Factors Influencing U.S. Homebuilders’ Adoption of Green Homebuilding Products

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Abstract
While many researchers have analyzed the obstacles to the diffusion of innovation in building construction, little empirical evidence has been gathered about the factors associated with U.S. homebuilders’ adoption of innovative building products. In this paper, we develop a theory-driven diffusion of innovation conceptual model of homebuilders’ adoption of high performance building product innovations. We are among the first to operationalize a regression model to demonstrate an application of the model using a large dataset from the National Association of Homebuilders. Model results indicate that builders’ selections of high performance products are influenced by internal or firm attributes, external attributes, as well as the attributes of the high performance innovations. These results suggest that the adoption rates of future innovative building products will likely be influenced by product and climate and have the potential to be amplified by bandwagon effects.
Factors Influencing U.S. Homebuilders’ Innovation Adoption Choices

Given the shortage of residential specific empirical adoption and diffusion models, this paper draws on recent analyses of innovation within commercial construction (Kale and Arditi, 2009; Rose and Manley, 2014; Koebel et al., 2015), commercial real estate (Kok, McGraw, and Quigley, 2011; Malkani and Starik, 2013), high performance consumer technologies (Johnstone, Hascic, and Popp, 2010; Altwies and Nemet, 2012), and other fields (Wejnert, 2002; Venkatesh, Morris, Davis, and Davis, 2003; Greenhalgh et al., 2004) to develop a theory-driven conceptual model. We then operationalize the conceptual model and demonstrate an application of the model using a large dataset from the National Association of Homebuilders (NAHB) that describes homebuilders’ yearly adoption and use of nearly 1,100 construction products. The purpose of this paper is to analyze the factors associated with U.S. homebuilders’ adoption of thermostat and piping innovations from 2000 to 2010.

We examine several technologies from a group of ten construction product innovations the U.S. Department of Housing and Urban Development (HUD) linked to housing affordability: optimum value engineering (OVE), structural insulated panel systems (SIPS), insulating concrete form systems (ICFSs), spray foam insulation, installing HVAC and duct systems in conditioned space, customizing the HVAC system, and programmable thermostats and polyethylene plastic piping (PEX or PEX al PEX).

Noting that green technology innovation in windows was rapidly adopted by builders from 2000 to 2010 (Koebel et al., 2015), we examine two important technologies from the HUD list—programmable thermostats and high performance water piping. Each product cluster is a factor in a home’s total energy consumption and both categories have experienced significant product innovation over time (e.g., although Google’s Nest thermostat was introduced after our study period, it represents a significant leap forward in thermal comfort management and energy consumption. It is illustrative of the type of innovation we investigate during our study period).

Construction innovation scholarship has revealed that factors internal to the adopting firm tend to be stronger influences on the adoption decision than external factors (Tatum, 1987; Kale and Arditi, 2009), with conclusions generated predominantly from mixed-methods analyses of survey and interview data (Cheng, Wen, and Jiang, 2014; Murphy, 2014). For example, where building information modeling (BIM) software has been available since the mid-1980s, empirical evidence on adoption rates is rare (Cao, Li, and Wang, 2014), although qualitative and case-based evidence indicates it is growing more widely used all the time (Taylor and Bernstein, 2009; Azhar, 2011). Further, this research has confirmed,
much like the construction innovation literature, that there are significant internal and external obstacles to broader BIM adoption (Azhar, Nadeem, Mok, and Leung, 2008; Aranda-Mena et al., 2009; Succar, 2009; Azhar, 2011; Bynum, Issa, and Olbina, 2012).

Although the large data set we employ is useful, the scale limited the collection of internal attribute data as well. Given this limitation, we make observations about the extent to which homebuilders’ high performance innovation adoption decisions can be explained when information describing the internal attributes of the adopter is limited. With the recent publication of our work on the diffusion of high performance windows (Koebel et al., 2015), in this paper we are the first to make comparisons between the findings of the other empirical diffusion model and offer insight into the adoption and diffusion patterns of high performance housing technologies.

Background and Conceptual Model Development

Theoretical frameworks and empirical models have been used to examine the adoption and spread of products and processes within markets. Designed to examine S-shaped curves that describe a typical pattern of cumulative adoption of an innovation over time, scholars have developed multiple theoretical and empirical frameworks to contextualize and explain the curve and how it changes over time (Bass, 1969; Burt, 1973; Easingwood, Mahajan, and Muller, 1983; Mahajan, Muller, and Bass, 1990; Moore, 1991; Baumol, 2010; Kok, McGraw, and Quigley, 2011). The residential construction industry is often noted for having low levels of innovation and being constrained by path dependency (Lutzenhiser, 1994; Xue, Zhang, Yang, and Dai, 2014) and other industry-specific attributes (Koebel and McCoy, 2006; McCoy, Koebel, and Sanderford, 2013). Emphasis on the laggard status of the industry has, until recently, been compounded by limited empirical investigation of the diffusion of specific construction innovations (Taylor and Levitt, 2007; Rose and Manley, 2014).

Construction innovation researchers have often noted the importance of diffusion of innovation frameworks and models (e.g., Larsen, 2005; Pries and Dorée, 2005; Koebel, 2007; Sargent, Hyland, and Sawang, 2012), although few have embraced mathematical models to analyze the factors associated with the diffusion of specific construction innovation. Several papers have advanced empirical diffusion of innovation models relative to innovation adopting organizations with foundations in Bass (1969) or Rogers’ (1995) work. These researchers have analyzed heavy equipment (Arditi, Kale, and Tangkar, 1997), innovative software (CAD) (Kale and Arditi, 2005), concrete technology (Kale and Arditi, 2006), and road construction product adoption (Rose and Manley, 2012, 2014). Confirming results outside the construction domain, these papers illustrate strong roles for internal and external factors firm adoption. Kale and Arditi observed strong influence from internal adopter attributes while Rose and Manley, like recent non-construction diffusion models (e.g., Kok, McGraw, and Quigley, 2011), focused on external factors.
Until quite recently, analyses of the diffusion of innovation of specific housing technologies into the housing market were based on very small samples, case studies, or remained theoretical. We are the second group to analyze the factors associated with the diffusion of residential building technologies using an empirical model (Koebel et al., 2015). We are the first to examine the diffusion of programmable thermostats and PEX piping as innovations among U.S. homebuilders and to control for their adoption of additional high performance technologies during the same time period.

To define a conceptual model relative to U.S. homebuilders for this work, we first conducted a literature review. At the broadest level, the review indicated that diffusion of information models have several important tasks and components. First, models should recognize that diffusion of innovation is a complex process that must be integrated into existing firm, political, and cultural contexts (Venkatesh, Morris, Davis, and Davis, 2003; Ansari, Fiss, and Zajac, 2010). Second, models should be theory-driven, process-oriented, ecologically-sensitive (setting based), and reflect contributions from multiple disciplines (Greenhalgh et al., 2004; Greenhalgh and Rogers, 2009). Third, models should identify the factors of the innovation, adopter, and environment that replace time as an explanatory factor and are associated with the decision to adopt or not adopt (Wejnert, 2002).

Bass (1969) or Rogers (1995) models of the diffusion of innovation models typically analyze the adoption decision as a function of the factors that could be associated. The literature indicates that dichotomous choice is one of the more common ways of modeling the adoption decision (Feder, Just, and Zilberman, 1985) as it captures the adopt versus not-adopt framework (Mercer, 2004). Both logit and probit models can be applied to a binary choice and Tobit and multinomial logit applied to reflect choice complexity. While the binary nature of the traditional framework reflects a good deal about the adoption choice, research also indicates that multiple stage adoption dependent variables can also be used for analysis (Dimara and Skuras, 2003).

The attributes of the innovation that influence the adoption decision have been well documented in the literature. Rogers’ (1995) omnibus work distilled five central factors: observability, trialability, relative advantage, complexity, and compatibility. Together, these attributes relate to the adopter’s ability to see, touch, try, compare, and understand the innovation in their market context. An array of literature confirms the role each plays in the adoption decision, including a meta-review by one of the modern experts of innovation theory and practice (Greenhalgh et al., 2004).

With respect to the internal factors that influence the adoption of innovation, the literature highlights the presence of technology champions (Koebel, 2007), levels of research and development funding, project manager support for innovation (Damanpour and Schneider, 2006), the firm’s sense of how innovation will create value, whether they adopt early or later, and the extent to which firms see the availability of competing innovations (Hartmann, 2006). Outside of the construction literature, research has shown that the adopter’s characteristics and their perception of the attributes of the innovation are linked and influence the
duration of the adoption process (Ostlund, 1974). Additional traits included: firm size (Kimberly and Evanisko, 1981; Dewar and Dutton, 1986), managerial attitude toward change, technical knowledge resources, administrative intensity, internal/external communications, centralization (Damanpour, 1991), and concerns about reputation (Gann and Salter, 2000).

Research shows that the contextual (Dale and McQuater, 1998) or external factors that influence the adoption of an innovation are time (Rogers, 1995), client orientation, climate (Andrews and Krogmann, 2009; Kok, McGraw, and Quigley, 2011), industry structure or relationships, attributes of the built environment (Ewing and Hamidi, 2013; Ewing, Meakins, Hamidi, and Nelson, 2014), communication networks (Rogers, 1995), and market area control variables are each important (Koebel, 2007), as are the spillover effects between markets (Simcoe and Toffel, 2011). Additionally, where research is often concerned about substitution innovations or the process of supplanting old with new, industrial economics literature supports the concept of complementarity, or the adoption of substantively or functionally related innovations that play a role in the adoption of innovation (Freeman, 2002; Cassiman and Veugelers, 2006; Miravete and Pernias, 2006; Gilli, Mancinelli, and Mazzanti, 2013). While identifiable, scholars have noted that assessing causal relationships from complementarity can be a challenge given the timing of adoption and available data (Fagerberg, Mowery, and Nelson, 2006; Greenhalgh and Rogers, 2009).

Regulation is also a significant and complex factor in the adoption of innovation and warrants more in-depth discussion as it connects to sustainability. Research shows that regulation influences adoption decisions in construction and other built environment disciplines (Choi, 2009; Simons, Choi, and Simons, 2009; Hardie and Newell, 2011; Kontokosta, 2011). For example, recent raising of building code standards and efficiency requirements for markets indicates growing rates of the diffusion of energy efficiency in buildings (Kok, McGraw, and Quigley, 2011). Additionally, researchers have observed accelerated diffusion where the cost of achieving increased performance has dropped (Beerepoot and Beerepoot, 2007; Harvey, 2013; El-Shagi, Michelsen, and Rosenschon, 2014). To wit, the diffusion of energy innovations appears to be reflected and capitalized in the prices of commercial (Eichholtz, Kok, and Quigley, 2010; Eichholtz, Kok, and Yonder, 2012; Harvey, 2013; Nappi-Choulet and Decamps, 2013; Geiger, Cajias, and Fuers, 2014) and residential buildings (Costa and Kahn, 2009; Brounen and Kok, 2010; Aroul and Hansz, 2011; Bloom, Nobe, and Nobe, 2011; Dastrup, Graff, Costa, and Kahn, 2012).

Given the guidance that diffusion of innovation models are theory-driven and contain attributes of the innovation, the adopter, and additional external factors, Exhibit 1 represents a conceptual model of the adoption of building product innovations among U.S. homebuilders.

**Operationalizing the Conceptual Model and Data**

To mimic the adoption decision, the researchers operationalized dependent variables as binary, single-stage decisions to adopt a higher energy performance
product from a cluster of economic substitutes. In Spring 2012, the U.S. Department of Housing and Urban Development (HUD) proposed 10 energy performance products that could be leveraged toward affordability: framing-optimum value engineering (OVE), structural insulated panel systems (SIPs), insulating concrete form systems (ICFs), spray foam insulation, installing HVAC and duct systems in conditioned space, customizing the HVAC system, programmable thermostats, and polyethylene plastic piping (PEX or PEX-AL-PEX).

Complete records for each energy performance product from 2000 to 2010 were not available within the BPS. Therefore, we specified our first dependent variable as a homebuilder’s use (or non-use) of cross-linked polyethylene water distribution piping known as PEX (or PEX-AL-PEX when it includes an aluminum component) in each year from 2000 to 2010.

We specified the second dependent variable as a homebuilder’s use (or non-use) of a programmable thermostat from among a cluster of lower energy performance economic substitutes in each year from 2000 to 2010. In the context of the cross-sectional non-longitudinal data in the BPS, Exhibit 1 illustrates the cumulative adoption curve or diffusion trajectory of the high performance piping alternatives against their traditional substitutes during the study window. It is clear that the higher energy performance alternative grows to become the market leader over time.

We chose the specification of the dependent variable for several reasons. First, the specification imitates the dichotomous choice homebuilders are faced with when...
deciding to install building products. It also reflects the central tendency of the innovation literature to use binary single-stage dependent variables to model adoption decisions. Second, recent literature (Kok, McGraw, and Quigley, 2011; Malkani and Starik, 2013) has noted that green and high performance attributes of buildings represent innovation. Third, these building technologies both play key roles in increasing the environmental performance of a home. Higher performance thermostats increase precision for heating-and-cooling-based energy consumption, the highest consumption of energy in the home. Similarly, high performance piping significantly reduces thermal transmission loss as water travels from the hot water heater to the tap (water heating being another large energy consumer). Fourth, these technologies exhibit important attributes that can affect use; for example, differences in adoption patterns for technology innovations that are placed inside the wall versus outside the wall (observability) or other important product attributes (McCoy, Koebel, and Sanderford, 2013). Finally, with binary dependent variables describing the adoption of a high performance product from among a cluster of economic substitutes, our specification allowed for controlling two Rogers’ (1995) defined attributes of innovations: compatibility and complexity.

The embedded assumption in this simplification is that as the technologies are economic substitutes for one another, the adopter is aware of the complexity and compatibility of the products and adopts the product based on other characteristics. An associated challenge in modeling the adoption process as described is that it is extremely difficult to understanding builders’ tacit knowledge or knowledge acquisition processes about innovative technologies. For example, some may be slow to adopt because the innovations require substantial research and education to understand and use. This tacit knowledge level would be an internal factor and is, in this model, not something for which we can account beyond their signaling about innovation through the use of other products. Based on the technology adoption literature, it would reasonable to expect that how knowledge about the attributes of the innovations is acquired (e.g., how much effort is required to learn about something new or find new vendors and whether or not to trust them) would significantly influence the adoption decision.

To gain some insight into the tacit knowledge associated with the adoption of high performance housing technology innovations and their inclination towards innovation, we introduce an independent variable measuring the builder’s other high performance innovation choices. The variable seeks to account for the respondent’s tendency to adopt higher performance building products and reflects their orientation toward innovation in high performance products. While it does not control for the difficulty of knowledge acquisition, it should help signal the firm’s orientation towards the adoption of high performance innovation.

Data for the dependent variable from the Builders’ Practices Survey (BPS), an annual survey conducted by Home Innovations Research Lab, a subsidiary of the National Association of Homebuilders (NAHB). The BPS documents the self-reported material selections of NAHB member respondents (NAHB, 2014). The survey covers nearly 1,100 products, across more than 40 categories, and has been conducted since the late 1990s. Our research utilizes data from 2000 to 2010 in
the dependent variable specification representing approximately 30,000 builder respondents. We limited the sample to respondents that reported operating in the contiguous 48 states during the sample period. With each of these restrictions, the total number of observations in each model (described below) was approximately 10,000.

It appears that the BPS is the largest set of cross-sectional data available to analyze research questions focused on builders’ annual use of individual construction technologies. Although it cannot be considered a random sample of the universe of residential builders in the U.S. or a longitudinal data set, as respondents’ product choices cannot be tracked across time, the distribution does appear representative of the U.S. homebuilding industry. Comparing the distribution of the BPS to the distribution of homebuilders in the U.S. Census’ County Business Patterns data in randomly selected years of our analysis period revealed an average coefficient of determination of 0.70, indicating sufficient similarity between the distributions (McCoy, Koebel, and Sanderford, 2013). The BPS data do not contain any information about the characteristics of the firms beyond the city and county of the respondents’ addresses and summary measures of the number, size, building type, and price of the housing units built during the previous year.

Independent variables were classified into three categories: (1) attributes of the innovation (Exhibit 2), (2) attributes of the adopter (Exhibit 3), and (3) contextual or external conditions (Exhibit 4). Given the extensive literature describing factors influencing the adoption of innovations across many industries, there has been consistent focus on the attributes of the innovation—linking directly to Rogers’ (1995) historical classification of attributes that most significantly influence product adoption: observability, trialability, complexity, compatibility, and relative advantage. The total number of construction wholesalers, as measured by the county business patterns, in the respondent’s Core Based Statistical Area (CBSA), accounted for trialability, complexity, and observability of each of the high performance products. Relative advantage, a function of price, was measured, using RS Means data, as a ratio of the price of the dependent variable over the average price of its economic substitutes. Where prior sustainable real estate literature has focused on the price of green buildings relative to the economic value they generate, the ratio specification of the relative advantage attempted to capture the quick calculus a builder might use in selecting a product among its

### Exhibit 2 | Attributes of Innovation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td># of Construction Wholesale Firms</td>
<td>Total number of construction wholesaling firms in CBSA</td>
<td>County Business Patterns</td>
</tr>
<tr>
<td>Relative Advantage</td>
<td>Average cost per unit of high performance technology/average cost per unit of economic substitutes</td>
<td>RS Means</td>
</tr>
<tr>
<td>Construction Cost</td>
<td>Average cost of construction in CBSA</td>
<td>RS Means</td>
</tr>
</tbody>
</table>
### Exhibit 3 | Internal Attributes of the Adopter

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complementarity Index</td>
<td>Sum of respondent’s binary choices to adopt high performance window, framing, foundation, insulation, and either piping or thermostat technologies (dependent variable excluded per model)</td>
<td>BPS</td>
</tr>
<tr>
<td>Total # of Homes Built</td>
<td>Total # of homes built by respondent (hundreds)</td>
<td>BPS</td>
</tr>
<tr>
<td>% of Multifamily HU</td>
<td>% of MF units built within respondent’s annual housing unit total</td>
<td></td>
</tr>
<tr>
<td>Weighted Avg Size</td>
<td>Average of single-family housing unit size weighted by type: starter, move-up, luxury. Type defined by NAHB.</td>
<td>BPS</td>
</tr>
<tr>
<td>Weighted Avg Price</td>
<td>Average of single-family housing unit price weighted by type: starter, move-up, luxury. Type defined by NAHB.</td>
<td>BPS</td>
</tr>
<tr>
<td>Gravity-Network Index</td>
<td>Distance decay calculation: distance and total # of SF building contracting firms in CBSA</td>
<td>Author</td>
</tr>
</tbody>
</table>

### Exhibit 4 | External Attributes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010 Median Housing Value</td>
<td>2010 median value of housing units</td>
<td>Census</td>
</tr>
<tr>
<td>% Owner Occupied HU</td>
<td>2010 percentage of owner occupied housing units in CBSA</td>
<td>Census</td>
</tr>
<tr>
<td>2010 Med. HH Income</td>
<td>Median household income in CBSA</td>
<td>Census</td>
</tr>
<tr>
<td>2010 GDP / Capita</td>
<td>2010 gross domestic product / capita of CBSA</td>
<td>BEA</td>
</tr>
<tr>
<td>2010 Total Population</td>
<td>Total Population in 2010 in CBSA</td>
<td>Census</td>
</tr>
<tr>
<td># of Pluming or Electrical Contractors</td>
<td>Total of plumb &amp; HVAC contracting firms in CBSA</td>
<td>County Business Patterns</td>
</tr>
<tr>
<td>DSIRE: Energy Rebates</td>
<td>Count of local, regional utility energy rebates available to all parties in the state</td>
<td>EPA</td>
</tr>
<tr>
<td>DSIRE: Energy Grants</td>
<td>Count of energy grants available to all parties in the state</td>
<td>EPA</td>
</tr>
<tr>
<td>DSIRE: Other Incentives</td>
<td>Count of other (non-rebate or grant) energy incentives available to all parties in the state</td>
<td>EPA</td>
</tr>
<tr>
<td>5 Year KWH Price</td>
<td>Prior 5-year average of electricity prices by state</td>
<td>EIA</td>
</tr>
<tr>
<td>ARRA Funds / Capita</td>
<td>$/Capita of federal stimulus funds spent in state</td>
<td>ARRA</td>
</tr>
<tr>
<td>Heating Degree Days</td>
<td>30-year average of heating degree days in state</td>
<td>NOAA</td>
</tr>
<tr>
<td>Cooling Degree Days</td>
<td>30-year average of cooling degree days in state</td>
<td>NOAA</td>
</tr>
<tr>
<td>Sprawl Index</td>
<td>Factor analysis of multiple measures of compact growth</td>
<td>R. Ewing</td>
</tr>
</tbody>
</table>
substitutes. An additional variable describing the cost of construction in a CBSA was included to control for market-to-market cost variation.

Given the size of the data set, creating detailed measures about the attributes of the adopter was impractical. Therefore, the model is agnostic to the firm’s investment in research and development, the executive’s support for innovation, the presence of an innovation champion, its perceptions about the innovation, or other related attributes. However, a model without internal attributes of the adopter would be incomplete. Variables included in the conceptual model of this work are: firm size, total number of homes produced, average home price and average home size, and a complementarity index. The complementarity index sums the number of adoptions of high performance technologies in large building systems by the builder. The index variable is included to reveal information about the inclination of the respondent towards high performance product innovations. Additionally, where the diffusion of innovation is largely a communicative process, the researchers also included a variable (Gravity Network Index) describing the potential linkages or communication networks amongst single-family home builders. Each variable, with the exception of the Gravity Network Index metric, was drawn from BPS data.

External or contextual factors are the third category of independent variables. We included these variables in the conceptual model as economic, climate, regulatory, demographic, industry, and built environment attributes. We collected each variable from public data. We specified data at the level of the CBSA, or in some cases the state that respondent listed as their primary business address.

**Methods of Analysis**

Based on the collected variable set for the conceptual model, specifically the homebuilder’s decision to adopt a product innovation from among a cluster of its economic substitutes, the research team then designed a logistic regression framework to operationalize our conceptual model on the two focus technologies (Agresti, 2002). The model is represented generically through the following equation:

\[
\ln \left( \frac{p}{1 - p} \right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k
\]

and then functionally reduced, given the data, as:

\[
\text{Use of High Perf Product}_n \ln \left( \frac{P_n}{1 - P_n} \right) = \mu + \beta_1 + \beta_2 + \cdots + \beta_n,
\]
where $n$ equals one of the two high performance products, $\mu$ is the y-intercept, and $\beta_j$ for $x = 1, 2, \ldots, n$ are time, attributes of the innovation, attributes of the adopter, and external or contextual attributes.

Analytically, we created two logistic regression models for each dependent variable: (1) a univariate model where $\text{Year}$ was the only predictor and (2) a model that included the full list of candidate predictors described above. Comparison of the univariate to the multivariate models provided an opportunity to gauge improvement in the model's ability to identify factors other than time influencing a builder’s innovative product decisions. As the data set contains a large number of predictors, adding additional factors beyond time is expected to improve model fit; however, there is risk of producing an over-fit model as well.

To reduce risk of over-fit and move towards a parsimonious final model, we implemented a penalized regression technique from the generalized linear modeling toolkit known as the least absolute shrinkage and selection operator (LASSO). LASSO has not been widely deployed in the planning literature and offers a new possibility for analysis that $p$-value selection does not. LASSO’s class of analytical tools is well suited to both dichotomous choice analysis and large data sets, where the large number of predictors may not correlate appropriately. The LASSO minimizes the residual sum of squares subject to the constraint that the sum of the absolute values of the independent variable coefficients is less than some constant. Thus, the LASSO variable selection technique tends to result in some coefficients being 0, leading to a parsimonious and interpretable model (Tibshirani, 1996). Specifically, the LASSO has superior abilities over stepwise-based variable selection techniques in identifying a meaningful list of predictors from a constellation of candidates.

Mechanically, LASSO works by setting a constraint assumption that forcibly shrinks the size of independent variable coefficient estimates towards zero, optimizing model selection, decreasing prediction variance, and decreasing prediction error (Friedman, Hastie, and Tibshirani, 2010). Typically, the LASSO constraint is chosen using k-fold cross validation. For our modeling purposes, we used 10-fold cross-validation to choose the constraint parameter $\lambda$. The formulation of the LASSO technique for variable selection and coefficient estimation is as follows:

\[
\hat{\beta}_\text{lasso} = \text{argmin}_\beta \left\{ \sum_{i=1}^{n} (y_i - \beta_0 - \sum_{j=1}^{p} x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\}.
\] (3)

At the lambda threshold selected, the selection technique produced a 16 variable model for piping and a 9 variable model for thermostats. Unlike a stepwise selection technique that only allows variables to be in or out of the model, the LASSO continuously allows variables to enter and exit the model with different effect sizes. Thus, with different values of the constraint come different values of the estimated coefficients. In the general linear model framework, the LASSO
Exhibit 5 | Model Fit Statistics

<table>
<thead>
<tr>
<th>Model Type</th>
<th>C-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Univariate PEX</td>
<td>0.528</td>
</tr>
<tr>
<td>Univariate Programmable Thermostat</td>
<td>0.575</td>
</tr>
<tr>
<td>Adoption of PEX</td>
<td>0.693</td>
</tr>
<tr>
<td>Adoption of Programmable Thermostat</td>
<td>0.701</td>
</tr>
</tbody>
</table>

produces a path diagram over all values of λ, where the paths are found using the coordinate descent algorithm presented by Friedman, Hastie, and Tibshirani (2010). The PEX path diagram illustrates how variables are tested for inclusion in the model, from a univariate model to the reported model then onto a fully over-fit model.

**Findings: Model Fit**

With respect to model fit (Exhibit 5) for both the thermostats and piping models, when moving from the base case univariate model (Year only) to the full model, the c-statistic or area under the receiver-operating curve grows substantially. For example, the standard, univariate piping model is more capable of discriminating users from non-users than a coin flip (c-statistic: 0.5), although not by a great deal. When the full cluster of independent variables is regressed, the LASSO selects a model that can far more accurately discriminate between high performance piping selection and non-selection (Hosmer and Lemeshow, 2000). A similar trend can be observed in the thermostat model. In practical terms, both models grow significantly in their ability to discriminate between high performance technology adopters and non-adopters. This growth confirms the hypothesis embedded in the analytical strategy that time alone is an insufficient predictor of adoption decisions. Rather, the adoption decision is more complex.

**LASSO Selected Models**

The LASSO selected models indicate that the internal, external, and innovation-specific measures are each associated with U.S. homebuilder’s high performance product adoption choices. Relative to internal attributes of the adopting firm, the results show that firm size is associated with the adoption and diffusion of innovative products. Builders that produce a larger number of units and those that produce multi-family housing units in addition to single-family units tend to have higher odds of adopting high performance piping alternatives. Builders building larger sized housing units are less likely to adopt and install high performance pipe systems.

While we would expect that expect smaller homes would be more energy efficient, higher performance piping is not one of the tools builders have tended to use to achieve this. One reason that builders might not use higher performance piping
in smaller houses is the shorter distance between the hot water heater and points of use. Where PEX piping reduces thermal loss over the water transmission distance, perhaps builders do not see significant efficiency gains in smaller houses over shorter piping distances. The finding on unit sizes is consistent with Koebel et al. (2015), where evidence showed builders producing larger homes were more likely to use higher performance windows—the more exterior surface that could be windowed, the higher the odds of using a window with a superior energy rating. However, with respect to greater odds of PEX use with greater production of multi-housing units, this paper differs from those presented by Koebel et al. (2015).

Additionally, the respondent’s inclination towards innovation, as measured by the complementarity indices, was positively associated with adoption decisions. These results confirm previous literature and suggest that despite lacking a significant volume of data describing the internal aspects of the firm, it is plausible to generate new insight into how U.S. homebuilders make decisions about high performance product innovations based on what else they are adopting and installing. This finding is consistent with Rogers (1995).

Relative to the attributes of the innovation, the number of construction wholesale suppliers but not the number of specialized contractors has positive effects on high performance piping and thermostat selection (Exhibit 6). Suppliers appear to play important roles in the adoption of early technologies as hubs for communication, product trial, and discussion. Further, as suppliers are open to the public, they could easily be a place where the end user, the homeowner, can experiment with the innovations.
The variables representing the external attribute category illustrate that climate, energy-specific regulatory incentives, built environment factors, and economic or market factors are each associated with builders’ innovative product adoption decisions. With respect to incentives, despite being available to an array of parties and not just builders, the presence of incentives in the marketplace is associated with builders’ adoption choices. The difference in signs illustrates that type of policy intervention influences builders’ choices differently. Further, confirming the findings from previous research on windows and energy certifications, both heating degree-days and cooling degree-days are significant predictors of PEX adoption (Exhibits 7 and 8) while only heating degree-days are associated with the selection of thermostats (Exhibit 9). Although small in effect, this sensitivity climate is not reflected in sensitivity to energy costs; longer term energy prices were not selected into the thermostat model. Taken together and with the sprawl index findings, the results confirm aspects of the broader narrative in the green real estate literature that built environment and its physical context influence stakeholders’ choices.

Increases in total population, GDP/capita, and the percentage of owner-occupied housing units are market characteristics negatively associated with builders’ choices to adopt high performance piping products. The population and GDP/capita variables indicate that the adoption of high performance piping innovations is occurring in smaller markets with lower economic output per resident. The ownership rate warrants cautious interpretation while the population and economic
output variables help provide more context to the findings for construction cost and income of the potential housing buyers. The odds ratio for median household income is positive, linking broadly with previous research indicating green home buyers tend to have higher annual incomes. Odds ratios for total building cost indicate that it has a large, negative effect on the selection of PEX. Similar to findings from the green real estate literature around green building certifications
and home prices, newer products with low market penetration are disadvantaged by both actual and perceived higher building costs.

**Differences in Models**

Builders’ adoption patterns for thermostats vary differently around both internal attributes and external factors. With respect to internal factors, evidence from the application of the model to thermostat choice showed that the greater the home price, the greater the probability of selecting a programmable thermostat. Likely heavily influenced by home size, this may be a reflection both of a “trickle down” effect and the “in front” (observability) of the wall effect that influences adoption of some innovations. Construction literature considers the lack of observability (innovative products exist behind walls here) to be a barrier to adoption and diffusion; they do not get nearly as much attention—an “out of sight, out of mind” logic. Here, where programmable thermostats are something occupants interact with and see regularly as their interface with energy consumption, this finding supports the literature.

With respect to external factors, public policy, climate, and market factors produced different model results. For example, as the number of utility rebates increases, the odds that a builder will select a programmable thermostat grow. Increases in the number of “other incentives” are also positively associated with builder’s thermostat choices. With respect to climate, only heating degree-days (HDDs) play a significant role in the builder’s choice to adopt programmable thermostats, deviating from the piping model and previous work on windows and energy certifications. Further, market area factors were not selected into the full thermostat model. While somewhat surprising, this finding suggests a non-volatile diffusion trajectory of a technology that is already the market share leader within its cluster. In other words, the maturity of the product in the market plays a significant role in the adoption decision and bandwagon effects may play stronger roles.

Finally, time is not selected into this model, indicating that the year-to-year adoption pattern is not associated with builders’ high performance thermostat selection. This exclusion is expected given the high and flat market penetration curve of the mature technology.

Additionally, when comparing the results of the LASSO selected models with the findings about the adoption of high performance windows from Koebel et al. (2015), it is clear that climate and public policy are positively associated with builders’ technology innovation adoption decisions. In both Koebel et al. (2015) and here, HDDs and grants and rebates available to consumers through various state channels were significant predictors of whether or not a builder would select the high performance window, pipe, or thermostat technology over each of their more traditional economic substitutes.

However, across the attributes of the builder and their housing portfolio in a given year, the results are a bit less clear and tell a more technology-specific story about product adoption and diffusion. For example, there was a positive influence on
window and thermostat adoption but not on PEX pipe adoption. Additionally, the overall construction cost in a market was negatively associated with both high performance window and piping selection but not thermostats.

These similarities start to form a preliminary picture of the cluster of factors and attributes that may be common to high performance construction innovations. We are cautious in attempting to explain the model differences without more formal review. However, model specification nuances and dependent variable product nuances likely play a role though we recognize that this is a question that future research should address.

Conclusion

Methodologically, this work provides two contributions to the sustainable real estate literature. Primarily, the work is one of the first to adapt a diffusion of innovation model to the analysis of U.S. homebuilders’ high performance building product use. Beyond the novelty of being first adopters, there is also utility in adapting the traditional diffusion model to the specifics of the homebuilding industry. Where previous research had focused on smaller sample analyses heavily weighted towards identifying the internal or firm-specific factors related to the adoption of innovation, this paper shows that when such information is limited, it is possible to generate insight into the builder’s adoption decision. Secondly, the LASSO model selection technique shows that it could provide diffusion of innovation modelers with a tool for creating modeling parsimony. Parsimony benefits future researchers that wish to use mixed-method approaches to dig deeper into the causal relationships between variables, obstacles, and innovations.

Empirically, the LASSO selected models confirm that despite a lack of understanding about the firm’s orientation to innovation, there are significant associations between builders’ high performance product choices and each of the three category types of variables (internal, external, and attributes of the innovation). For example, although the model did not contain much information about the internal attributes of the buyer, using a measure of the builder’s other sustainable product choices helped provide significant context to the adoption decision. In other words, the constellation of high performance products a builder uses influences the way that the builder makes choices about other high performance product selections.

Further, although there is similarity in the findings between models [both between PEX and thermostats as well as with Koebel et al.’s (2015) windows analysis], the factors that influence builders’ innovation decisions vary between technologies. This variation illustrates the lack of a single narrative associated with builders’ high performance innovation choices. In some cases, the inside versus outside wall or mature versus earlier stage distinction helps elucidate the choice patterns. Alternatively, variation in regulatory climate factors shows the importance of context in the adoption of high performance product innovations. Seemingly a self-evident conclusion—builders’ choices in Arizona will differ from those made
in Vermont—it is, nevertheless, useful to confirm that climate and regulation serve as the backdrop against which adoption decisions are made.

**Endnote**

1 Gambastese and Hallowell (2011) are excluded as exceptions here as they focused on empirical diffusion of innovation among innovation generating organizations rather than innovation adopting organizations.

**References**


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