occur. This points to the importance of considering interactions between market failures.

## 2. EMPIRICAL EVIDENCE OF SUPPLY-SIDE MORAL HAZARD

We now present three empirical facts that together suggest that energy retrofit contractors engage in moral hazard by poorly installing energy efficiency measures when the quality of their work is hard to verify. We do so using a rich data set from a utility-sponsored retrofit program run in Florida.

We first find that realized energy savings after completing an energy retrofit are below predicted engineering savings for several retrofit measures, a puzzle that is increasingly documented (Metcalf and Hassett 1999; Fowlie et al. 2015). The discrepancy is specifically large for measures where the quality of installation is hard to observe ex post. For other measures, with easy-to-observe installation quality, the sign of the gap is ambiguous. We then find that the discrepancy varies as a function of the day of the week on which a measure was installed and that this variation follows a particular pattern—realized savings are lower toward the end of the week, notably on Fridays, but only for measures whose quality is hard to verify ex post. Finally, we find that this Friday effect is not driven by selection. That is, contractors do not choose to install particular measures on a specific day of the week (though they might during the weekend). Crucially, retrofit prices are not lower on Fridays when realized savings fall.

The second and third empirical facts are a novel contribution to the debate about predicted-versus-realized energy savings. Together, they suggest that installation quality is undersupplied on Fridays for measures specifically prone to moral hazard. To explain the Friday effect, we argue that workers are more likely to experience negative productivity shocks toward the end of the workweek and are thus more likely to shirk on quality if the informational context gives them the opportunity to do so.

### 2.1. Data

From 2006 to 2012, Gainesville Regional Utilities (GRU) ran rebate programs for home energy retrofits. The programs targeted a variety of measures, including attic insulation, duct sealing, air conditioners, pool pumps, refrigerators, and windows. Eligibility for rebate required that measures be installed by pre-approved contractors. Prior to completion, each project had to undergo an assessment of the potential energy savings associated with the measures, based on ex ante engineering calculations.[6]

We restrict our analysis to homes where only one retrofit measure was undertaken and for which only one technology requiring labor input was installed, which ensures that we focus on households that had only one interaction with the contractors. We further restrict the sample to projects that cost under $10,000. The reasoning to exclude expensive retrofit projects is that they are likely to take more than one day to complete.[7] The refrigerator removal program is also excluded from the analysis because there was no installation of a technology required. Under these criteria, our sample contains 2,936 projects for which the following information is available: type of measure completed, predicted engineering energy savings, rebate amount, price paid to the contractor, and, crucially for our empirical exercise, the date on which a measure was installed. Table 1 provides summary statistics. We match the program data with monthly electricity and natural-gas billing data recorded by GRU between 2002 and 2013. This procedure allows us to link the characteristics of a retrofit measure to its impact on energy use.

## 2.2. Empirical Strategy

A first challenge in detecting moral hazard is that quality is not directly observed in our setting. Neither inputs to (e.g., hours worked and skills mobilized by installers, grade of the products and materials installed) nor outputs of the measures (e.g., number and type of defects) are documented. Our strategy to detect changes in quality, then, relies on estimating realized energy savings, which is strongly correlated with the quality of installation.

Our empirical strategy consists in uncovering heterogeneity in realized savings along two dimensions. First, we classify the quality of installation as either easy or hard to observe by the homeowners, and distinguish energy savings for these two categories of measures. We consider a measure hard to observe (HTO) if it meets two criteria: (i) the installation is an arduous task that requires significant labor input and (ii) the quality of installation is difficult to verify by a nonexpert. Attic insulation and duct sealing, which both require significant installation work and can hardly be verified after completion, belong to this category. Other retrofit measures that mostly consist of replacing equipment, such as air conditioners or pool pumps, are deemed easy to observe

6. Engineering estimates of energy savings are measure specific. They take into account home-specific features (building period, etc.) when necessary, namely, for all measures except pool pumps. In some cases, they were performed by a third party that came to the house.

7. The data do not allow us to ascertain that completion of a single measure takes exactly one day, that is, approximately 8 hours. We nevertheless think this is a reasonable assumption for the technologies considered.

Table 1. Summary Statistics by Energy Efficiency Measure

| | Predicted Energy Savings (MWh/Year) Mean (SD) | Predicted Energy Savings (kWh/Month) Mean (SD) | Maher (2016)'s DiD Energy Savings (kWh/Month) Coefficient (SD) | Project Price($) Mean (SD) | Rebate Amount($) Mean (SD) | Day of Installation Median | Observability | No. Observations |
|---|---|---|---|---|---|---|---|---|
| Attic insulation | 1.55 | 129.17 | 78.65*** | 761 | 199 | Wednesday | Hard | 575 |
| | (.04) | (3.33) | (26.91) | (501) | (77) | | | |
| Duct repair | 1.29 | 107.46 | 38.36 | 861 | 359 | Wednesday | Hard | 366 |
| | (.04) | (3.31) | (33.57) | (911) | (98) | | | |
| Low-interest loans | . . . | . . . | 73.04 | . . . | 1,089 | Wednesday | Hard | 84 |
| | . . . | . . . | (79.79) | . . . | (505) | | | |
| Super-SEER central AC | 1.93 | 160.83 | 208.9*** | 7,291 | 555 | Wednesday | Easy | 623 |
| | (.53) | (44.17) | (27.11) | (1,467) | (62) | | | |
| SEER-15 central AC | .55 | 45.83 | 161.3*** | 5,672 | 295 | Wednesday | Easy | 297 |
| | (.12) | (10.00) | (37.60) | (1,412) | (44) | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Pool pump | 1.76 | 146.67 | 101.6** | 1,452 | 284 | Wednesday | Easy | 394 |
| | (.16) | (13.33) | (47.05) | (505) | (97) | | | |
| Low-income grant | 1.12 | 93.33 | 52.87 | 301 | 2,170 | Wednesday | Easy | 227 |
| | (.82) | (68.33) | (38.52) | (339) | (1,528) | | | |
| Whole home performance | 2.49 | 207.50 | 131.1*** | 654 | 967 | Wednesday | Easy | 342 |
| | (1.00) | (83.33) | (43.88) | (239) | (289) | | | |
| Low-E window | .66 | 55.00 | 155.2** | 3,511 | 159 | Wednesday | Easy | 28 |
| | (.36) | (30.00) | (72.66) | (2,205) | (81) | | | |
| Total | | | | | | | | 2,936 |

Note. The estimates in the column labeled "Maher (2016)'s DiD" are technology-specific estimates of energy savings taken directly from Maher (2016). They are computed using a difference-in-differences estimator similar to that used to estimate the savings with day-of-the-week effects. The regression model does not consider heterogeneity with respect to the day of installation and estimates average savings for each measure. Standard errors are clustered at the household level. The column "Observability" classifies the quality of a measure as "Easy" or "Hard" to observe ex post. MWh = megawatt-hour. SEER refers to seasonal energy efficiency ratio, the metric used to measure the efficiency of air conditioners. Low-E refers to low emissivity windows, a particular technology that helps reflecting heat.

* $p < .10$.
** $p < .05$.
*** $p < .01$.

(ETO). Window replacement, which requires significant labor input but leaves few features hidden, could fall in either category. In our preferred specification, we classify this measure as easy to observe. In a robustness check, we exclude it from the ETO category and find little impact. In table 1, we present how we classify each type of measure considered in our analysis. From the working sample that contains 2,936 projects, 1,025 are HTO measures and 1,911 are ETO measures.

Second, we allow for heterogeneity based on the day of the week that the installation of the retrofit was performed. We hypothesize that workers' productivity is subject to systematic variation over the week which is unaccounted for in the retrofit contract. In particular, we expect that workers must deploy more effort to perform a retrofit project of a given quality toward the end of the week, namely, on Fridays and during weekends. Therefore, installation quality should be lower at the end of the workweek. This hypothesis is motivated by labor studies showing that productivity tends to be lower on Fridays, especially in the construction sector (e.g., Bryson and Forth 2007). Workers' fatigue is the reason most frequently invoked. Other explanations that apply in our setting include staff shortage, for example, workers calling out "sick" on Friday; quit time, for example, workers leaving early to start the weekend; backlog, for example, workers rushing to finish a job to avoid having to revisit a site for a few hours on the weekend or the week after.

Our test of existence of moral hazard is that a day-of-the-week effect is more likely to exist for HTO measures because workers can shirk on installation quality if it is hard to observe ex post. HTO measures should then deliver fewer energy savings if they have been completed when workers' productivity is lower, that is, at the end of the workweek, but ETO measures should not be subject to such a day-of-the-week effect.

We estimate realized energy savings using a difference-in-differences estimator where the estimate can vary with respect to the two categories of measures and the day of installation. The estimation strategy follows the quasi-experimental approach of Fowlie et al. (2015), Graff Zivin and Novan (2016), and Maher (2016), only extended with interactions with day-of-the-week dummies, denoted $DW$, and dummies that identify HTO and ETO measures. We consider the following regression model:

$$\begin{aligned} \log(kWh_{it}) &= \eta HTO_{it} + \phi ETO_{it} + \eta_d \cdot DW_{id} \cdot HTO_{it} \\ &\quad + \phi_d \cdot DW_{id} \cdot ETO_{it} + \lambda_{im} + \nu_t + \varepsilon_{it}, \end{aligned} \tag{7}$$

where the dependent variable is the logarithm of the total monthly energy use (electricity plus natural gas) of a particular household. The rationale to combine the two energy sources is to account for possible substitution effects where the reduction in usage from one energy source induces an increase in usage from the other. For this reason, we consider the regression with total energy use the most conservative. As a robustness check, we also run the same regression with only electricity or natural gas as the dependent variable. The dummy $HTO_{it}$ turns from zero to one the month $t$ household $i$ invests in an HTO retrofit measure. The dummy $ETO_{it}$ is defined similarly for investments in ETO measures. The terms $\lambda_{im}$ and $\nu_t$ denote household-calendar-month fixed effects and month-of-sample fixed effects, respectively, and implement the difference-in-differences estimator to estimate energy savings. Finally, $DW_{id}$ is a dummy that identifies a specific day of the week, denoted with subscript $d$, and estimates heterogeneity in average realized energy savings with respect to the day of installation. Each dummy takes a value of one if household $i$ got the measure installed on day $d$ and zero otherwise. The coefficient $\eta_d$ estimates the specific effect of installation day $d$ on realized energy savings for HTO measures; we expect it to be positive if moral hazard exists. The coefficient $\eta$ estimates the savings for HTO measures installed on one of the remaining days of the week. For instance, "Friday effects" are estimated by having a dummy, $DW_{iFriday}$, that turns on if the measure was completed on a Friday. In this specification, the coefficient $\eta$ then estimates the savings for a retrofit installed on any day between Monday and Thursday. The coefficients $\phi$ and $\phi_{Friday}$ estimate the same effects for ETO measures.

Our formal hypothesis test to detect the existence of moral hazard is the null hypothesis: $H_0 : \eta_d = \phi_d$. Rejection of this null hypothesis combined with $\eta_d > 0$ implies that HTO measures save less energy on day $d$ of the week.

## 2.3. Identification

The difference-in-differences estimator is implemented by two sets of fixed effects. The dummies $\lambda_{im}$ capture all household-specific characteristics that influence energy use. Note that we allow for variation by calendar month $m$, which captures any seasonal pattern in household-specific energy usage. Exploiting several years of monthly consumption allows us to identify the coefficients $\lambda_{im}$. The month-of-sample fixed effects, $\nu_t$, control for weather and any other contemporaneous shocks that may affect monthly consumption. Our large sample of retrofits allows us to identify the coefficients $\nu_t$. We thus effectively assume that conditional on $\lambda_{im}$ and $\nu_t$, households were subject to similar trends in energy usage prior to the retrofit measure. By the end of our time horizon, all households are treated.

The validity of the test for moral hazard relies on the assumption that contractors do not select the day of the week on which they installed a particular measure. Such selection can be directly tested by comparing projects along key dimensions using observable attributes of the retrofit contracts. Table 2 compares the average retrofit prices, average predicted energy savings, average rebate amounts, and number of retrofits performed across day (or period) of completion. For all four variables, we observe no statistically significant difference during the days of the workweek. Importantly for our identification, Friday jobs are of the same size as other jobs, as measured by both their price and predicted energy savings; any difference in realized energy savings is therefore due to other factors. In contrast, weekend projects, which happen to be very few, do exhibit

Table 2. Summary Statistics by Day of the Week

| Retrofit Observability | Day of the Week Installed | | | | | | Mean | Diff Mean | No. | No. |
|---|---|---|---|---|---|---|---|---|---|---|
| | M | T | W | Th | F | WE | M–Th (SD) | (M–Th vs. F) (SE)/[$p$-Value] | Observations (M–F) | Observations (All) |
| A. Ex Ante Energy Savings Prediction (MWh per Year) | | | | | | | | | | |
| HTO | 1.44 | 1.45 | 1.44 | 1.44 | 1.44 | 1.52 | 1.44 | –.000849 | 830 | 941 |
| | (.14) | (.14) | (.14) | (.13) | (.14) | (.11) | (.14) | (.01) | | |
| | | | | | | | | [.94] | | |
| ETO | 1.6 | 1.56 | 1.57 | 1.43 | 1.59 | 1.47 | 1.54 | .0582 | 1,550 | 1,641 |
| | (.71) | (.73) | (.77) | (.78) | (.78) | (.87) | (.75) | (.05) | | |
| | | | | | | | | [.22] | | |
| B. Project Price (Dollars) | | | | | | | | | | |
| HTO | 806 | 868 | 891 | 754 | 813 | 672 | 831 | –18.22 | 653 | 732 |
| | (648) | (770) | (1,029) | (503) | (662) | (617) | (768) | (70.4) | | |
| | | | | | | | | [.8] | | |
| ETO | 4,348 | 3,935 | 4,389 | 4,452 | 4,332 | 3,063 | 4,277 | 55.11 | 993 | 1,048 |
| | (3,108) | (3,042) | (3,099) | (3,038) | (3,014) | (2,595) | (3,072) | (239.1) | | |
| | | | | | | | | [.82] | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | C. Rebate Amount (Dollars) | | | | | | | | | |
| HTO | 286 | 335 | 373 | 412 | 295 | 254 | 351 | −12.52 | 905 | 1,025 |
| | (181) | (250) | (369) | (375) | (243) | (236) | (308) | (9.62) | | |
| | | | | | | | | [.19] | | |
| ETO | 767 | 689 | 690 | 774 | 666 | 752 | 729 | −75.48 | 1,805 | 1,911 |
| | (871) | (746) | (716) | (887) | (718) | (921) | (808) | (51.01) | | |
| | | | | | | | | [.14] | | |
| Observations | 504 | 534 | 556 | 547 | 569 | 226 | 2,141 | | 2,710 | 2,936 |

Note. Mean and standard deviation (in parentheses) for the three main variables, presented separately in panels A, B, and C. Differences in the number of observations across variables are due to missing information. The number of observations for a given day include all contracts with information for at least one variable. The label HTO refers to hard-to-observe measures and ETO refers to easy-to-observe measures. The last column reports the difference in means between Friday and the rest of the workweek (Monday–Thursday), the standard error for this difference (SE), and the $p$-value for a two-tailed $t$-test where the null hypothesis is that the difference between a Friday mean and Monday–Thursday mean is equal to zero. We find no difference in means that is statistically significant at the 10% level. MWh = megawatt-hour.

some differences. This suggests that selection might be at play during the weekend, which leads us to treat weekends separately in the estimation with a dummy for measures installed on weekends. The selection problem on weekends could come from the way contractors either favor certain projects or decide to work during the weekend.

## 2.4. Results

The second and third columns of table 1 replicate the findings of Maher (2016). Most retrofit measures subsidized by GRU exhibit a discrepancy between predicted and realized savings. For the two main retrofit measures classified as hard to observe—attic insulation and duct repair—realized savings are 60% and 32% of predicted savings, respectively.[8] For ETO measures, the discrepancy varies widely in magnitude but also in sign. For three out of six of them, realized savings are in fact well above predicted ones.

We present the regression results that account for heterogeneity with respect to the day of the week and observability of the measure (eq. [7]) in table 3 (and in table 4 for electricity only). Each column corresponds to a specification that identifies a specific day-of-the-week effect on energy savings. The interaction terms are the additional savings for the day identified. For instance, for the model that estimates the Friday effect (fifth column), the coefficient represents the additional savings relative to the average savings for Monday to Thursday. A positive estimate suggests that realized savings on Fridays are lower than for other days of installation. The last row of table 3 reports the $p$-value ($F$-test) of the two-tailed hypothesis test: $H_0 : \eta_d = \phi_d$.

For HTO measures, we find a positive Friday effect that is statistically different from the Friday effect for the ETO measures ($p$-value $= 0.0547$). However, we do not find any such effect for other days of the workweek. All models include an interaction for weekend effect, which is always positive but not statistically significant. The end-of-the-week effect is still present if we group Friday and weekend estimates together (sixth column, $p$-value $= 0.0234$). The magnitude of the estimates, obtained by adding the coefficients for the dummies $HTO$ and $HTO \cdot DW_{Friday}$ implies that the realized energy savings for HTO measures completed at the end of the week are close to zero and not statistically significant. For other days of the workweek, the savings are of the expected sign, economically large and statistically significant. The magnitude of the Friday effect for HTO measures is economically large and explains a large fraction of the discrepancy between realized and predicted savings. Table 5 displays estimates of the realized savings with and without controls for the Friday effect and compares them to the predicted savings. After controlling for the Friday effect for HTO retrofit measures, the discrepancy between predicted and realized energy savings shrinks by as much as 70%.

The above results are robust to numerous robustness checks presented in the appendix. We show that our designation of HTO and ETO categories has little impact

8. The estimate of the realized savings for duct repair is not statistically different from zero, while predicted saving are 107.5 kWh/month.

on the results. For instance, if we exclude from the analysis the measures that are the most ambiguous—low-interest loans, low-income weatherization grants, and home performance projects—it has little impact on the estimates (table A2; tables A1–A6 are available online). Removing windows replacement from the ETO category does not qualitatively change the results either. Table A3 also presents an extensive set of robustness checks for different ways of classifying measures and shows that the estimated Friday effect for HTO and ETO measures is very stable across designations and suggests that duct sealing is an important driver of the effect for HTO measures.

Performing the estimation in level instead of logarithm still produces a positive Friday effect for HTO measures. The coefficient is, however, marginally statistically significant.[9]

If we run regressions using only electricity or natural gas as the dependent variable, we find that the Friday effect is driven predominantly by electricity consumption. Table 4 presents the results where the log of monthly electricity use is the dependent variable, and a similar table is presented in the appendix for natural gas. Given that the sample focuses on energy efficiency retrofits in Florida, this result is not surprising. The two important technologies that we classified as prone to moral hazard, that is, attic insulation and duct repair, should have most of their effect on energy use during the hot summer days of Florida, that is, on air conditioning usage and thus electricity.

Altogether, the results give support to our hypothesis that undertreatment occurs on Fridays for measures where quality is hard to verify. Though essentially a positive test of existence of moral hazard, our analysis additionally indicates that the problem is important, perhaps enough to undo a large fraction of energy savings.

## 3. NUMERICAL WELFARE ANALYSIS

We now integrate the theoretical and empirical approaches to assess the welfare consequences of moral hazard in home energy retrofits. Building on the theory developed in section 1, we specify a model simulating the interactions between retrofits, air conditioning, and electricity usage in Florida. We calibrate the model using data from the GRU program and the US Residential Energy Consumption Survey (RECS).

We reach three main findings. First, the deadweight loss due to moral hazard is substantial, typically twice as large as that due to associated carbon dioxide externalities, a finding robust to model specifications. Second, welfare effects can be accurately approximated by a sufficient statistic that abstracts from consumer behavior. Third, minimum quality standards tend to be more effective in addressing moral hazard than energy-savings insurance, especially when externalities remain unpriced.

### 3.1. Model Specifications

We consider a market involving a homogeneous, competitive industry of home retrofits and a population of homeowner-occupiers with heterogeneous preferences for energy

9. The $p$-value for the two-tailed test $H_0 : \eta_d = \phi_d$ on Friday is $p$-value $= 0.135$.

Table 3. Day-of-the-Week Effects: All Energy Sources

| | Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| Log(kWh+Natural Gas/Month) | Monday Effect | Tuesday Effect | Wednesday Effect | Thursday Effect | Friday Effect | Friday + WE Effect |
| HTO = 1 | –.0371** | –.0416** | –.0410** | –.0520*** | –.0625*** | –.0625*** |
| | (.0156) | (.0167) | (.0169) | (.0166) | (.0171) | (.0171) |
| ETO = 1 | –.0592*** | –.0642*** | –.0593*** | –.0693*** | –.0618*** | –.0618*** |
| | (.0112) | (.0113) | (.0114) | (.0114) | (.0112) | (.0112) |
| HTO = 1 × Monday | –.0511 | | | | | |
| | (.0470) | | | | | |
| ETO = 1 × Monday | –.0191 | | | | | |
| | (.0209) | | | | | |
| HTO = 1 × Tuesday | | –.0268 | | | | |
| | | (.0336) | | | | |
| ETO = 1 × Tuesday | | .00724 | | | | |
| | | (.0215) | | | | |
| HTO = 1 × Wednesday | | | –.0276 | | | |
| | | | (.0308) | | | |
| ETO = 1 × Wednesday | | | –.0163 | | | |
| | | | (.0192) | | | |
| HTO = 1 × Thursday | | | | .0272 | | |
| | | | | (.0335) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| ETO = 1 × Thursday | | | | .0314 | | |
| | | | | (.0204) | | |
| HTO = 1 × Friday | | | | | .0718** | |
| | | | | | (.0318) | |
| ETO = 1 × Friday | | | | | −.00463 | |
| | | | | | (.0239) | |
| HTO = 1 × Friday + WE | | | | | | .0581** |
| | | | | | | (.0274) |
| ETO = 1 × Friday + WE | | | | | | −.0750** |
| | | | | | | (.0346) |
| HTO = 1 × WE | .00939 | .0139 | .0133 | .0243 | .0347 | |
| | (.0391) | (.0399) | (.0401) | (.0399) | (.0401) | |
| ETO = 1 × WE | −.0625* | −.0575 | −.0623* | −.0525 | −.0599 | |
| | (.0377) | (.0377) | (.0378) | (.0378) | (.0376) | |
| Constant | 7.204*** | 7.204*** | 7.204*** | 7.204*** | 7.204*** | 7.204*** |
| | (.00647) | (.00647) | (.00647) | (.00647) | (.00646) | (.00647) |
| $R$-squared | .652 | .652 | .652 | .652 | .652 | .652 |
| $F$–$H_0$: $\eta_d = \phi_d$ | .388 | .725 | .0970 | .0116 | 3.695 | 5.146 |
| Prob > $F$–$H_0$ | .534 | .394 | .755 | .914 | .0547 | .0234 |

Note. Standard errors are clustered at the household level. The number of observations is 490,954. The first two rows of estimates correspond to the energy savings for the days of the week not captured by the interaction effect in the lower rows. The last column groups Fridays and weekends together. All regressions include fixed effects for house by month and month of sample. WE = weekend; HTO = hard to observe; ETO - easy to observe.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Table 4. Day-of-the-Week Effects: Electricity Only

| | Dependent Variable | | | | | |
|---|---|---|---|---|---|---|
| Log(kWh/Month) | Monday Effect | Tuesday Effect | Wednesday Effect | Thursday Effect | Friday Effect | Friday + WE Effect |
| HTO = 1 | –.00181 | –.0115 | –.0132 | –.0188 | –.0313* | –.0313* |
| | (.0157) | (.0168) | (.0166) | (.0168) | (.0168) | (.0168) |
| ETO = 1 | –.0512*** | –.0529*** | –.0485*** | –.0606*** | –.0534*** | –.0534*** |
| | (.0113) | (.0114) | (.0113) | (.0115) | (.0114) | (.0114) |
| HTO = 1 × Monday | –.0711 | | | | | |
| | (.0450) | | | | | |
| ETO = 1 × Monday | –.0116 | | | | | |
| | (.0200) | | | | | |
| HTO = 1 × Tuesday | | –.0193 | | | | |
| | | (.0319) | | | | |
| ETO = 1 × Tuesday | | –.00213 | | | | |
| | | (.0210) | | | | |
| HTO = 1 × Wednesday | | | –.00926 | | | |
| | | | (.0323) | | | |
| ETO = 1 × Wednesday | | | –.0228 | | | |
| | | | (.0194) | | | |
| HTO = 1 × Thursday | | | | .0183 | | |
| | | | | (.0309) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| ETO = 1 × Thursday | | | | .0351* | | |
| | | | | (.0204) | | |
| HTO = 1 × Friday | | | | | .0735** | |
| | | | | | (.0321) | |
| ETO = 1 × Friday | | | | | .000544 | |
| | | | | | (.0234) | |
| HTO = 1 × Friday + WE | | | | | | .0537** |
| | | | | | | (.0271) |
| ETO = 1 × Friday + WE | | | | | | −.0669** |
| | | | | | | (.0340) |
| HTO = 1 × WE | −.00986 | −.000155 | .00165 | .00711 | .0196 | |
| | (.0377) | (.0385) | (.0385) | (.0385) | (.0385) | |
| ETO = 1 × WE | −.0642* | −.0625* | −.0668* | −.0548 | −.0620* | |
| | (.0373) | (.0372) | (.0373) | (.0373) | (.0371) | |
| Constant | 6.909*** | 6.909*** | 6.909*** | 6.909*** | 6.909*** | 6.909*** |
| | (.00676) | (.00676) | (.00676) | (.00676) | (.00676) | (.00676) |
| *R*-squared | .680 | .680 | .680 | .680 | .680 | .680 |
| $F–H_0{:}\eta_d = \phi_d$ | 1.461 | .203 | .128 | .204 | 3.390 | 4.338 |
| Prob > $F–H_0$ | .227 | .652 | .720 | .652 | .0657 | .0374 |

Note. Standard errors are clustered at the household level. The number of observations is 489,217. All regressions include fixed effects for house by month and month of sample. WE = weekend; HTO = hard to observe; ETO - easy to observe.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

Table 5. Gap Realized-Predicted Savings without Friday Effect

| | Realized Savings MWh/Year | Predicted Savings MWh/Year | Gap Predicted-Realized Savings |
|---|---|---|---|
| HTO Monday–Thursday | 1.17 | 1.44 | .27 |
| | (.33) | (.14) | |
| HTO Monday–Friday | .98 | 1.44 | .47 |
| | (.28) | (.14) | |
| Difference (%) | −16.49 | −.02 | 70.4 |

Note. The realized savings in the first row of the first column are computed after controlling for the Friday effect using a regression similar to the sixth column in table 3, but where the dependent variable is in level. The monthly estimates are scaled by 12 to obtain an annual estimate. The realized savings in the second row of the first column are for a similar regression that does not control for the Friday effect. Regressions estimates are reported for HTO measures only. The estimates in the first and second rows of the second column are sample means for all HTO measures installed on Monday through Thursday or Monday through Friday, respectively. Controlling for the Friday effect reduces the discrepancy between realized and predicted savings (third column) by 70.4%.

services. Consistent with the empirical analysis, technology is a combination of insulation and duct sealing, and we examine its impact on electricity use for air conditioning. We impose minimal structure on the functional forms so as to satisfy the basic convexity assumptions introduced in section 1. We calibrate the model using empirical moments obtained from the GRU and RECS data.

#### *3.1.1. Demand Side*

We consider a population of heterogeneous homeowners using electricity for air conditioning. Homeowners demand an energy service, denoted $s$, measured in cooling degree days (CDDs with base temperature of 65°F). The utility derived from using $s$ is:

$$U(\theta, s, q) \equiv (\theta V(s) - pE(s, q))\Gamma(r, l) - T + \delta,$$

where the comfort and usage functions are respectively specified as follows:

$$V(s) \equiv V_{\max}\left(1 - e^{-\alpha(s - s_{\min})}\right), \tag{8}$$

$$E^0(s) \equiv \beta(s - s_{\min})^{\gamma}, \tag{9}$$

with $s_{\min} \leq s \leq s_{\max}$, $\alpha > 0$, $\beta > 0$, and $\gamma > 1$. We assume that parameter $\theta$, which represents preferences for thermal comfort, follows a log-normal distribution.

As detailed in the appendix, we use a RECS sample of 503 Floridian households to set the values of $p$, $s_{\min}$, $s_{\max}$, $V_{\max}$, $\alpha$, $\beta$, $\gamma$, and $\delta$, and the distribution of $\theta$. Parameter values are presented in table 6.

*3.1.2. Supply Side*

We consider a homogeneous competitive industry providing duct sealing and insulation installation. Contractors deliver with some dimensionless quality $q$, ranging from 0% to 100%, which affects the homeowner's electricity use as follows:

$$E(s, q) \equiv (1 - G_{\min} - (G_{\max} - G_{\min})(1 - e^{-aq}))E^0(s), \tag{10}$$

with $a > 0$. Parameters $G_{\min}$ and $G_{\max}$ capture the minimum and maximum energy savings that a retrofit can technically generate. They are set to 1% and 30%, respectively.

Contractors have a quadratic cost function to provide quality $q$

$$C(q) \equiv b + \frac{c}{2}q^2, \tag{11}$$

with $b > 0$ and $c > 0$.

As detailed in the appendix, parameters $a$, $b$, and $c$ are calibrated to match empirical moments obtained from the GRU program.

*3.1.3. Market Environment*

Based on the RECS data, the electricity price $p$ is set to \$0.1254/kWh (kilowatt-hour). It is held constant in current value over the time horizon $l$, set to 35 years, the conventional lifetime of insulation measures. The discount rate $r$ is set to 7%, the value recommended by the US Office of Management and Budget (US OMB 2009) to assess private investment.

We consider that electricity use generates carbon dioxide externalities contributing to global warming. Externalities are valued at \$31/ton of $CO_2$ ($tCO_2$) (Nordhaus 2017), which, given an emission rate of 550 g $CO_2$/kWh for power generation in Florida (US EPA 2015), translates into a social cost $p_{CO_2} = \$0.0169$/kWh. We assume that this cost increases at the discount rate and, hence, is constant in present value. Under these assumptions, saving 1 kWh of electricity monthly has a private value of \$1.62 and a social value of \$0.59 in lifetime discounted terms.

## 3.2. Quantification of the Energy Efficiency Gap

*3.2.1. Reference Case*

We consider various market environments—perfect and asymmetric information, with and without a Pigouvian price on carbon dioxide externalities (see fig. 1). For each environment, we compute the equilibrium actions for all market participants. We then aggregate participants and map the resulting market equilibria in the framework proposed by Jaffe, Newell, and Stavins (2004),[10] so as to visualize the trade-offs between economic efficiency (measured as present discounted welfare) and energy efficiency (fig. 3). Detailed numerical results are presented in table 7.

10. This is the ultimate version of a diagram that first appeared in Jaffe and Stavins (1994).

Table 6. Model Parameters

| Parameter | Symbol | Value | Unit | Source |
|---|---|---|---|---|
| Demand side: | | | | |
| Minimum cooling service | $s_{min}$ | 2,139 | CDD | Minimum of the RECS sample |
| Maximum cooling service | $s_{max}$ | 5,246 | CDD | Maximum of the RECS sample |
| Maximum valuation of comfort | $V_{max}$ | 2,816 | $ | 95th percentile of the income share dedicated to air conditioning (3.9%) applied to the median income ($55,000) of the RECS sample |
| Comfort sensitivity | $\alpha$ | .0011 | | Calibrated with the RECS data (see appendix) |
| Scale of energy use | $\beta$ | 2.0749 | | Calibrated with the RECS data (see appendix) |
| Sensitivity of energy use | $\gamma$ | 1.0643 | | Calibrated with the RECS data (see appendix) |
| Nonenergy attributes | $\delta$ | 260 | $ | Calibrated with the RECS data so that the median homeowner is the marginal investor under asymmetric information (see appendix) |
| First parameter of the log-normal distribution of $\theta$ | $\mu$ | 0 | | Ensures that $\theta = 1$ is the median type |
| Second parameter of the log-normal distribution of $\theta$ | $\sigma$ | .5 | | Best fit of the distribution of CDDs found in the RECS data (see appendix) |
| Supply side: | | | | |
| Minimum energy efficiency | $G_{min}$ | 1% | | Conventional value |
| Maximum energy efficiency | $G_{max}$ | 30% | | Conventional value |
| Efficiency sensitivity | $a$ | 1.0694 | | Calibrated with the GRU data (see appendix) |
| Fixed cost of retrofit | $b$ | 373 | $ | Calibrated with the GRU data (see appendix) |
| Slope of marginal retrofit cost | $c$ | 5,090 | | Calibrated with the GRU data (see appendix) |

Table 6 (*Continued*)

| Parameter | Symbol | Value | Unit | Source |
|---|---|---|---|---|
| Market environment: | | | | |
| Price of electricity | $p$ | .1254 | \$/kWh | Median price paid for electricity for air conditioning in the RECS sample |
| Social cost of $CO_2$ | $p_{CO_2}$ | .0169 | \$/kWh | Social cost of \$31/t$CO_2$ (Nordhaus 2017) applied to an emission factor of 550g$CO_2$/kWh for power generation in Florida (US EPA 2015) |
| Discount rate | $r$ | 7% | | Value recommended to assess private investment (US OMB 2009) |
| Physical lifetime of retrofits | $l$ | 35 | Years | Conventional value |

Note. CDD = cooling degree day; RECS = Residential Energy Consumption Survey; GRU = Gainesville Regional Utilities.

Undoing moral hazard—which is calculated by comparing perfect- and asymmetric-information equilibria—produces present-value benefits of about \$600 per retrofit.[11] If, in addition, carbon dioxide externalities were internalized through a \$0.0169/kWh price, welfare improvement would be about \$300 larger. In the context studied here, moral hazard is therefore about twice as large a market failure as carbon dioxide externalities. This ratio is partly determined by the 2.7 ratio (i.e., 1.62/0.59) between the marginal private and social values of energy savings that characterizes our market environment.

*3.2.2. Sensitivity Analysis*

We vary the key parameters of the model according to assumptions outlined in table 8. Each scenario is meant to mimic different barriers to energy efficiency, which, according to the taxonomy referred to in the introduction, are categorized either as market failures, nonmarket failures, or behavioral anomalies. Figure 2 displays the resulting deadweight losses and their elasticities with respect to each parameter (in absolute value).

11. Moral hazard can also be restated as an implied discount rate of 15%. This value is computed by solving and averaging the $\theta$-specific discount rates that match the quality offered under perfect information with the 7%-discounted net present value enjoyed by the homeowner under asymmetric information. It is consistent with the estimates reported in the empirical literature on energy efficiency investments (Hausman 1979; Train 1985).

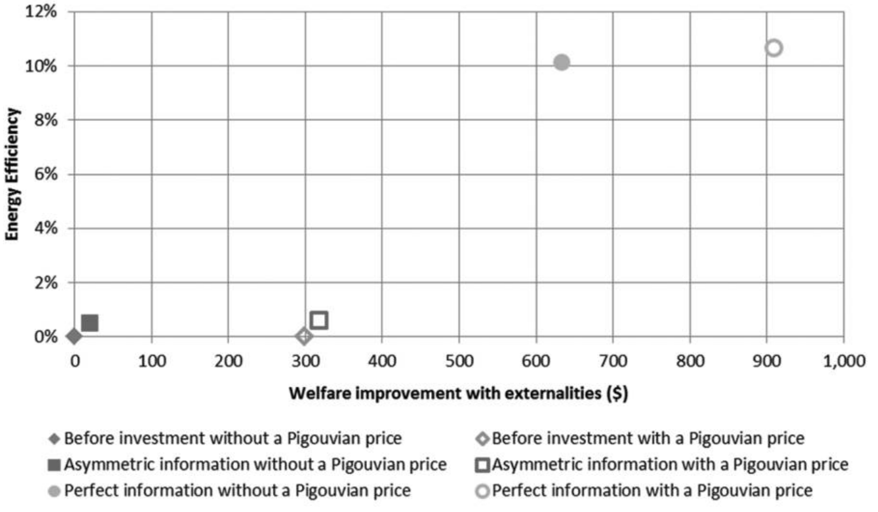


Figure 1. Energy-efficiency gap in the reference scenario

In all but two scenarios, moral hazard still generates more deadweight loss than externalities, in proportions ranging from 1.3 to 2.3. The reverse, however, occurs when discounting is sharp and the time horizon is short. Both scenarios imply short-sightedness, which necessarily lowers the deadweight loss associated with moral hazard, which is decreasing in present value, relative to that of externalities, which is constant in present value.

Elasticity values point to electricity price and the time horizon as the most sensitive determinants of the deadweight loss. This illustrates the extent of interactions between moral hazard and other market failures, namely, distortions in energy markets and other information asymmetries in housing markets. Technology cost and efficiency are the next important determinants. This underlines the importance of reducing measurement errors in engineering tests to perform accurate welfare analysis of energy efficiency programs. The discount rate also exerts some influence on the deadweight loss. In contrast, other demand-side parameters such as homeowners' comfort valuation and heterogeneity have negligible influence.

### 3.2.3. *A Sufficient Statistic of the Deadweight Loss*

We now propose a sufficient statistic that helps rationalize the sensitivity analysis discussed above. The deadweight loss from suboptimal quality can be approximated by the following formula (see appendix for a complete derivation):

$$\overline{\Delta_q W} = -p\Gamma(r, l)\Delta_q E - \Delta_q C. \qquad (12)$$

Recall from equation (5) that welfare is defined as the sum of utilities derived by homeowners from comfort, net of electricity expenditures, and contractors' profits.

Table 7. Welfare Analysis of the Reference Case

| Model Output | Unit | Without Pigouvian Price | | | | With Pigouvian Price | | |
|---|---|---|---|---|---|---|---|---|
| | | Before Investment | Asymmetric Information | Perfect Information | Optimal Insurance | Before Investment | Asymmetric Information | Perfect Information |
| Welfare improvement, without externalities | $ | 0 | 10 | 488 | 150 | −267 | −256 | 243 |
| Welfare improvement, with externalities | $ | 0 | 20 | 634 | −133 | 299 | 317 | 909 |
| Homeowners' equilibrium energy service | CDD | 3,667 | 3,676 | 3,762 | 3,867 | 3,395 | 3,404 | 3,495 |
| Annual electricity use for air conditioning | kWh | 5,110 | 5,094 | 4,864 | 5,553 | 4,156 | 4,144 | 3,987 |
| Annual electricity expenditure | $ | 641 | 639 | 610 | 696 | 521 | 520 | 500 |
| Annual $CO_2$ emissions | $tCO_2$ | 2.8 | 2.8 | 2.7 | 3.0 | 2.3 | 2.3 | 2.2 |
| Annual external cost of $CO_2$ emissions | $ | 87 | 86 | 82 | 94 | 70 | 70 | 68 |
| Contractor's equilibrium quality | % | | 0 | 36 | 10 | | 0 | 39 |
| Energy efficiency of retrofit | % | | .5 | 10.1 | 3.5 | | .6 | 10.7 |
| Rebound effect | % | | 38 | 53 | 345 | | 51 | 62 |
| Cutoff type of the marginal participant | | | 1.00 | .30 | .56 | | .88 | .35 |
| Participation rate | % | | 50 | 99 | 88 | | 60 | 98 |
| Zero-profit retrofit price | $ | | 343 | 690 | 375 | | 343 | 761 |
| Homeowner's net present value | $ | | 20 | 493 | 171 | | 31 | 622 |
| Insurance premium | $ | | | | 1,862 | | | |
| Insurance optimal coverage | % | | | | 16 | | | |

Note. "Energy efficiency" is averaged over the whole population of mass 1. The average over participants is obtained by dividing "Energy efficiency" by "Participation rate." Welfare improvements are measured against present discounted welfare before investment, without a Pigouvian price ($18,068 without externalities, $15,036 with externalities). CDD = cooling degree day.

Table 8. Sensitivity Analysis

| Parameter Varied | Symbol | Reference Value | Scenario Value | Scenario Interpretation and Nature of the Economic Problem Addressed | Size of Moral Hazard ($) | Size of Externalities ($) | Elasticity | Precision of Sufficient Statistic (%) |
|---|---|---|---|---|---|---|---|---|
| Electricity price | $p$ | $.1254/kWh | $.1054/kWh | Lower price reflecting marginal cost pricing (market failure)* | 482 | 321 | 1.57 | –8.6 |
| Time horizon | $l$ | 35 years | 10 years | Low capitalization of energy efficiency due to information asymmetries in housing markets (market failure) | 253 | 479 | .93 | –6.4 |
| Technology efficiency | $G_{max}$ | 30% | 35% | Better technology (nonmarket failure) | 563 | 277 | –.56 | –8.0 |
| Discount rate | $r$ | 7% | 20% | Undervaluation of energy savings by homeowners (behavioral anomaly) | 158 | 638 | –.44 | –5.4 |
| Technology cost | $c$ | 5,090 | 10,000 | Costlier technology (nonmarket failure) | 370 | 284 | –.42 | –6.2 |
| Comfort valuation | $V_{max}$ | $2,165 | $2,500 | Higher valuation of comfort (nonmarket failure) | 621 | 274 | .07 | –8.7 |
| Preference heterogeneity | $\sigma$ | .5 | .2 | Narrower distribution of homeowners' valuations (nonmarket failure) | 589 | 275 | .05 | –4.8 |

Note. The size of moral hazard is the difference in welfare (with externalities) between perfect- and asymmetric-information equilibria, both without a Pigouvian price. The size of externalities is the difference in welfare (with externalities) between perfect-information equilibria with and without a Pigouvian price. Elasticities are calculated as the percentage change in the size of moral hazard compared to the reference scenario, divided by the percentage change in the parameter value. The precision of the sufficient statistic is calculated by comparing formula (12) to the exact deadweight loss, calculated without externalities. The precision in the reference scenario, not reported in this table, is –7.7%.

* In this scenario variant, a market failure is actually removed, namely, the average cost pricing that prevails in the reference scenario.

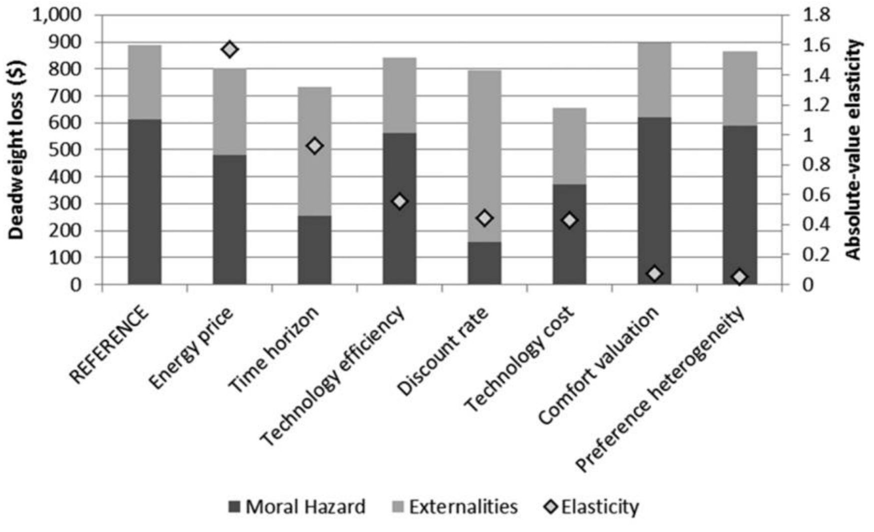


Figure 2. Sensitivity analysis

The formula above expresses its variations simply as a net present value balancing the cost of quality against its effect on energy expenditures. Crucially, it does not require knowledge of a homeowner's characteristics, namely, her comfort valuation $V(\cdot)$ or electricity usage $E^0(\cdot)$. The rebound effect can therefore be ignored when assessing the deadweight loss from moral hazard.

The results of sensitivity analysis are fully consistent with the sufficient statistic. All parameters that we found have nonnegligible elasticities (above 0.4) enter its expression. Reciprocally, the formula does not include those parameters that have negligible elasticities, namely, the homeowner's characteristics $V_{\max}$ and $\sigma$ (0.07 and 0.05, respectively).

Finally, as we show in the appendix, the sufficient statistic provides a lower bound of the size of the deadweight loss. Our simulations confirm this and the accuracy of the formula, which is found to never underestimate the exact deadweight loss by more than 9% across scenarios.

### 3.3. Insurance versus Standard

Figure 3 displays the welfare effects of energy-savings insurance and minimum quality standards in the reference scenario, with and without carbon dioxide externalities. Optimal insurance contracts, which are homeowner specific, have a coverage of 16% and involve a present-discounted cost of $1,862 for insurance premia, on average. Since homeowner types may not be perfectly observable, it is also worth considering uniform insurance contracts. As depicted in the figure, incremental coverage initially improves

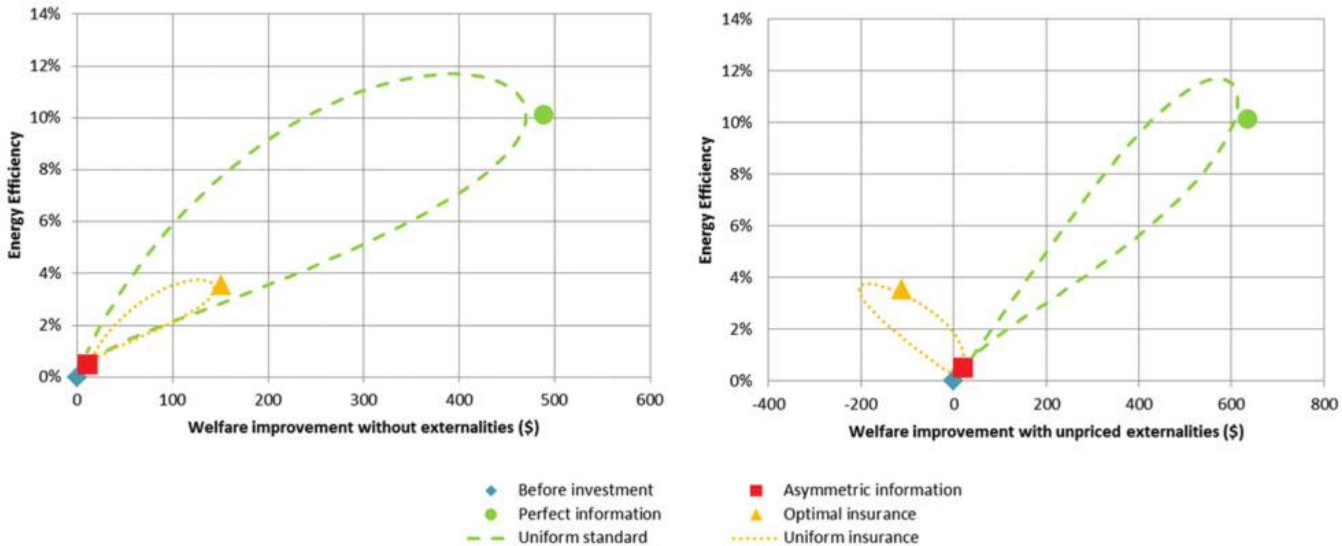


Figure 3. Policy comparison in the reference scenario. Uniform insurance draws a parametric curve with coverage increasing counterclockwise by 1%, from 0% to 100%. Similarly, uniform standards draw a parametric curve with mandated quality increasing counterclockwise by 1%, from 0% to 100%.

both energy efficiency and welfare, up to a point where higher efficiency becomes so expensive that it starts deterring participation, hence a backward bend in both efficiency and welfare trajectories. The best such contract is located farthest to the right of the horizontal axis. The associated coverage is 19% without externalities and only 1% otherwise. The welfare gains with the best uniform insurance are only slightly below those produced by optimal homeowner-specific contracts. This means that in the context considered here, ignoring consumer heterogeneity in policy design has little implication. The point also applies to minimum quality standards. Just like uniform insurance, standards draw an ellipse driven by increasing stringency. The best standard mandates a quality of 37% absent externalities and 42% otherwise. In all cases, it brings the market very close to the social optimum.

Overall, the insurance mitigates about a third of the deadweight loss due to moral hazard if externalities are absent or perfectly internalized. Otherwise, it is counterproductive. The best standard appears substantially more efficient, regardless of the environment. Yet unlike insurance, standards require verification, monitoring, and enforcement. As reported by Palmer et al. (2013), the cost of an audit for retrofits is on average $347 in the United States. Accounting for this as enforcement cost substantially reduces the benefits from standards, thus making policy comparison ambiguous.

An important takeaway is that unlike insurance, standards are relatively unaffected by carbon dioxide externalities. This is due to the nature of the rebound effect induced by each instrument. Both policies induce a direct rebound effect, as they increase energy efficiency and thus lower the marginal cost of energy services. In addition, insurance coverage further reduces marginal energy expenditures. This causes demand-side moral hazard—overuse of energy which exacerbates externalities. Minimum quality standards should therefore be preferred to energy-savings insurance if externalities remain unpriced.

## 4. CONCLUSION

Many energy efficiency measures can be thought of as credence goods, the performance of which is never fully revealed to the buyer. This characteristic creates a variety of information asymmetries, some of which can generate a discrepancy between predicted and realized energy savings. Ultimately, investment in energy efficiency is underprovided, a phenomenon known as the energy efficiency gap. In this paper, we investigate the existence of and solutions to one such information asymmetry, namely, moral hazard in the quality of installation.

We provide empirical evidence of the problem in home energy retrofits. Using data from a utility-sponsored retrofit program implemented in Florida, we find that for measures such as attic insulation and duct sealing, the quality of which is hard to observe ex post, energy savings are significantly lower when the retrofit was completed on a Friday—a day particularly prone to negative shocks on workers' productivity—than on any other weekday. We interpret this outcome as evidence of supply-side moral hazard and show that it can explain a large fraction of the discrepancy between predicted and realized energy savings. In theory, the problem can be addressed by private interventions, such as energy-savings insurance, or public interventions, such as minimum quality standards. We show that neither intervention can eliminate the welfare loss: insurance contracts induce demand-side moral hazard, as lower marginal expenditures encourage overuse of energy; standards incur enforcement costs. The comparison between the two is therefore context specific. Our numerical model suggests that while energy-savings contracts with small insurance coverage (typically 10%–20%) can significantly mitigate the moral hazard, they also amplify carbon dioxide externalities. Minimum quality standards therefore seem more desirable if externalities are left unpriced.

We see several interesting extensions to our analysis. On the theoretical front, attention should be focused on reputation strategies. The finding that energy efficiency providers do offer some quality during most of the workweek suggests that reputational concerns might be important. On the empirical front, new experiments allowing for direct observation of quality should be designed in order to directly investigate the link between installation defects and realized energy savings. On the policy front, efforts should be devoted to ex post evaluation of energy performance contracts, quality certifications, and other remedies to moral hazard.

## REFERENCES

Abbring, Jaap H., James J. Heckman, Pierre-André Chiappori, and Jean Pinquet. 2003. Adverse selection and moral hazard in insurance: Can dynamic data help to distinguish? *Journal of the European Economic Association* 1 (2–3): 512–21.

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

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky. 2014. Energy policy with externalities and internalities. *Journal of Public Economics* 112:72–88.

Balafoutas, Loukas, Adrian Beck, Rudolf Kerschbamer, and Matthias Sutter. 2013. What drives taxi drivers? A field experiment on fraud in a market for credence goods. *Review of Economic Studies* 80 (3): 876–91.

Brounen, Dirk, and Nils Kok. 2011. On the economics of energy labels in the housing market. *Journal of Environmental Economics and Management* 62 (2): 166–79.

Bryson, Alex, and John Forth. 2007. Are there day of the week productivity effects? Technical report, Manpower Human Resources Lab, Centre for Economic Performance, London School of Economics.

Campolieti, Michele, and Douglas E. Hyatt. 2006. Further evidence on the "Monday effect" in workers' compensation. *Industrial and Labor Relations Review* 59 (3): 438–50.

Cooper, Russell, and Thomas W. Ross. 1985. Product warranties and double moral hazard. *RAND Journal of Economics* 16 (1): 103–13.

Davis, Lucas W. 2012. Evaluating the slow adoption of energy efficient investments: Are renters less likely to have energy efficient appliances? In *The design and implementation of U.S. climate policy*, ed. Don Fullerton, and Catherine Wolfram, 301–16. Chicago: University of Chicago Press.

Davis, Lucas W, Alan Fuchs, and Paul Gertler. 2014. Cash for coolers: Evaluating a large-scale appliance replacement program in Mexico. *American Economic Journal: Economic Policy* 6 (4): 207–38.

de Wilde, Pieter. 2014. The gap between predicted and measured energy performance of buildings: A framework for investigation. *Automation in Construction* 41:40–49.

Dulleck, Uwe, and Rudolf Kerschbamer. 2006. On doctors, mechanics, and computer specialists: The economics of credence goods. *Journal of Economic Literature* 44 (1): 5–42.

Dulleck, Uwe, Rudolf Kerschbamer, and Matthias Sutter. 2011. The economics of credence goods: An experiment on the role of liability, verifiability, reputation, and competition. *American Economic Review* 101 (2): 526–55.

Fowlie, Meredith, Michael Greenstone, and Catherine Wolfram. 2015. Do energy efficiency investments deliver? Evidence from the Weatherization Assistance Program. Working Paper 21331, National Bureau of Economic Research, Cambridge, MA.

Fuerst, Franz, Patrick McAllister, Anupam Nanda, and Peter Wyatt. 2015. Does energy efficiency matter to home-buyers? An investigation of EPC ratings and transaction prices in England. *Energy Economics* 48:145–56.

Gillingham, Kenneth, Matthew Harding, and David Rapson. 2012. Split incentives in residential energy consumption. *Energy Journal* 33 (2): 37–62.

Gillingham, Kenneth, Matthew J. Kotchen, David S. Rapson, and Gernot Wagner. 2013. Energy policy: The rebound effect is overplayed. *Nature* 493 (7433): 475–76.

Gillingham, Kenneth, Richard G. Newell, and Karen Palmer. 2009. Energy efficiency economics and policy. *Annual Review of Resource Economics* 1 (1): 597–620.

Gillingham, Kenneth, and Karen Palmer. 2014. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy*, ret021.

Graff Zivin, Joshua, and Kevin Novan. 2016. Upgrading efficiency and behavior: Electricity savings from residential weatherization programs. *Energy Journal* 37 (4): 1–23.

Hausman, Jerry A. 1979. Individual discount rates and the purchase and utilization of energy-using durables. *Bell Journal of Economics* 10 (1): 33–54.

Houde, Sébastien, and Joseph E. Aldy. 2017. Consumers' response to state energy efficient appliance rebate programs. *American Economic Journal: Economic Policy* 9 (4): 227–55.

Jaffe, A. B., R. G. Newell, and R. N. Stavins. 2004. Economics of energy efficiency. In *Encyclopedia of energy*, ed. C. J. Cleveland, 79–90. New York: Elsevier.

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

Krishnamurthy, Chandra Kiran B., and Bengt Kriström. 2015. How large is the owner-renter divide in energy efficient technology? Evidence from an OECD cross-section. *Energy Journal* 36 (4): 85–104.

Levinson, Arik, and Scott Niemann. 2004. Energy use by apartment tenants when landlords pay for utilities. *Resource and Energy Economics* 26 (1): 51–75.

Maher, Joseph. 2016. Measuring the accuracy of engineering models in predicting energy savings from home retrofits: Evidence from monthly billing data. Working Paper.

Maruejols, Lucie, and Denise Young. 2011. Split incentives and energy efficiency in Canadian multi-family dwellings. *Energy Policy* 39 (6): 3655–68.

Metcalf, Gilbert E., and Kevin A. Hassett. 1999. Measuring the energy savings from home improvement investments: Evidence from monthly billing data. *Review of Economics and Statistics* 81 (3): 516–28.

Mills, Evan. 2003. Risk transfer via energy-savings insurance. *Energy Policy* 31 (3): 273–81.

Murphy, Lorraine. 2014. The influence of energy audits on the energy efficiency investments of private owner-occupied households in the Netherlands. *Energy Policy* 65:398–407.

Myers, Erica. 2013. Asymmetric information in residential rental markets: Implications for the energy efficiency gap. Working Paper 246, Energy Institute at Haas, Berkeley, CA.

Nordhaus, William D. 2017. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences* 114 (7): 1518–23.

Palmer, Karen, Margaret Walls, Hal Gordon, and Todd Gerarden. 2013. Assessing the energy-efficiency information gap: Results from a survey of home energy auditors. *Energy Efficiency* 6 (2): 271–92.

Reynaert, Mathias, and James M. Sallee. 2016. Corrective policy and Goodhart's law: The case of carbon emissions from automobiles. Technical report, National Bureau of Economic Research, Cambridge, MA.

Schneider, Henry S. 2012. Agency problems and reputation in expert services: Evidence from auto repair. *Journal of Industrial Economics* 60 (3): 406–33.

Scott, S. 1997. Household energy efficiency in Ireland: A replication study of ownership of energy saving items. *Energy Economics* 19 (2): 187–208.

Sorrell, Steve. 2004. Understanding barriers to energy efficiency. In *The economics of energy efficiency: Barriers to cost-effective investment*, ed. Steve Sorrell, Eoin O'Malley, Joachim Schleich, and Sue Scott, 25–93. Cheltenham: Edward Elgar.

Sunikka-Blank, Minna, and Ray Galvin. 2012. Introducing the prebound effect: The gap between performance and actual energy consumption. *Building Research and Information* 40 (3): 260–73.

Train, Kenneth. 1985. Discount rates in consumers' energy-related decisions: A review of the literature. *Energy* 10 (12): 1243–53.

US EPA (US Environmental Protection Agency). 2015. Emissions and generation resource integrated database (eGRID).

US OMB (US Office of Management and Budget). 2009. Informing regulatory decisions: Report to Congress on the costs and benefits of federal regulations and unfunded mandates on state, local, and tribal entities. Technical Report Appendix D, OMB Circular A-4.

Zabin, Carol, T. William Lester, and Jessica Halpern-Finnerty. 2011. Chapter four: Case studies of the HVAC, residential retrofit, and commercial lighting control sectors. In *California workforce education and training needs assessment for energy efficiency, distributed generation, and demand response*, 89–118. Berkeley: University of California, Berkeley, Institute for Research on Labor and Employment.