ESTIMATION OF BRAND DEMAND ELASTICITIES

FOR SELF-OPERATING RADIATOR SENSORS IN UKRAINE

by

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LIST OF ABBREVIATIONS

DH District Heating

EUBAC European Building Automation Controls Association

EEFU Energy Efficiency Fund of Ukraine

IEA International Energy Agency

MFH Multi-family houses

NBU National Bank of Ukraine

RS Radiator sensor

SCNU State construction norms of Ukraine

SFH Single-family houses

SSSU State Statistical Service of Ukraine

TRV Thermostatic radiator valve

CHAPTER 1. INTRODUCTION

Demand elasticities estimations are widely used both at macro level for public policy analysis and at micro level for market analysis, particularly, for developing pricing strategies. Demand elasticities measure the responsiveness of the demanded quantity of a product to changes in such demand determinants as the product's price, customers' income, and prices of competing goods (Banerjee 2014, 14). If the demand function is represented with a linear equation, elasticity is calculated at a single point of the demand curve (so-called point estimate); to gain more insights about the linear demand, elasticities should be calculated at different points of the curve. Specifically, linear price elasticity of demand for point estimates is defined as:

$$\varepsilon_p = \frac{\Delta \mathrm{Q} / \mathrm{Q}(p_0)}{\Delta p / p_0} = \frac{\Delta \mathrm{Q}}{\Delta p} * \frac{p_0}{\mathrm{Q}(p_0)} \ , \tag{1}$$

where p_0 is the original price level, $\mathrm{Q}(p_0)$ is the quantity demanded at that price, Δp is the difference between the original price and the new price, and $\Delta \mathrm{Q}$ is the corresponding difference in quantity demanded.

Demand described with an exponential function allows for constant demand elasticity calculations. Logarithmic models (logarithmic functions are the inverses of exponential functions) are most commonly used in applied econometrics for calculating constant elasticities of demand determinants. To give an example, constant income elasticity of demand, which captures the impact of a change in the income level on the quantity demanded, keeping all other determinants fixed is defined as follows (Banerjee 2014, 16):

$$\varepsilon_i = \frac{\partial \mathrm{Q}}{\partial m} * \frac{m}{\mathrm{Q}} \ , \tag{2}$$

Where Q is quantity demanded, m is income level and $\frac{\partial Q}{\partial m}$ is quantity demanded differentiated with respect to income level.

In practical terms, it is worth stressing that although demand elasticities do measure responsiveness to changes in demand determinants, elasticity calculations *per se* are not sufficient for defining profitable pricing strategies. As John Daly puts it, "It is doubtful that many companies will routinely price their products by solving a single algebraic equation that determines the single best price for a product. The reason for this is that it is worthwhile to "play" with various pricing scenarios to obtain a deeper understanding of the customer demand curve and the cost–volume curve to understand the profit sensitivity if everything does not happen as planned" (Daly 2001, 29).

Admitting these considerations, quantified demand determinants and estimated demand elasticities are still valuable instruments for a firm navigating in the free market. In this research, our aim is to quantify demand determinants for the market segment of self-operating radiator sensors and calculate brand price[1] and income demand elasticities for the product. At our disposal is a panel dataset observing sales of two self-operating RS models in 65 Epicenter chain stores for 31 months. Panel data allows for applying unobserved effects econometrics models on which I rely in quantifying demand determinants. Limitations of the dataset, which will be explained further, are not allowing to estimate the log-log model, therefore I will present point estimates of the elasticities.

As for the product itself, a self-operating radiator thermostat was invented back in 1930s. It is designed to automatically maintain a preset room temperature in hot water radiator heating systems. It consists of two main components: a radiator sensor (also called a thermosensitive head) and a thermostatic radiator valve (TRV). The sensor reacts to changes in temperature in the room by mechanical expansion or contraction of a

[1] Brand price elasticity is defined as "the price response with regard to a particular brand within a product market" (Fujita, 2015: 3)

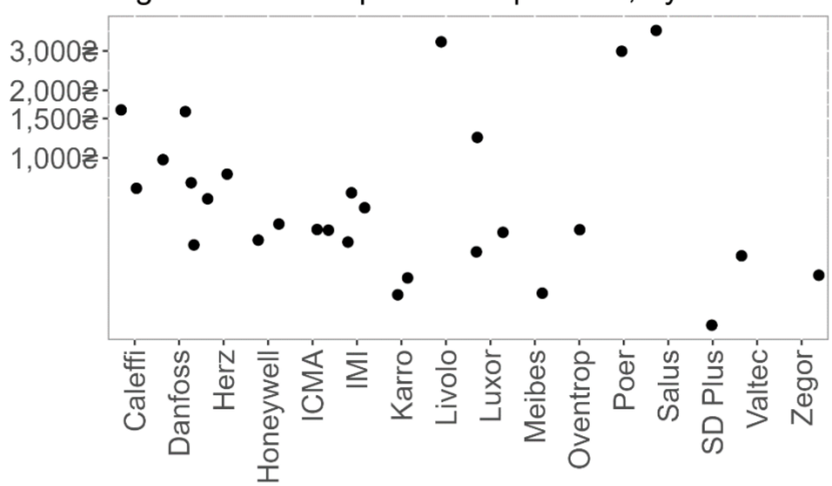
thermosensitive element (it may be wax in some cases, but more often it is a special liquid or gas), thus making the valve to restrict or release the amount of hot water flow passing through the radiator. From customer's perspective, the product is valuable for keeping the preset level of heat comfort throughout the day and reducing heat consumption by 18% on average (EUBAC Report 2017).

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

a. Industry overview

A sound way to start examining any market is to visit it. The website of the largest national retailer Epicenter, as for February 18, 2023, has 28 models of radiator sensors, available for sale[2]. Prices range from 180 to 3,698 UAH, with an average price of 909 UAH. There are 16 brands in total, while brands with the largest number of models available are Danfoss (Denmark) with 4 models, IMI Heimeier (Germany), and Luxor (Italy) have 3 models each (see Figure 1 for all brands available at Epicenter; the logarithmic scale on the y-axis is applied).

Figure 1. Sensor prices at Epicenter, by brand



as for Feb 18, 2023. Source: web-scraped data

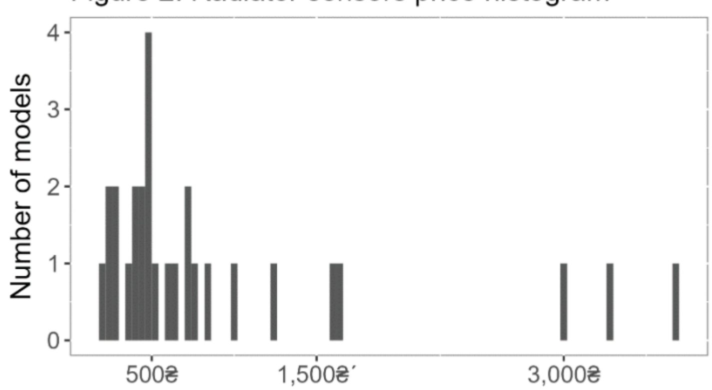
Other brands visible at the Ukrainian market, sold at national retailers like Romstal or Ukrinstal, are Herz (Austria), Karro, SD Plus (China), Comap (Czech Republic), Meibes, Oventrop, Siemens, Schlösser (Germany), Salus Controls (Hong Kong), Caleffi,

[2] Only distinct sensors for radiator valves are accounted here. Kits, consisting of a valve and a sensor, and sensors with temperature probes are excluded from the list. There are also other distinct sensor models at the website that are currently unavailable for sale, with no price quoted – and therefore also excluded from the list.

Giacomini, ICMA, Valtec (Italy), and Honeywell (The US). All radiator sensors are imported to Ukraine, there are no evidence of local manufacturers.

Significant price range and large variance of price distribution signals about some kind of products' heterogeneity. The price histogram (Figure 2) shows the distribution to be right skewed with a few outliers priced above 3,000 UAH. To understand the source of this heterogeneity, let us take a closer look at the characteristics of the products. Presumably, we will be able to find out whether we are dealing with sophisticated product differentiation, or whether there are separate market segments, implying different underlying demand functions.

Figure 2. Radiator sensors price histogram



In general, radiator valves might be controlled with manual caps, self-operating thermostatic sensors, and electronic sensors (EUBAC report 2017). We will exclude manual caps from this analysis, as current Ukrainian construction standards recommend applying sensors. By classifying radiator sensor models sold at Epicenter by type and sorting them by price, we can see the electronic sensors at the top of the list[3]. There is a distinct case of 'design' sensors: these are self-operating thermostatic sensors with fancy appearances, like Caleffi 200013 model with chrome coating.

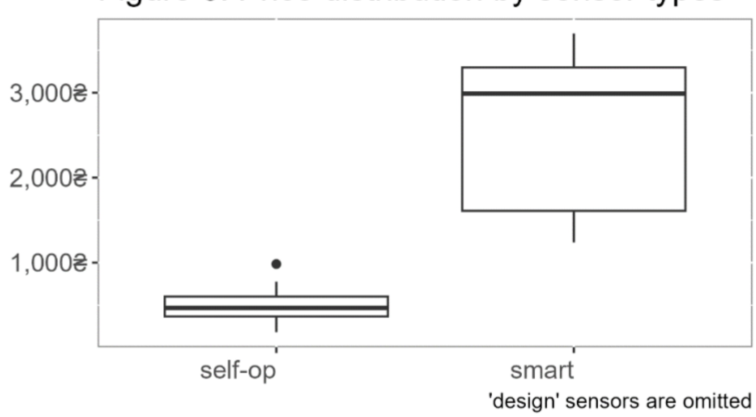
[3] See the full list is in Appendix, Figure A1

While both self-operating and electronic (also called 'smart') sensors provide automatic temperature control in premises, electronic sensors have additional functionality, e. g. remote control or programmability that allows to set schedule and temperature level individually for each room. Do self-operating and electronic sensors represent separate market segments and therefore have different factors driving demand? Dickson and Ginter (1987) suggest assuming separate market segments if "market demand could be disaggregated into segments with distinct demand functions". In its turn, demand, following Multi-Attribute Attitude Model (MAAM), might be represented as a function of price and a set of product attributes valuable for a consumer (where p is the price and $x_1 \dots x_n$ are product attributes):

$$Q = F(p, x_1 \dots x_n) \tag{3}$$

Dickson and Ginter note that the functional form depends on marketplace factors, such as disposable income or consumers' preferences. Assembling all the pieces together, I arrive at the following conclusion: given that the sensor types have different sets of attributes (or functional characteristics), and the average prices in the sample for the two differ by several times (2,566 UAH for smart sensors and 482.8 UAH for the self-operating ones – see Figure 3)[4], distinct demand functions for these sensor types may be assumed

Figure 3. Price distribution by sensor types

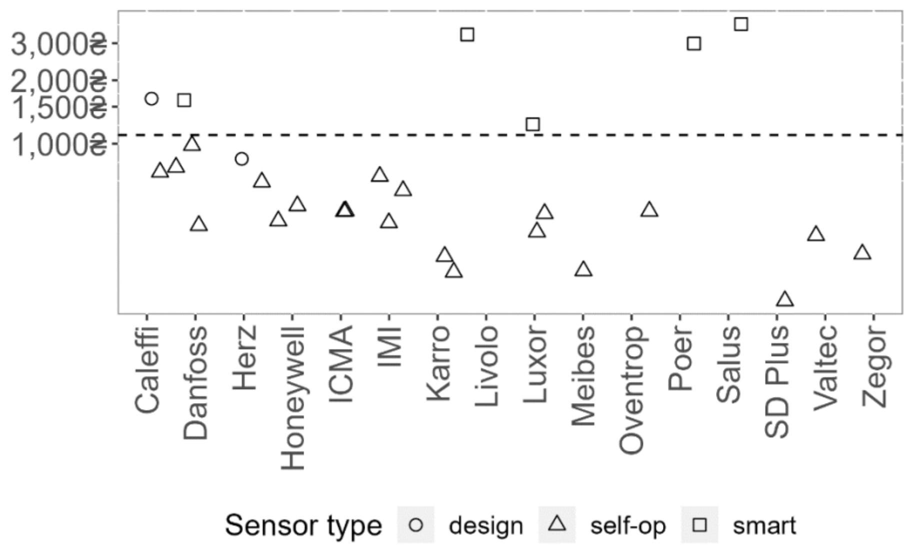


[4] boxplots at the Figure 3 show a median, not the mean as the central tendency.

and therefore electronic sensors and self-operating sensors constitute two separate segments of the radiator sensors market.

At the same time, 'design' sensors may be regarded as a case of product differentiation within the segment of self-operating sensors. The difference in physical appearance and price without additional functionality corresponds to the notion of product differentiation.

Figure 4. Sensor prices at Epicenter, by brand & type



With more than a dozen of competitors and a narrow price range in case of self-operating sensors (Figure 4), we see evidence of commoditization within the segment, meaning interchangeability of the models and heavy price competition. On the other hand, for the smart sensors segment, although our subsample contains just five observations, we can still see that models significantly differ in price. As smart radiator sensor improvements are closely linked to the ongoing progress in microelectronics and digital technologies sectors, this segment is clearly not as established. It allows manufacturers to compete by technology, functionality, and product differentiation efforts, resulting in significant price differences. Such a situation naturally raises the problem of further segmentation within the electronic sensors segment, but that is out of the focus of the current research.

To summarize this industry overview, we should say that the market is competitive, but with the lack of market-level data and market shares estimations[5], it is not easy to define the type of competition and market power of the firms. Yet, we have seen evidence of fierce price competition in the self-operating radiator sensors segment, which means that preserving long-term profitability would require the firms to invest in product differentiation, which is not a simple task for apparently homogenous products.

Following Porter's Five Forces model, higher competition and lower markup would rather prevent new entrants from entering the market segment unless cost leadership is a competitive advantage of a firm. Customers, as a result, are enjoying bargaining power, with an option to choose between a dozen of rather similar products; cross-price elasticity estimation would show the extent of this power, be industry-level data on quantities sold available. Therefore, in terms of profitability, an emerging smart radiator sensors segment seems more inviting for the new entrants, though a careful estimation of the addressable market segment is required, as the activity-based pricing approach suggests (see Daly 2001).

The empirical findings about the market and the industry we have gained so far are acquired with web-scrapping tools, data analysis, reading the professional associations' reports, and communicating with market professionals. Another source about the industry is several freely available in the web summaries of proprietary reports describing the global sensors market. Though little information is disclosed there, they yield some ideas for structuring our own research. The summaries tell us that there are several key players (manufacturers) that we do not see present in Ukraine, like Bosch, Purmo, Drayton, or Orkli. The radiator sensors market is segmented by geographical regions, types of sensors (these types we have already discussed), and applications[6]. As for the application part, we encounter interesting

[5] Ukrainian customs had announced the plans to make information on cross-border operations publicly available but closed access to even previously available information as Russian aggression broke out.

[6] Apart from different types of buildings, the 'application' classification is also applied to the type of heating system, either hot water (hydronic) or steam system. The steam radiator systems are not the case in Ukraine, so we will focus on buildings.

evidence that in 2014 globally the commercial buildings segment accounted for more than a half of all sales for radiator sensors. Let us have a closer look to areas of application to estimate the available market for radiator sensors in Ukraine.

b. Available market for radiator sensors in Ukraine

The addressable market for radiator sensors is naturally linked to the total amount of radiators in premises less the number of installed devices. We can estimate the number of installed radiators by addressing the number of buildings with hydronic radiator heating systems. State Statistics Service of Ukraine classifies all existing buildings as either residential or non-residential. Residential buildings are segmented into single-family, multi-family, and boarding houses. Non-residential buildings include seven segments: hotels, offices, wholesale and retail trade buildings, traffic infrastructure buildings, industrial, public, and 'other non-residential buildings.

As for the residential buildings, total housing stock at the end of 2020 amounted in total to 998.24 mln m^2 (USSS, Housing Stock by regions 2020) with the residential area being 627.35 mln m^2 (62.8% of total area). This area was shared by 9.164 mln buildings with 16.9 mln apartments. How had these apartments got their heat? 47% of all apartments in 2020 received space heating from district heating networks, 22% had individual heating systems (like natural gas boilers or electric floor heating), and all the others had either furnace heating or no heat at all. Considering that all apartments receiving heat from DH networks have hydronic (radiator) heating systems as well as most individual heating systems do[7], we are arriving at the conclusion that roughly 11 mln apartments in the residential sector in Ukraine are eligible for having radiator sensors. With, on average, 3 radiators per apartment

[7] There is no data found on the types of existing heating systems among single-house heating installations. There are rough estimations that up to 90% of individual heating systems utilize either natural gas or electric boilers and therefore have radiator systems.

(as for 2021, according to the USSS, average area of an apartment was 88.4 m^2), 33 mln radiators is the first figure we derive in our estimations.

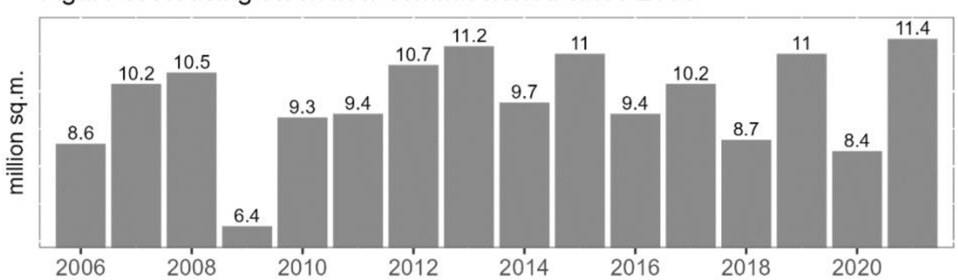
Yet, there are technological limitations in the MFH segment that do not allow to immediately service a considerable part of the market. By expert estimations, nearly 80% of existing multi-family buildings in Ukraine have one-pipe heating systems, which require substantial heating system modernization before mounting a sensor could happen (in particular, installing a by-pass on each radiator is needed). According to the current legislation, such a modernization presupposes a consensus among the building's co-owners, which by far was not a mass phenomenon. According to the Energy Efficiency Fund of Ukraine, launched in 2015 to promote energy efficiency in the housing sector, by the end of 2021, only 688 applications from multifamily houses were approved to receive financing and implement at least some steps in heating system modernization (EEFU Report 2020, 2021), which is around 0.05% of existing MFH stock with one-pipe heating systems[8].

On the other hand, since January 1, 2006, all new multi-family buildings are supposed to have horizontal two-pipe heating systems (State construction norms of Ukraine, B.2.2-15-2005: 5.26). Constructively, this type of heating system allows radiator sensors installation upfront without heating system modification. At the same time, norms recommend but do not require sensors installation (SCNU B.2.5-67:2013: 6.4.1). Therefore, market factors, which we will consider in Chapter 3, have their impact on the serviceable market size for the new multifamily houses.

[8] As for 2016, there are reportedly 163,041 multifamily buildings (Karp, Nikitin, 2021: 21), with nearly 80% of them having one-pipe heating system.

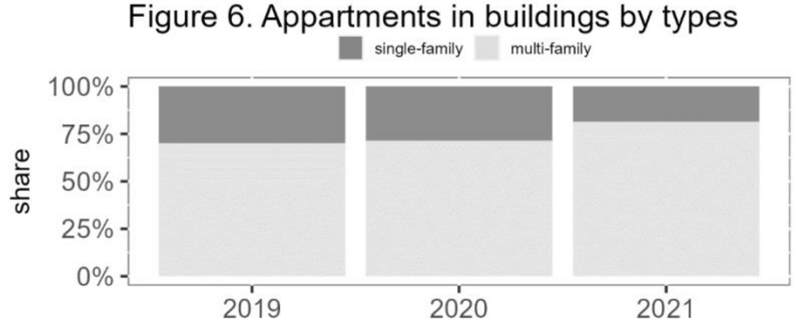
From 2006 to 2020 144.9 mln m^2 of new housing stock were commissioned (combined number for single- and multifamily buildings, see Figure 5), that is 14.5% of all existing housing stock. As the USSS is not quite consistent, reporting in some years the ratio of 'urban dwellings' to 'rural dwellings', and in the others 'single-family dwellings' to 'multi-family' ones, the precise number of apartments in multifamily houses (which ought to have a two-pipe heating system) is not available for this period. The USSS reports the second ratio for the period 2019-2021 (USSS, Number of dwellings in residential buildings, putting into service, by type by region, 2019:2021). For example, in 2020 8.4 mln m^2 of housing stock was commissioned, of which 4.27 mln m^2 were SFH and 4.17 – MFH. In its turn, there were 68,880 apartments in multifamily buildings and 27,684 in single-family ones.

Figure 5. Housing stock flow commissioned since 2006



For this period, the average ratio of apartments in SFH to MFH is nearly 1:3 (Figure 6), while the average area of an apartment is 154.5 m^2 and 58.7 m^2 respectively. Extrapolating these numbers retrospectively to the period 2006-2021, we obtain 117.3 mln m^2 of the MFH stock. With an average of three radiators per apartment in MFH, we have 1.998

Figure 6. Appartments in buildings by types



Source: USSS, Dwellings in residential buildings million apartments with almost 6 million radiators installed[9], upfront available for sensors installation. Provided that only a part of SFH has hot water radiator system, rough estimation of installed radiators for the period is 0.9 million pieces (for 253,000 single-family houses). For the housing stock constructed before 2006, our estimation of installed radiators is 18.7 and 9.9 million for MFH and SFH respectively.

All in all, by the end of 2021, in the residential sector we have 33.6 million radiators (a slightly increased number compared to the former estimation), of which 17.4 million, or 48.2% are technically feasible for sensors installation with no requirements for heating system modification. Annually, prior to the Russian invasion of Ukraine, the three-year average figures show that the size of the serviceable market for radiator sensors originating from new housing stock was equal to 390,000 pieces.

As for the non-residential buildings, an attempt to estimate the number of radiators installed is more problematic. On the one hand, the case of public buildings is relatively straightforward. Reportedly, as of 2018, there were 39,376 public buildings in Ukraine (Karp and Nikitin 2021, 17). Most of them have hot water radiator heating systems, receiving heat either from the DH network (41.3%) or from local boiler houses. Assuming that the average area of a public building is 2,000 m^2 (it could be both a large school or a small medical assistant's point – statistical data is unavailable here), with a radiator per each 50 m^2 of total area, we obtain 40 radiators per building and nearly 1.57 million radiators installed.

As the limitation of one-pipe heating systems is present here as well, this figure should be, in general, attributed to the addressable market, as potentially available for radiator sensors installation. For the years 2019-2021 the USSS reports (USSS, The total area of non-residential buildings at the start of building by type, 2019-2021) that 15.34 mln m^2 of public buildings we commissioned, implying more than 100,000 annual radiator installations in

[9] There are multifamily buildings on electrical heating, but their quantity is negligible on the national scope.

this segment. As the Bill "On the Energy Efficiency of Buildings", aligned with the EU Directives on Energy Efficiency and Energy Performance of Buildings, pays specific attention to energy consumption in public buildings, and the SCNU require two-pipe heating system installation, this number should be included to the size of the annual serviceable market.

As for the other segments of non-residential buildings, it is difficult to find the ground even for the rough estimations of installed radiators. There is some share of radiator heating systems in hotels and offices, but I found no data on the amount of these types of buildings in Ukraine, let alone the types of heating systems they have. As for the wholesale, trade, or industrial buildings, they would rather have no radiator heating system, utilizing instead installations like split system air conditioners, packaged terminal air conditioners, or ventilation make-up air units (Better Buildings Report 2021).

Therefore, to carefully summarize my calculations, I would rather indicate a lower threshold of the annual serviceable market for radiator sensors in Ukraine prior to the war amounting to 500,000 pieces.

Estimation of the amount of already installed radiator sensors (and its annual dynamics) is another challenging task. As we will see further, the key factor that motivates residents to care about heat saving, namely the heating bill, is virtually ineffective in Ukraine, as natural gas rates are heavily subsidized. As a result, the amount of already installed sensors is mostly defined by the residential sector developers who pay attention to the construction norms (this set is not equal to the set of all developers operating in the market); commercial buildings owners, who are unequally charged with higher natural gas and heat rates and therefore motivated by market forces; reconstruction projects of public buildings with international financing; a tiny number of multifamily buildings co-owners who managed to reach consensus to retrofit their buildings; SFH owners with an income above average. All that is intertwined with a lack of understanding on the consumers' side, how a radiator sensor works, and what it is used for (Dentz 2015, 24).

c. Related studies

Radiator sensor is a durable good, which period of use, at least in case of the self-operating ones, spans over several decades. There is an elaborated field of economic theories for durable goods. Waldman (2003) provides an overview of durable goods theories explaining strategies that manufacturers take to maximize their profit. In particular, he discusses the optimal durability theory by Peter Swan, who dismisses the 'planned obsolescence' approach as non-optimal for the manufacturer; Ronald Coase's studies focusing on intertemporal effects of durable goods sales; and George Akerlof's analysis of asymmetric information and adverse selection. Akerlof's idea of particular interest is that in a situation of asymmetric information that manufacturers and consumers have, consumers may tend to choose goods of inferior quality, squeezing out high-quality products from the market.

As for the demand side theories, explaining the variation in energy-related customers' behavior and picking relevant demand determinants driving the purchase of energy-saving appliances is not a trivial task. To illustrate the challenge: there is evidence that energy saving is a key demand factor for energy savings appliances, at least in countries with developed energy markets, like the US, where the actors have market incentives to adjust their behavior to changes in prices. On the other hand, the magnitude of this effect can significantly differ even in two neighboring households which have similar sociodemographic characteristics and residential conditions (Jensen, 2008).

Yoo et al. (2020) have developed a theoretical framework called Household energy involvement (HEI) that allows us to approach the complexity underlying customers' decisions to purchase energy-saving devices. Their findings are based on the analysis of a survey involving 5487 Korean households. The authors develop involvement theory, classifying the determinants of energy-related purchase decisions into several broad clusters.

The Consumer values and preferences cluster includes such ordinal categorical variables as 'automation', meaning stated willingness to invest in indoor heating/cooling automation systems; 'receptivity' as the readiness of a household to invest in new technologies; 'energy knowledge' regarded as awareness of the energy rate structures; there is self-explaining 'environmental concern' variable; 'tolerance' means a willingness to forego personal thermal comfort to save on bills; finally, 'importance' stands for a stated understanding of the role of energy in sustaining everyday life. The Housing characteristics cluster consists of variables coding the type of building's ownership, its heating system type, size of the dwelling, building's type, and its year of construction. The cluster of socioeconomic characteristics includes the following, mostly categorical or interval, variables: income, age, gender, job, education, and household size (the last variable, as opposed to the 'size of the dwelling', designates an area that exclusively belongs to a particular household).

To quantify the degree of HEI, i.e., the degree of conscious involvement in energy usage, two constructs were developed: one variable measuring daily involvement in energy-usage behavior, while the other captures an inclination to purchase energy-saving appliances. In one set of regression models, namely ordinal probit models, these HEI variables were regressed on all variables from the mentioned clusters to identify the actual determinants of energy-related behavior. In the other set of regression models, the probability of purchasing an energy-saving appliance was explained with HEI variables (this time as independent variables, controlling for values and preferences) and socioeconomic and house characteristics variables.

Their results are important in the context of our own research: "Our multidimensional analysis of HEI indicates that the consumer values and preferences attributes are strong explanatory factors for HEI, in contrast to the models consisting of sociodemographic and housing characteristics…, which exhibit very little explanatory power." (Yoo et al., 2020, 11). Particularly, in relation to the purchase of energy-saving devices, all values and preferences variables are statistically significant, with 'tolerance', measured as stated readiness to surpass own thermal comfort to save the bills, providing the largest contribution to purchase decision with each consequential seven-levels step adding .42 points to readiness to invest in energy-saving appliances (where 7 is 'highly likely'). On the other hand, the income variable predicts that with each additional 1 mln KRW of gross monthly income (appr. 760 USD), readiness to purchase appliances drops by .043 points; rented (contrasted to own) apartment contributes to this decision negatively with .112 points; while the newer the building, the less likely people buy the considered appliances – as expected, as far as a new building is usually more energy-efficient and have pre-installed devices. Gender is the only sociodemographic variable that consistently has statistical significance across all models, explaining that, on average, Korean women by .168 points are more likely to invest in energy-saving devices compared to men. All other socioeconomic and housing characteristics variables behave inconsistently and show little explanatory power (including age and type of heating system).

In that light, the data available for my research, which is mostly socioeconomic and related to housing stock, may raise concerns about the possibility to identify the actual demand determinants. Nevertheless, statistical techniques available for panel data that control for time-invariant omitted variables, which personal values and preferences variables I assume to be, could hopefully yield to reliable and significant results even with these kinds of independent variables at hand (Yoo and his colleagues deal with cross-sectional data). Moreover, understanding the theoretical limitations allows also to interpret the results we obtain more carefully, and in this sense stating the limitations is an important preliminary task.

In my research, I will apply a versification of the approach developed by Dale and Fujita (2008) and Fujita (2015) who calculate the demand elasticities for refrigerators, clothes washers, and dishwashers. Specifically, they present a literature overview, indicating the ranges for market-level price elasticities for household appliances in the US to be -0.14 to -0.42 for the period 1980-2009, while most estimates for brand price elasticities are much more elastic, starting with -2.0 and more (Fujita, 2015). The basic economic model they rely on in their own estimation explains Shipments (quantity demanded) by, on the one hand, a new house stock flow and regular appliances replacements, which altogether explain up to 89-97% (for different appliances) of variation in shipments, and, on the other hand, Relative price variable, which is total price (defined as price plus operating costs) weighted by real income. The elasticity of relative price (at market level) is estimated to be -0.4 for refrigerators, -0.31 for clothes washers and -0.32 for dishwashers (Dale and Fujita, 2008).

CHAPTER 3. METHODOLOGY

a. Model and estimators

Our basic model explains the demand for self-operating radiator sensors sold in Ukraine's largest retail chain with eight determinants, controlled for trend and seasonality:

$$\begin{aligned} Quantity_{it} = \ & \beta_0 + \beta_1 Price_t + \beta_2 Income_t + \beta_3\, MFH_{t-k} \\ & + \beta_4\, SFH_{t-k} + \beta_5\, Ngas.Price_{t-k} + \beta_6 Promoters_{it} \\ & + \beta_7 Discount_t + \beta_8 Promoters_{it} * Discount_t + a_i \\ & + f_t + u_{it} \end{aligned} \tag{4}$$

Independent variables, collectively denoted as X_{it}, include price and income as fundamental determinants. There are three lagged variables to count for delayed effect of commissioning new residential area and change in natural gas price, where *k* is some constant. The interaction term of two dummy variables, apart from these dummies stated separately, is intended to check whether promoters in the periods of discounts are more efficient in selling the firm's sensors. The error term a_i represents store-specific, time-invariant unobserved effects, like customers' values and preferences in geographic areas close to a given store *i:* for example, consumers in Kyiv metropolitan area might have values set determining purchase decision to be different from the consumers' values sets in other regions. The error term f_t, to the contrary, captures store-invariant, time-specific effects, which might include national campaigns promoting energy efficiency in residential sector, or effects of relevant legislation coming into force (like the bill "On Energy Efficiency" adopted on October 21st, 2021). The term u_{it} is the overall time-varying error.

The appropriate estimation method for the unobserved effects model depends on the properties of the error terms (Croissant and Millo, 2008). Assuming the u_{it} to be identically distributed and independent of both the X_{it} and a_i[10], we need to check whether a_i itself correlated with X_{it} or not. If it does, a_i is regarded as a fixed effects component, and either fixed effects (FE) or first differences (FD) estimator is applied. In case a_i is uncorrelated with the regressors, using a transformation to eliminate a_i results in inefficient estimators (Wooldridge 2016, 470) and then random effects (RE) estimator is preferred. For our model, in the context of the previous discussion, the time-invariant consumers' values are supposed to be uncorrelated with X_{it}, meaning that RE estimator should be preferred. Presence of the both time specific and store-specific effects justify a two-ways estimation procedure, though one-way models should be checked as well.

It is important to mention that both the FE or RE models require additional tools to solve the problem of time-varying omitted variables that are correlated with the explanatory variables (Wooldridge, 2016, 495). For our case, sales figures of the competing firms is an appropriate example of such an omitted variable. The estimation method that recognizes the presence of an omitted variable of this kind is either an introduction of the instrumental variable or proxy variable to the model. Unfortunately, due to proprietary nature of this data, we cannot control for their effect in our model.

To deal with the autocorrelation of the errors within stores, the cluster-robust covariance estimation (CRVE) is used, which introduces G = *i* disjoint clusters. Cameron and Miller (2012) explain the ratio behind using CRVE being that the unobserved effects estimators themselves do not control for all the within-cluster correlation of the error, while with the CRVE any pattern of dependance or heteroscedasticity is allowed within the cluster (but the independence across clusters is assumed).

[10] Escape homoscedasticity and independence assumptions is possible with sandwich estimators. Sandwich estimators replace unknown actual variance of the errors with the function of the residuals from the regression, which allows for correlation and heteroscedasticity – See Pustejovsky and Tipton (2018)

In our estimations it is interesting also to check how brand demand elasticities depend on the model of radiator sensor. This question might be not as trivial as it appears considering the competitive landscape in the segment of self-operating RS. The thing is competing firms design different types of both TRVs and sensors, so that in one case, when firm's specific TRV is already installed on the radiator, only specific sensor of the same firm is likely to be installed. In our case, that is the G2991 model, which is virtually the only choice for the customer, when corresponding TRV model is already installed on the radiator. On the other hand, firms attempt to design a universal type of sensor, applicable to installing even in case competitors' TRV is already installed on the radiator – this is the case of G5030 model, which fits to most of the competitors' TRVs. We shall see whether these strategies have their effect on the brand demand determinants.

b. Variables describing the market for radiator sensors in Ukraine.

Variables that appear to account for RS demand, and which are practically available, may be divided into three broad categories: (1) physical household and appliance variables, (2) economic variables, and (3) marketing variables.

Table 1. Summary of the Model variables

Variable	Definition
$Quantity_{it}$	Amount of self-operating RS sold each month, in pieces, in each retailer's chain store *i*
$Price_t$	Price of a self-operating sensor at time *t*, price is the same across all chain stores, in real terms
$Income_t$	Average monthly income per person, at time *t*, in each oblast, in real terms
$Hous.Flow_t$	Flow of new residential buildings per oblast per quarter, in thousand m^2, separately for SHF and MFH
$Ngas.Price_t$	Average monthly natural gas price per 1 m^3, in each oblast, in real terms

Promoters$_{it}$	Dummy variable, indicates whether a promoter was present at each store *i* at given month
Discount$_t$	Dummy variable, indicates whether the discount for radiator sensor was available at time *t* across all stores.

Quantity sold, price of the radiator sensors and average real income are the variables needed to quantify brand demand elasticities, which is the main objective of this paper. As for the income, it should be noted that Ukraine is the country with a significant share of shadow economy. In 2020 economic activities hidden from official authorities constituted at least one quarter of country's GDP (NBU report, 2020), therefore upward bias should be expected at estimation of this parameter.

Housing stock variables is another interesting case. In Dale and Fujita's paper housing variables, namely new residential buildings and the number of appliances reaching the end of their operating life (replacements), explain up to 97% of variation in shipments. I believe that for the radiator sensors in Ukraine things would differ, as since 2006, when construction norms had begun to require installation of RS in residential buildings, operating life of the installed sensors has not yet been exhausted. In addition, energy-saving appliances do not reach, unfortunately, the household penetration shares of domestic comfort appliances, like dishwashers or refrigerators that Dale and Fujita deal with. In this paper, to control for housing variables that I still expect to have statistical significance, I include amount of new residential area, commissioned in each quarter in each oblast (Ukraine's regions). SFH and MFH areas are distinguished, as different behavior of households' owners and number of installed radiators is expected to be in each case.

Natural gas price stands for nearly 80% in heating bill cost structure in case of district heating, and exhausts heating bills' cost in case of individual natural gas boilers or central heating with boiler houses (the last ones mostly used by public buildings). In 2021 Ukraine's state budget paid 249 bn UAH for indirect subsidies to cover non-market natural gas tariffs for inefficient housing sector (Naftogaz Annual Report 2021, 18)[11]. As a result, households have less economic incentives to save their bills with heating saving appliances – we shall see the actual effect of the variable, which normally would be expected to have the major effect on the demand.

Finally, we have two marketing variables, which influence consumers' purchase decisions when he or she has already decided to invest in RS: these are discounts available at a given month across the retailer's chain stores, and presence of a promoter in a particular store, whose job is to promote firms' radiator sensors directly in the store. It should be noted that competing promoters are also present in the stores. In addition, firm's promoters deal with broader set of firms' products; RS is not the product which sale has the largest contribution to promoter's earnings.

[11] Ukraine's total spending on the Armed Forces in the same year were 117.5 bn UAH.

CHAPTER 4. DATA

The panel data at our disposal observes sales of two radiator sensor models in 65 Epicenter chain stores for 31 months, from June 2019 to December 2021. It is a balanced panel consisting of 2015 observations, i. e. it has the same number of observations *t* for each individual store *i*. The sales data, which is provided by company Danfoss TOV, comprises the number of sold pieces for two models of self-operating sensors, recommended retail price (which is the actual price established by the retailer), periods of discounts, and presence of promoters in each store.

Table 2. Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Quantity sold, G5030 model	2,015	2.7	12.3	0	186
G5030 price, nominal UAH	2,015	425.6	28.1	402.0	478.8
G5030 price, real UAH	2,015	389.2	8.5	376.1	409.8
Quantity sold, G2991 sensor	2,015	3.5	16.8	0	250
G2991 price, nominal UAH	2,015	520.4	35.5	490.8	586.8
G2991 price, real UAH	2,015	475.8	10.9	459.2	499.5
Promoters (1 = present)	2,015	0.4	0.5	0	1
Discount (1 = available)	2,015	0.4	0.5	0	1
New SFH stock, thousand m^2	2,015	58.3	66.0	2.6	408.8
New MFH stock, thousand m^2	2,015	84.6	131.8	0.0	941.1
Consumer price index	2,015	109.3	5.7	102.7	120.2
Nominal income, thousand UAH	2,015	12.0	2.9	8	27
Real income, thousand UAH	2,015	10.9	2.4	7.6	22.5
Natural gas price, nominal UAH	2,015	7.3	1.9	3.1	10.1
Natural gas price, real UAH	2,015	6.6	1.5	2.9	8.7

Descriptive statistics (Table 2) show that the average sales of both RS models are relatively small, reaching 2.7 monthly sold pieces per store in the case of the G5030 model and 3.5 pieces in the case of the G2991. Maximum monthly sales per store are 186 and 250 pieces respectively. Moreover, with a closer look at the dataset, we can see that only in 36 out of

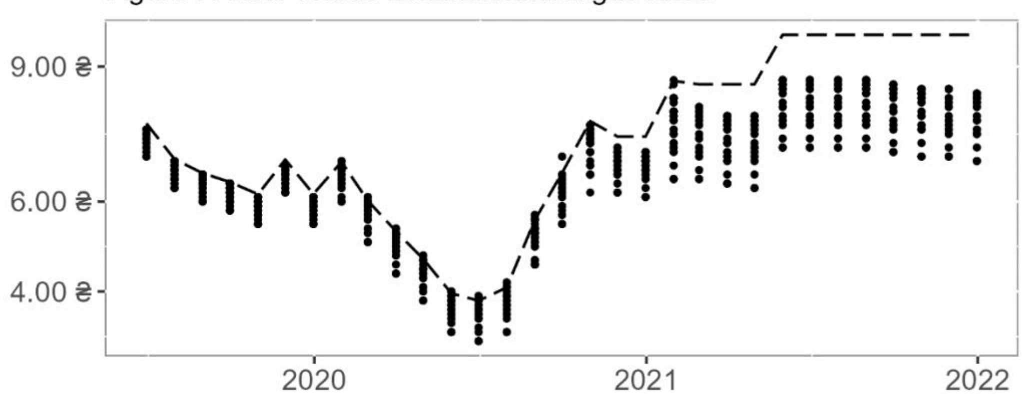
65 stores at least one radiator sensor was sold during the researched period; the abundance of nulls in quantity sold poses limitations to applying a logarithmic functional form of the dependent variable in our basic model (2), as a log of 0 is undefined. The options to fix this are either to drop the corresponding observations or transform nulls to the closest integers. For our case any of these options is not sound, as dropping the nulls, apart from losing 83% of observations, will make the panel unbalanced, while transforming nulls to units increases sales by more than 40%, making the estimated parameters biased. A better alternative would be leaving the dependent variable observations as they are, using the linear functional form. The trade-off here is that instead of estimates of constant demand elasticities, we will be able to obtain point estimates.

Buildings' characteristics and economic variables are obtained from two publicly available sources. SSSU provides quarterly regional data on newly commissioned residential areas both for single- and multifamily houses (USSS, Number of dwellings in residential buildings, putting into service, by type by region, 2019:2021). In some quarters only the overall area is reported, therefore the share of SFH to MFH from the preceding period was applied to obtain the values' estimations. Although we operate with monthly-level data, the same quarterly value is indicated in each correspondent month – to avoid artificial data mining.

Average monthly income, natural gas rates, and consumer price index (CPI) were gained from the Ukrainian finance and investment web-portal Minfin. The CPI is calculated with December 2018 as a base month, the overall inflation rate from January 2019 to December 2021 amounted to 20.19%. All monetary variables (sensor prices, average income, natural gas rates) used in further estimations are taken in real terms, i. e. inflation adjusted.

Real natural gas rates increased slightly during the studied period. In June 2019 average price for 1,000 m^3 was 7.44 UAH, while in December 2021 it was 7.98 UAH, meaning a 6.7% rise. At the same time, the dispersion of rates at the regional level had more than doubled during the same period: if in June 2019 difference in rates between regions with the highest rates (sixteen regions had the same rate, 7.6 UAH) and region with the lowest rate (city of Kyiv, 7.0 UAH) was 0.6 UAH, in December 2021 it was 1.5 UAH (8.4 UAH in seven regions, while the lowest rate, 6.9 UAH was, again, in the city of Kyiv). This shift in range should be associated with natural gas market reform: starting from January 2020 households are charged separately for the cost of natural gas and for the cost of its transportation. As a result, natural gas suppliers and transportation network operators bring more variability in resulting rates across regions. The transportation cost, since its introduction, is accounted for in natural gas rates in our dataset. Surprising or not, the city of Kyiv, the region with the lowest natural gas rates, has the highest average income. Apart from the outlying capital with 22.5 thousand UAH per person, the top five regions with the highest average real income in December 2021 were Mykolayiv, Donetsk, Zaporizhzhia, Kyiv (Kyiv region is different from the city of Kyiv), and Rivne regions: 15 thousand UAH for Mykolayiv, the other having 14.1 thousand UAH. The lowest income in the same month was reported in Ternopil, Chernivtsi, Kherson, Cherkasy, and Kirovohrad regions (10.8 thousand UAH in Kirovohrad, all others had, on average, 11.6

Figure 7. Real versus nominal natural gas rates

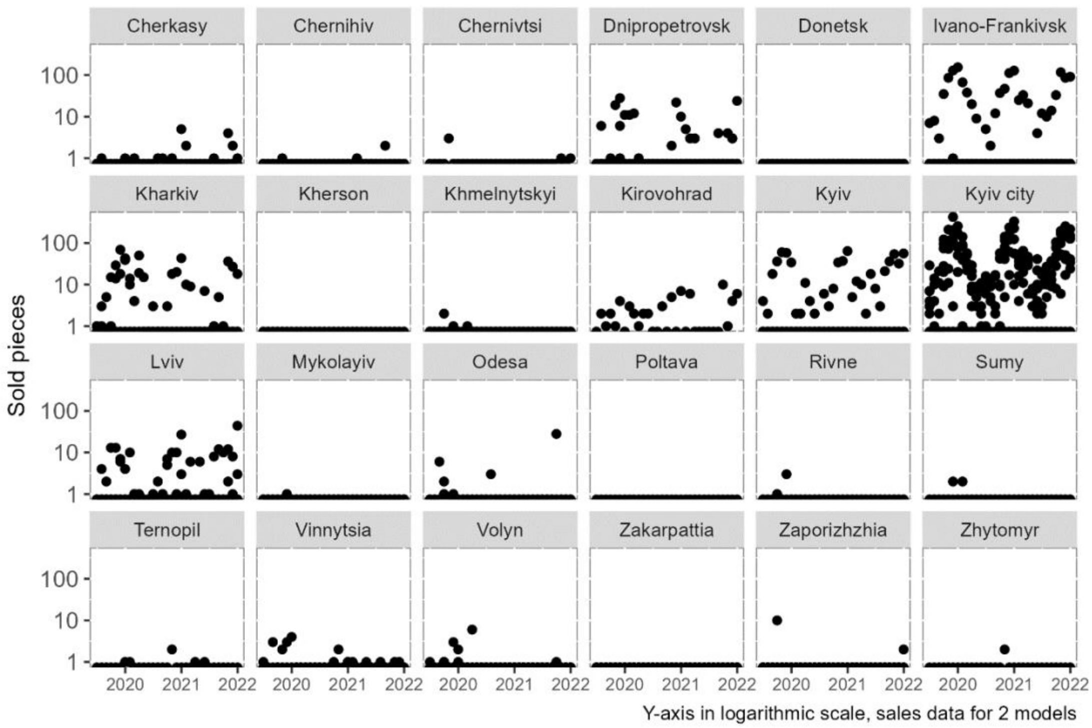


Line represents average nominal gas rates across regions, while points - regional real rates range

thousand UAH per person).

As we can see from Figure 8, there is a correspondence between average income per person and sensors sales, though some exogenous factors influencing sales have their effect. While the city of Kyiv and Kyiv region show, as real income numbers suggest, higher sales volumes (as well as regions where major cities are located, like Dnipropetrovsk, Kharkiv, and Lviv), at the same time Ivano-Frankivsk region and Kirovohrad, the region with the lowest average income, are performing above average.

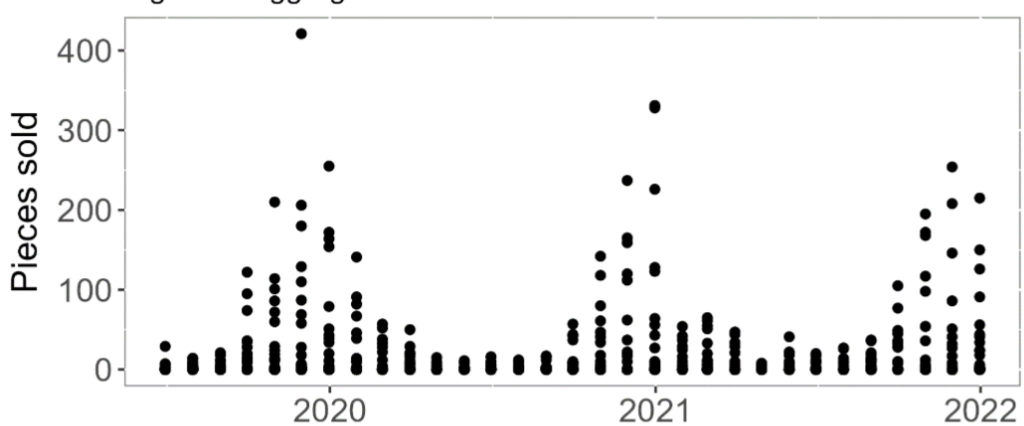
Figure 8. Sensors sales by region



During the studied period the real income had increased, on average, by 27.2%. In its turn, RS price, in real terms, rose only by 2.6% in the case of the G5030 model (from 387.9 to 398.4 UAH; in nominal hryvnia the price increased by 16%, from 402 to 478.8 UAH). In the case of the G2991 model, the increase was 3% and 16.3% respectively.

Finally, it is worth mentioning that sensors' sales dynamics demonstrate clear evidence of seasonality, with peak sales in December and January. This sale dynamics corresponds with a heating season in Ukraine, which, for buildings receiving their heat from DH networks, usually starts in late October, and ends in mid-April. As heat consumption increases in the coldest months, which are December, January, and February, consumers have more incentives to install radiator sensors as a means to save the bills.

Figure 9. Aggregated sales of sensors



Data for two models of self-operating sensors

Estimation results show that both the FE and RE one-way models fit the data well at a .05 significance level (p< .0000), though the RE model has a higher F-statistic and adjusted R^2, compared to the FE model: 461.5 against 32.15 for the F-statistic and .198 against .158 for the adjusted R^2. Modified Wu-Hausman test also signals strongly in favor of the RE model with p=.97. Both F-test for individual effects (p< .0000) and the Breusch-Pagan time effects test (p< .000) indicate that the time trend should be included in the specification:

Table 3. Comparison of one-way FE and RE models estimations – G5030

	Dependent variable:		
	Sales of 5030 sensor model, in pieces		
	the FE model	the RE model	the RE model - CRVE
Price of Sensor, UAH	0.105^{**} (0.045)	0.105^{**} (0.045)	0.105^{***} (0.029)
Average Income, UAH	1.500^{***} (0.276)	1.341^{***} (0.230)	1.341^{***} (0.455)
Promoter (1 = present)	-0.753 (1.328)	-0.583 (1.093)	-0.583 (1.818)
Discount (1 = available)	-1.975^{***} (0.680)	-1.864^{***} (0.672)	-1.864^{**} (0.748)
Natural gas price, k = 2	0.527 (0.321)	0.586^{*} (0.316)	0.586^{*} (0.336)
SFH, th. m^2, k = 1	-0.017^{**} (0.008)	-0.018^{**} (0.007)	-0.018 (0.011)
MFH, th. m^2m, k = 3	0.033^{***} (0.003)	0.033^{***} (0.003)	0.033^{**} (0.014)
Promoter*Discount	4.505^{***} (0.892)	4.524^{***} (0.892)	4.524^{**} (1.963)
Spring Season	1.503^{**} (0.754)	1.399^{*} (0.750)	1.399^{***} (0.542)
Autumn Season	1.037 (0.785)	0.928 (0.779)	0.928^{***} (0.257)
Winter Season	1.343^{*} (0.692)	1.316^{*} (0.692)	1.316^{**} (0.532)
Year 2019	1.607^{*} (0.844)	1.573^{*} (0.840)	1.573^{***} (0.486)
Year 2021	-4.854^{***} (0.812)	-4.799^{***} (0.808)	-4.799^{**} (1.901)
Constant		-57.157^{***} (16.271)	-57.157^{***} (15.640)
F Statistic (df = 13; 1742)	32.159***	461.452***	2.502***
Observations	1,820	1,820	1,820
R^2	0.194	0.204	0.204
Adjusted R^2	0.158	0.198	0.198
Note:			*p<0.1; **p<0.05; ***p<0.01

With robust standard errors, parameters estimates explaining sales of the G5030 model are the following:

$$
\begin{aligned}
&\widehat{Sold.pieces}.5030 \\
&\qquad = -\widehat{57.16} + .\widehat{11} * Price + \widehat{1.34} * Income - \widehat{1.86} * \\
&\qquad * Discount \ + .\widehat{59} * NGas.Price + .\widehat{033} * MFH + \widehat{4.52} \\
&\qquad * (Promoter * Discount) + \widehat{1.4} * Spring.S + .\widehat{93} \\
&\qquad * Autumn.S + \widehat{1.32} * Winter.S + \widehat{1.57} * Year2019 \\
&\qquad - \widehat{4.8} * Year2021
\end{aligned} \tag{5}
$$

The estimated regression equation (3) states that increase in G5030 sensors' price is associated with increase in sensors' sales. Both statistical (p<.000) and practical significance of the estimated parameter (model predicts that increase by 10 real UAH will lead, on average, to sales of 1 additional sensor per store per month) is not aligned with the basic economic theory and, most likely, implies presence of omitted variable(s) in the model. In case the omitted variable is both time-varying and store invariant, two-way estimation procedure will eliminate its effect from the estimation results. It should be noted also that actual total price increase in real terms for this model was 10.5 UAH during the researched period of 31 months, from 387.9 to 398.4 UAH.

Other estimated parameters behave as expected. Rise of real income and natural gas rates are predicted to increase sales: each 1000 UAH of real income is associated with additional 1.34 monthly sold sensors per store, while 2 UAH increase in natural gas rate brings additionally 1.17 pieces. Estimation with cluster robust standard errors made impact of newly commissioned SFH statistically insignificant, while MFH is consistently significant in all three model, explaining that each newly commissioned one hundred thousand m^2 of MFH makes monthly sales higher, on average, by 3.3 pieces in each store (p=.0017). The equation also supports the hypothesis that promoters sale more G5030 sensors in the periods of discounts, selling extra 4.5 pieces comparing to the periods without discounts. With Summer as the base season, three other seasons show the statistically significant increase in sales, with Spring, rather unexpectedly, showing slightly higher positive effect on sales than Winter (adding 1.399 pieces to average monthly sales, with extra 1.316 pieces during Winter). At the same time, there is a clear downward time trend in sales dynamics: in 2021 monthly sales had dropped by 4.79 pieces per store compared to 2020.

In the case of G2991 sensor model data, the Hausman test also reports the RE estimator to be both consistent and efficient, compared to the FE (p=.996). Utilizing cluster-robust standard errors, F-statistics, which measures the joint significance of the estimated parameters, drops significantly, from 460.93 to 15.53, though small p-value (p<.0000) still suggests rejection of the H_0.

Table 4. Comparison of one-way FE and RE models estimations - G2991

	Dependent variable:		
	Sales of 2991 sensor model, in pieces		
	the FE model	the RE model	the RE model - CRVE
Price of Sensor, UAH	0.032 (0.047)	0.037 (0.047)	0.037 (0.022)
Average Income, UAH	0.808^{**} (0.356)	1.077^{***} (0.307)	1.077^{**} (0.448)
Promoter (1 = present)	-1.109 (1.713)	-0.578 (1.465)	-0.578 (2.255)
Discount (1 = available)	-1.175 (0.892)	-1.341 (0.882)	-1.341^{**} (0.579)
Natural gas price, k = 2	0.819^{*} (0.420)	0.762^{*} (0.414)	0.762 (0.519)
SFH, th. m^2, k = 1	-0.011 (0.011)	-0.016^{*} (0.010)	-0.016 (0.024)
MFH, th. m^2, k = 3	0.053^{***} (0.003)	0.053^{***} (0.003)	0.053^{**} (0.021)
Promoter*Discount	1.886 (1.150)	1.855 (1.148)	1.855 (1.128)
Spring Season	2.236^{**} (0.940)	2.365^{**} (0.934)	2.365^{***} (0.863)
Autumn Season	-0.070 (1.006)	0.081 (0.997)	0.081 (0.357)
Winter Season	1.546^{*} (0.890)	1.575^{*} (0.889)	1.575^{**} (0.648)
Year 2019	1.975^{*} (1.063)	2.140^{**} (1.057)	2.140^{**} (1.032)
Year 2021	-5.162^{***} (1.044)	-5.291^{***} (1.039)	-5.291^{**} (2.417)
Constant		-32.754 (21.077)	-32.754^{**} (13.217)
F Statistic (df = 13; 1742)	32.024***	460.927***	15.526***
Observations	1,820	1,820	1,820
R^2	0.193	0.203	0.203
Adjusted R^2	0.157	0.198	0.198
Note:			*p<0.1; **p<0.05; ***p<0.01

Adjusted R^2 shows that the RE-CRVE model explains 19.8% of the total variance in data (exactly as in the G5030 case). The reason why the R-squared statistic is relatively low is, probably, due to the fact that consumers' values and preferences, which Yoo et al. have shown to be significant in explaining the variation of energy-related behavior, are stored in the error term a_i that is eliminated in the unobserved effects estimation procedure.

As the parameters' estimates show, demand determinants for the G2991 sensor model significantly differ from the G5030 case. Sensor's price, natural gas rate, as well as promoters' efforts in periods of discount, are estimated to be statistically insignificant. I assume that the main reason for these differences, as it was explained before, is related to the different market strategies the manufacturer implements in the RS market. While the G5030 sensor model is a universal fit for the most of competitors' TRVs and in this sense, it competes with the other sensors, the G2991 sensor requires a specific type of TRV; in case this type of TRV is already installed in customer's apartment, the odds that customer will choose another sensor than G2991 are quite small (in most cases it would require changing the installed TRV, incurring additional expenses for the customer).

$$\begin{aligned} Sold.\widehat{pieces}.2991 &= -\widehat{32.75} + \widehat{1.08} * Income - \widehat{1.34} * Discount \\ &+ .\widehat{053} * MFH + \widehat{2.37} * Spring.S + \widehat{1.58} * Winter.S \\ &+ \widehat{2.14} * Year2019 - \widehat{5.29} * Year2021 \end{aligned} \tag{6}$$

In support of these considerations, we see that the coefficient of the MFH independent variable is almost 40% higher for G2991 model than in G5030 case: each newly commissioned one hundred thousand m^2 of MFH is associated, other things equal, with additional 5.3 monthly sold pieces in each store. Income has lower effect on sales compared to the G5030 model: 1000 UAH of real income is expected to increase average monthly sales by 1.08 pieces (with 1.34 pieces for G5030). Seasonality effect remains present, as well as declining, in terms of sales, time trend.

Finally, estimation of the two-way models, which account for both store- and time-specific unobserved effects (though again, this procedure does not capture time-varying omitted variables that are correlated with the explanatory variables), this time shows that the FE estimator provides consistent coefficients for both G5030 and G2991 cases (Hausman test suggests rejection of the RE estimators with p=.004 for G5030 and p<.0000 for G2991 model). At the same time, F-test, utilizing cluster-robust variance estimation, reports p=.13 for the G2991 case, meaning we cannot reject the null hypothesis that the joint significance of model's coefficients is zero even at 10% significance level. This is why we cannot rely on two-way model for independent variables parameters estimates in the case of G2991 sensor. For G5030 case, the same test provides p=.0556, which is rather low though acceptable threshold to account for the model's results:

Table 5. Two-way FE model estimation - G5030

	Dependent variable:	
	Sales of 5030 sensor model, in pieces	
	the FE model	the FE model - CRVE
Price of Sensor, UAH	0.065 (0.077)	0.065 (0.047)
Average Income, UAH	1.931*** (0.478)	1.931** (0.944)
Promoter (1 = present)	-0.395 (1.322)	-0.395 (2.567)
Natural gas price, k = 2	5.068*** (1.321)	5.068* (2.632)
SFH, th. m^2, k = 1	-0.019** (0.008)	-0.019* (0.011)
MFH, th. m^2, k = 3	0.036*** (0.003)	0.036** (0.015)
Promoter*Discount	4.316*** (0.889)	4.316** (1.873)
F Statistic (df = 7; 1721)	41.353***	2.104*
Observations	1,820	1,820
R^2	0.144	0.144
Adjusted R^2	0.095	0.095
Note:		*p<0.1; **p<0.05; ***p<0.01

As two-way model eliminates time-specific store-invariant effects, season and year independent variables has been excluded from the estimation, leading also to smaller R^2, namely 9.5% – comparing to 19.8% in one-way models. In the context of our research, the key difference with one-way model's parameters estimates is that two-way model reports price to be insignificant in predicting demand for G5030 radiator sensor (p=.17). Another noticeable change is that parameter estimate of the natural gas rate independent variable increases by almost ten times, from .57 to 5.1. Coefficient of the real income variable increased as well, though the change is not that significant: now it predicts for 1.93 pieces of additional sales with each 1000 UAH instead of 1.34 pieces in case of one-way model. Parameter estimates for MFH and promoters' activity during discount period remain practically the same.

Choosing between one-way and two-way models regression results to calculate demand elasticities, I proceed assuming that the time-varying omitted variables correlating with X_{it} are present in our model. These omitted variables remain uncontrolled, as neither marketing budgets of the key competitors (which could be used as a proxy variable), nor their sales figures are unavailable. In this situation the two-way model adds little value, eliminating store-invariant time-specific data at cost of lower percent of the explained variation.

Thus, as the coefficient of the price determinant is supposedly biased, we will estimate only income elasticity of demand, as income variable shows consistent statistical significance in all models we have estimated. As the functional form of our models is linear, it is possible to obtain point estimates (using mean sales and mean income):

Table 6. Brand income elasticity of demand

Radiator sensor model	Brand income elasticity
G5030	5.475
G2991	3.389

In both cases demand for radiator sensors is income elastic, $|\varepsilon|>1$; for the G5030 model elasticity value is higher, stating that at 10,916 of real UAH income and 1065 UAH of sales, 1% increase in income leads to 5.48% increase in sales.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

Summarizing the key findings of the thesis, we started our research by proving that self-operating radiator sensors constitute a separate market segment in the RS market, implying different demand drivers compared to the smart sensors segment. According to our estimations, the lower threshold of the annual serviceable market for RS, prior to the Russian invasion of Ukraine, was amounting to 500,000 pieces annually.

The paper of Yoo et al. (2020) provided valuable insights into the explanation of variations in energy-related customers' behavior. As their finding demonstrates, customers' values and preferences are more important for purchasing energy-saving devices than physical housing or socio-economic characteristics. Market factor that undoubtedly influences the formation of appropriate values, namely the heating bill, which is also assumed to be one of the main demand determinant for energy-saving appliances in the developed countries, underperforms in Ukraine: as we have stressed, in 2021 Ukrainian government paid twice as much to subsidize natural gas tariffs for energy inefficient residential sector than it had invested in the Armed Forces. As a result, consumers in Ukraine have less incentives to invest in energy-efficiency.

I assume that the key result of my own research is demonstrating that manufacturer's market penetration strategy, namely different construction design of the valve and the head for different RS models, is effective. The demand for G5030 sensor model, which is a universal fit for the most of competitors' TRVs, is responsive to a wider set of determinants. Statistically significant determinants here are price, income, discount, promoters' activity in the periods of discounts, new MFH stock, as well as seasonality factors. At the same time, in case the specific type of TRV for the G2991 sensor is already installed in customer's apartment, the odds that customer will choose another sensor than G2991 are quite small: our estimation results show that sensor's price, natural gas rate and promoters' efforts in periods of discount are statistically insignificant, implying that customers, at present values of these factors, do not consider them as determining in their purchase decisions. For the G2991 case new MFH residential area, income, and discount variables demonstrated statistically significant results.

As competitors' sales figures were unavailable for this research, we did not have tools to control for time-varying omitted variables correlated with the model's independent variables. With the coefficient of the price determinant to be supposedly biased, we have calculated only income elasticity of demand, as income independent variable consistently showed statistical significance in all models we estimated. The point estimate of brand income elasticity, using mean sales and mean income values, is 5.48 for G5030 model and 3.39 for the G2991, meaning that demand for the both RS models is income elastic.

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APPENDIX

1. **Figure A1**. The complete list of sensor models available at Epicenter. Source: web-scraped data.

List of all sensor models

Available at Epicenter, sorted by price. As for Feb 18, 2023

Model	Type	Price
Salus TRV10RAM	smart	3698.00
Livolo ZigBee	smart	3297.00
Poer PTV30	smart	2990.00
Caleffi 200013	design	1636.00
Danfoss Eco	smart	1609.10
Luxor TE 3010	smart	1236.20
Danfoss RA2945	self-op	982.80
Herz 1926006	design	847.90
Danfoss RA 2991	self-op	775.20
Caleffi 30 x 1.5	self-op	733.00
IMI Heimeier K 6-28	self-op	700.57
Herz Project 1726018	self-op	657.70
IMI Heimeier DX, RAL 9005	self-op	600.00
Honeywell Thera-4	self-op	508.00
ICMA SD00022312 - N1101	self-op	480.00
Oventrop VINDO	self-op	478.52
ICMA 28x1.5 - N1100	self-op	477.00
Luxor TT 211	self-op	466.80
Honeywell Thera-100	self-op	431.00
IMI Heimeier DX, RAL 9016	self-op	421.64
Danfoss RA-CLICK	self-op	410.00
Luxor TT 3000	self-op	382.00
Valtec VT.3000.0.0	self-op	367.00
Zegor QS-7001	self-op	300.00
Karro KR2023	self-op	292.00
Meibes Simplex Standard TC-S3	self-op	250.00
Karro KR2110-1	self-op	246.00
SD Plus	self-op	180.00