Estimation of demand with decreasing block pricing and market-level data

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Abstract

Discrete-continuous choice models (DCC) are commonly used to estimate demand for products with decreasing/increasing block rates. Standard estimation methods for DCC models require individual-level consumption data, which is not always readily available. Using the pure characteristics model of Berry and Pakes (2007), I propose a discrete-continuous choice model to estimate demand for products with block rates. The idea is to use block market shares and characteristics to recover consumers' preferences. I apply this method to estimate demand for natural gas in Quebec. This paper also proposes new instruments inspired by the interesting institutional background. I found conditional and unconditional price elasticities close to previous estimates in the literature.

Keywords: Discrete continuous choice, non-linear budget set, market share inversion, block level data, natural gas.

1 Introduction

Block pricing is a scheme where the marginal price is a step function of the consumed quantity. It is used in sectors such as insurance (deductibles depend on cumulative expense), utility in-

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dustries (water, gas), and telecommunications (data caps). With this pricing structure, the budget constraint becomes piecewise linear, reflecting the marginal price's non-uniformity. This implies that the demand function is discontinuous in both marginal and infra-marginal prices, unlike uniform tariffs, where demand depends on a single price (Terza and Welch, 1982; Moffitt, 1990). The consequence of this singular functional form for the demand is a simultaneity issue between the marginal price and consumption. This is because price is both a deterministic function and a determining factor of consumption. Therefore, choosing a level of consumption is equivalent to choosing a block, and consumers self-select into the blocks of the pricing structure (Terza and Welch, 1982; Moffitt, 1990). A naive regression of the consumed quantity on the corresponding marginal price may yield misleading estimates because it ignores both the simultaneity issue and the actual demand functional form (Terza and Welch, 1982; Moffitt, 1990).

In this paper, I propose a structural model of discrete-continuous choice with block pricing, and I use market-level data to recover consumers' preferences. The idea is to rationalize aggregated block-level information using an estimator consistent with individual choices, both for the discrete choice of the optimal block and the continuous choice of the optimal consumption within the block (henceforth, conditional demand). Like the standard DCC model, the proposed model delivers a closed-form analytical expression for conditional demand, and therefore, the choice of the optimal block *only* depends on the block characteristics and the consumer's type. The blocks may also be conceptualized as vertically differentiated products. Thus, block market shares are helpful to apply the pure characteristics model of Berry and Pakes (2007) (henceforth PCM). Furthermore, the proposed model accounts for the primary choice of whether or not to consume by adopting a framework similar to the discrete model of Song (2015).

Two approaches are used in the literature to estimate demand with block pricing. The first approach uses instrumental variables (IV) estimators to address the endogeneity of the price (Arbués, Garcia-Valiñas, and Martinez-Espineira, 2003; Worthington and Hoffman, 2008b). The idea is to use exogenous characteristics that predict the block within which consumer demand lies. The second approach is the discrete-continuous choice model (henceforth DCC) from the seminal contribution of Burtless and Hausman (1978) in labor economics and later applied to demand estimation under a block pricing scheme by Hewitt and Hanemann (1995); Olmstead (2009). The idea is to explicitly account for the block choice by modeling the consumer's optimal one. This approach does not make use of instruments, unlike the previous approach, since factors explaining block selection are directly accounted for.

However, both approaches require individual-level information on consumption, price, and socio-demographic variables. This information is not always readily available. As a result, most of the literature uses data sets with information aggregated at some geographic units such as district, county, and province (Miller and Alberini, 2016; Marzano et al., 2018; Arévalo et al., 2021). With aggregate data, the literature usually uses either an average price or the marginal price corresponding to the observed per capita consumption as the price signal. This is a textbook example of endogeneity since the price signal computed from demand is also used as an explanatory variable. The literature relies on instrumental variables estimators to correct for endogeneity. Also, the estimated demand parameters may not preserve their structural interpretation since the demand function is estimated by *linearizing* the pricing structure. Consumption is modeled as a function of a weighted average of the block prices rather than a discontinuous function of multiple prices leading to possible biased estimates (Moffitt, 1986; Arbués, Garcia-Valiñas, and Martinez-Espineira, 2003; Reiss and White, 2005). This bias may be exacerbated by using aggregate information since it is impossible to control for individual heterogeneity and how this heterogeneity affects the choice of the optimal block (Miller and Alberini, 2016; Marzano et al., 2018; Arévalo et al., 2021).

This paper's first and main contribution is to propose a micro-founded structural model that can be estimated with aggregate information. To my knowledge, demand analysis with block pricing and aggregate data only relies on instrumental variable estimators. The second contribution is to leverage well-known methods of differentiated product demand analysis, such as the PCM, to analyze demand in this environment. Market share inversion proposed by Berry (1994)[1] is used to recover demand parameters. The PCM allows for accounting for heterogeneity in consumption at both the market and block levels in two ways. Firstly, it incorporates market/block unobserved demand shocks to capture common behavior at the market/block level. Secondly, it allows the use of distributional information about unobserved consumer

[1] See the vertical model example, page 9

characteristics in addition to available exogenous relevant information (income, household, and house characteristics). To my knowledge, the current paper is the first to propose a method with aggregate data that can use this kind of information disaggregated at the market level in the block pricing scheme literature. Previous research with aggregate data only accounts for market heterogeneity by using either aggregate socio-demographic variables at the market level (average income, average household size...) or fixed effects with panel data (Arbués, Garcia-Valiñas, and Martinez-Espineira, 2003; Worthington and Hoffman, 2008a; Rinaudo, Neverre, and Montginoul, 2012; Marzano et al., 2018)

I use a nested fixed-point algorithm for estimation, which is commonly employed in the literature on demand estimation with aggregate data. In the first step, the market share inversion is performed to recover the vector of unobserved demand shocks that matches observed and predicted market shares for a given value of the parameters. The contraction mapping method proposed by Berry, Levinsohn, and Pakes (1995) cannot be applied, and the market shares function of the PCM may be discontinuous with respect to the unobserved shock for a given value of the parameters (Berry and Pakes, 2007; Pang, Su, and Lee, 2015). The market share inversion method borrows from Berry (1994) and Song (2015) and exploits the closed-form expression of the market share function. The outer part of the algorithm consists of a non-linear search of parameters using the generalized method of moments. The simulation results show that the parameters can be identified, and the method performs well in moderate and large samples.

The paper proposes an empirical demonstration with data from a natural gas distributor in Quebec covering 2011-2022. For each year of this period, I observe block-level data on the number of customers and total consumption. Unlike in the DCC approach, the identification still requires instrumental variables because the price may be correlated with the block-level unobserved demand shocks. Observed cost shifters are used as instruments since they affect the equilibrium price and are uncorrelated with the demand shocks. In the literature on block pricing schemes, cost shifters have been rarely used because they may not be readily available. In addition, they are sometimes inappropriate since the unit of observation is the customer/geographical market rather than the firm. Cost shifters do not usually provide the customer/geographical variation required to correct price endogeneity. Furthermore, I leverage an interesting institutional feature to introduce two novel instruments in this literature. As a regulated monopoly, the prices of the studied firm are set by a regulator based on an initial proposal by the firm. The first instrument is the deviation of the implemented prices from the firm's initial proposal. The second instrument is the delay in price implementation. Since the firm has a guaranteed profit, the later the implementation date, the higher the final price. The two variables affect the implemented price and are plausibly exogenous from the demand shock.

The empirical application results show that industrial consumers are price-insensitive because the price coefficient is non-significant. This result should be interpreted with caution because of the small sample size and the low variation in block market shares observed in the sample. I find that, conditional on remaining in the same block, a 1% increase in the price of a block decreases consumption by between 0.132% and 0.174%, depending on the block. This elasticity falls in the range reported by the most recent meta-analysis (Labandeira, Labeaga, and López-Otero, 2017). The model allows the computation of unconditional elasticities. If all marginal prices increase by 1%, the average consumption and the market size are expected to decrease by 0.14% and 0.76%, respectively. Those numbers are relevant for policy intended to encourage the transition from natural gas to environmentally friendly energy.

This paper is organized as follows: Section 2 presents the literature on demand estimation with a block pricing scheme. Section 3 presents the model with some extensions. Sections 4 and 5 present the estimation strategy and some simulation results. Section 6 is dedicated to the empirical analysis.

2 Literature review

Estimating demand/supply in block pricing schemes has been an active research field shared by multiple economic disciplines (labor economics, health economics, industrial organization, development economics, environmental economics, etc). With this pricing scheme, the consumer faces different marginal prices by block of consumption, which generates a piecewise budget constraint (Figure 1). It follows that the demand function is a discontinuous function of all block prices as suggested by economic theory (Taylor, 1975; Moffitt, 1986; Hewitt and Hanemann, 1995). Therefore, choosing consumption is equivalent to choosing a price such that consumers self-select among blocks. One advantage of this environment is that the price elasticity may be identified using a cross-section of consumers facing the same pricing rate. Since the marginal price is constant over ranges of consumption, consumer-level information may help control for both non-price determinants and price effects of consumption (Reiss and White, 2005).

2.1 Demand identification with consumer-level data

Two main approaches have been used with consumer-level data. The first approach consists of estimating the regression of the consumed quantity on either the marginal price or the average price. With this approach, the demand is typically estimated as if each consumer faces a uniform price corresponding to the price signal. In addition to being a possible misspecification of the demand (Moffitt, 1986; Hewitt and Hanemann, 1995; Reiss and White, 2005), the price endogeneity should be corrected to avoid possible biased estimates. In the case of the marginal price of the block within which consumption lies serving as a price signal, the price endogeneity is explained by the marginal price being a step function of the quantity. With the average price, the endogeneity comes from the simultaneity of consumption and price, since this price signal is computed as the total expense-to-consumption ratio. This made earlier studies conclude that the ordinary least squares estimator is biased and inconsistent in this environment (Taylor, 1975; Moffitt, 1986; Arbués, Garcia-Valiñas, and Martinez-Espineira, 2003).

To solve this problem for the specification of the marginal price, Taylor (1975) proposes to add the average of previous blocks marginal prices as an explanatory variable while Nordin (1976) proposes to add the difference between the expense and what the expense would be if all inframarginal prices were equal to the marginal price (the difference variable[2]). The idea was to control for the block in which the consumer is consuming to get a cleaner price effect.

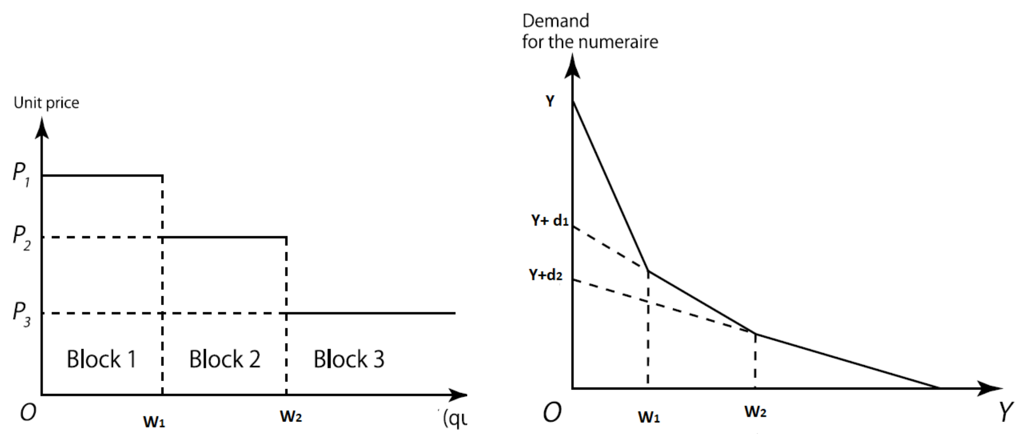
Later contributions in the literature use instruments meant to predict the price faced by the consumer while being uncorrelated with consumption shocks. Variables like consumer characteristics, previous consumption, the pricing structure, and neighborhood average price have been used (Taylor, 1975; Ito, 2014). Since this information is not always available, exogenous variables such as climate conditions and the pricing structure[3] (price difference between two

[2]The difference variable is interpreted in the literature as an income effect. see (Train, 1991) for further discussion.

[3]Since utilities are regulated industries, it is reasonable to consider the pricing structure is exogenous (Tay-

successive blocks, fixed fees, and sometimes marginal price) are used (Flyr et al., 2019; Puri and Maas, 2020). Having good instruments is required for identification, which is what sometimes lacks, as highlighted by Reiss and White (2005) (Moffitt (1986) for labor literature). Instruments from the pricing structure may be weak because the pricing structure has a low variability from one period to another, which leads to weak instruments without cross-sectional variation in the pricing structure.

Figure 1: Budget set and marginal price in decreasing block tariff



(a) Decreasing block tariff

(b) Budget set

The other approach[4] is the structural discrete-continuous model from the seminal paper Burtless and Hausman (1978). This model from the labor literature was introduced in demand analysis for utilities by papers like Hewitt and Hanemann (1995), Corral, Fisher, and Hatch (1999),Olmstead, Hanemann, and Stavins (2007), and Olmstead (2009). This is a likelihood approach that models both block choice and consumption within the block. This method has the advantage of allowing for heterogeneity in consumption and possible optimization error. In fact, these are the two mechanisms that drive consumer dispersion across blocks and within-block variability in consumption. This approach accounts for the price endogeneity

lor, 1975).

[4]There have been some recent advances in labor economics literature on the non-parametric side. In their seminal work, Blomquist and Newey (2002) propose to *regress the consumption on the budget constraint* for each observation. This utility-based model can only be applied in the increasing block pricing scheme. It also requires, in addition to individual data, that the budget set, and therefore the whole pricing structure, varies sufficiently from one consumer to another. This may be the case in labor economics because the tax rates may depend on individual characteristics. The closest strategy, still using individual data in demand estimation, is Reiss and White (2005).

issues without instruments because the drivers of block choice are explicitly accounted for. Another advantage of this approach is the possibility to compute the unconditional price elasticity, which accounts for both block switching behavior and the response to infra-marginal and marginal price changes (Olmstead, Hanemann, and Stavins, 2007). Each of these three components may be isolated, unlike with the previous approach. This method is, however, less used in the literature. It may be because it requires individual-level information, which seems rarely available (Marzano et al., 2018). Another reason may be the debate about which price signal consumers react to. In fact, this model assumes the consumer is rational and reacts to the marginal price (Olmstead, 2009; Borenstein, 2009; Ito, 2014). This assumption has been challenged in the literature because the price schedule has been shown to be sometimes confusing to the consumer[5]. Recent applications of this method are Reiss and White (2005),Olmstead, Hanemann, and Stavins (2007),Vásquez Lavín et al. (2017), Miyawaki, Omori, and Hibiki (2018),Arévalo et al. (2021).

2.2 Demand identification with aggregate data

Because of the difficulty of accessing consumer-level information, much of the literature on utilities uses aggregate data (Marzano et al., 2018; Arévalo et al., 2021). These are geographical market data about aggregate consumption, prices, and household characteristics. In this case, demand is usually estimated with the instrumental variables approach. Unlike in the case of consumer-level data, the marginal price is computed from observed consumption in the market[6]. The marginal price is usually defined for each market as the price of the block within which the per-capita consumption lies. Both marginal and average prices are endogenous because they are computed from observed consumption.

Using aggregate data adds more issues besides those coming from the methodology. The first problem is that aggregation hides individual heterogeneity. Given the importance of consumers' characteristics in choosing the block and the self-selection phenomenon, the estima-

[5]See the discussion below.

[6]The regression model looks like : $\text{per capita consumption} = \beta_0 + \beta_1 \text{price} + \text{controls}$, with $\text{price} = \frac{\text{per capita expense}}{\text{per capita consumption}}$ if the average price is used. For the marginal price, the variable price is $P(\text{per capita consumption})$, which is the marginal price of the block to which the per capita consumption belongs.

tion may yield biased estimates (J. A. Espey and M. Espey, 2004; Marzano et al., 2018). Recent papers in the literature show that the level of aggregation affects the estimated price elasticity (Miller and Alberini, 2016; Arévalo et al., 2021).

Another issue is that price elasticity may have no economic interpretation because it describes the relationship between the average quantity and the average price rather than the actual demand function. This may lead to misconceived policies if the goal is to influence consumer behavior. It is worth mentioning that the block-switching behavior and the response to infra-marginal prices cannot be isolated.

Some previous contributions tried to solve this aggregation issue. Schefter and David (1985) shows that the discontinuous nature of the individual demand function may yield biased estimates if the marginal price is used with aggregate consumption. The idea is that the observed per capita consumption is an aggregation of individual consumption and, therefore, of block market shares and average consumption in each block. They propose to use the average of block prices weighted by their market shares as a price signal. They also propose to use simulation in the case the block market shares are not observed. Corral, Fisher, and Hatch (1999) extended the method by Schefter and David (1985) by considering the way the market shares are formed. They proposed using instruments for market shares since they are endogenously determined. Market characteristics such as climate variables and socio-demographics were used as instruments for the market shares. Unfortunately, with these approaches, the choice probabilities of blocks are not explicitly modeled, which precludes isolating block-switching behavior and unconditional price elasticities. Using household-level data, Reiss and White (2005) proposes an extension to the DCC model to deal with data in which individual consumption is aggregated over several decision periods. This paper, however, relies on individual data, unlike the present paper.

I propose to use aggregate data at the block level to estimate demand parameters. This is a micro-founded approach similar to the DCC model. The idea is to recover individual preference parameters consistent with observed aggregated observations. This choice depends on block and consumer characteristics, which differ from Corral, Fisher, and Hatch (1999). Unlike the DCC approach, the proposed model requires instruments to address price endogeneity. This is because of the presence of block-varying unobserved shocks that may be correlated with the price.

2.3 Price signal

There is an active debate in the literature about which price signal should be used. According to economic theory, consumers should react to the marginal price. However, the complexity of the pricing structure and the limited information provided by bills may cause the consumer to be unaware of her marginal price[7]. The average price, or the lagged average price, was suggested as the price signal to consider [8]. Some researchers argue that the choice of the price signal should be an empirical question. Shin (1985); Opaluch (1982) proposed an empirical test to choose between the marginal and average prices. Some later contributions provide empirical evidence[9] of the consumer being more reactive to the average price (Ito, 2014; Borenstein, 2009; Puri and Maas, 2020), or lagged average price (Binet, Carlevaro, and Paul, 2014; Flyr et al., 2019) or marginal price (Nataraj and Hanemann, 2011). There is also evidence of heterogeneity in price perception and responsiveness. K. Luo, Qiu, and Xing (2022) shows that heavier consumers react to the average price while others react to the marginal price. Studying electricity consumption in British Columbia, (Shaffer, 2020) shows that the observed unresponsiveness to marginal price is explained by heterogeneity in price perception. The author suggested that the majority of consumers react to the average price, while a minority respond to the marginal price. A third group of consumers misunderstands the pricing structure, thinking that the marginal price applies to all units.

Unfortunately, this question cannot be studied with aggregate data. Therefore, the model assumes a rational consumer who is fully aware of the pricing structure and has no optimization error, as did Reiss and White (2005); Blomquist and Newey (2002).

[7]See Olmstead (2009),Arbués, Garcia-Valiñas, and Martinez-Espineira (2003) for more discussion

[8]see Arbués, Garcia-Valiñas, and Martinez-Espineira (2003); Liebman and Zeckhauser (2003); Miller and Alberini (2016); Puri and Maas (2020) and references therein

[9]In other disciplines such as telecommunication, this debate was less perceptible since the marginal price is usually used when observed. This may be explained by consumption cap tariffs being a block pricing structure involving only two blocks, with a zero first-block marginal price. Therefore, those tariffs are less complex than electricity or water tariffs.

3 Model

3.1 Block pricing

I consider a monopolistic firm proposing a product using decreasing-block pricing with K blocks of consumption. Each block k in market[10] t is characterized by its price p_{kt} and two thresholds of consumption $x_{k-1,t}, x_{kt}$ such that $x_{k-1,t} < x_{kt}$, defining for which quantities the price applies. The total expense of consuming c in block k is:

$$p_{kt}(c - x_{k-1,t}) + p_{k-1,t}(x_{k-1,t} - x_{k-2,t}) + \cdots + p_{1t}x_{1t} = p_{kt}c + \sum_{l=1}^{k-1} x_{lt}(p_{lt} - p_{l+1,t}) \tag{1}$$

Let's define the *difference* variable for block k in market t as d_{kt}:

$$d_{kt} = \sum_{l=1}^{k-1} x_{lt}(p_{lt} - p_{l+1,t})$$

Then the total expense in equation (1) can be written as $p_{kt}c + d_{kt}$. This characteristic can be viewed as a sort of lump sum required to access quantities in block k.

In this environment, the consumer has to choose whether to have a positive consumption and, conditional on a positive consumption, the optimal amount to choose. For the latter choice, the consumer faces a decreasing block pricing scheme and has a piecewise linear budget constraint. Following Moffitt (1986) and Hewitt and Hanemann (1995), the optimal consumption with a piecewise linear budget set is determined by a two-step optimization process. In the first step, the consumer determines the sequence of conditional demand,i.e., the quantity she would demand if she were to consume in each block[11]. The conditional demand of each block depends on the marginal price, the difference variable, and the consumer's demographics. In the second step, she chooses, in this sequence, the optimal consumption and therefore, the optimal block. This consumption corresponds to the one yielding the highest level of utility.

It is worth noticing two things. First, the second step is a discrete choice among consumption blocks. Given the consumer's characteristics, the optimal block corresponds to the one

[10] The market may be defined by a geographical and/or temporal variation.

[11] The conditional demand of a block corresponds to the optimal consumption if the budget set were linear. The price will then be the marginal price of the corresponding block, and income will be the virtual income, the consumer's income net of the difference variable.

whose marginal price and difference variable yield the highest indirect utility. Secondly, for each consumer, the indirect utility of each block is a deterministic function of the block characteristics. There is no random shock once the consumer characteristics are fixed. Therefore, a multinomial logit is not appropriate to model this discrete choice[12]. This is because, unlike the PCM, the logit model assumes that, conditional on the alternative and the consumer's observed characteristics, the utility of each alternative is random due to the logit shock. Another reason to use the PCM is that blocks can be viewed as vertically differentiated products. If the desirability assumption of the good is satisfied and the expense is block-invariant, everyone would prefer to consume in the last block.

The main objective is to recover the primitives of individual preferences using data on the observed number of customers and total consumption in each block. The blocks are viewed as vertically differentiated products such that there is a continuous choice of quantity for the chosen product. Each block has two characteristics: the price and the difference variable.

3.2 Consumer's problem

Optimal block choice conditional on consuming: The consumer is facing K blocks. The utility gained by consumer i from choosing a level of consumption c within block k in market t is:

$$U(c) = \beta + (1 + ln(\omega_i) - ln(c))c - \alpha(p_{kt}c + d_{kt}) + \xi_{kt} \tag{2}$$

where ω_i is the consumer's type, α is the sensitivity to the cost of consumption, ξ_{kt} is an unobserved demand shock, common to all i who choose k in t. This unobserved demand shock is useful for controlling the non-price determinants of consumption common to all consumers, such as weather effects. This unobserved effect ξ_{kt} may also be divided into a time-varying shock and a block-varying shock.

The consumer's type is meant to capture heterogeneity in consumption level. In the rest of the paper, the heterogeneity in consumption ω_i is unobserved and drawn from a distribution of

[12] Berry and Pakes (2007) discuss the implications of including or not the logit random shock. Lu and Saito (2022) explores the approximation properties of the mixed logit to pure characteristics models.

CDF $F(\cdot)$. ω_i may also be an index depending on consumers' demographics relevant to optimal consumption choice, such as household size, appliances, etc. Therefore, available distributions on non-price determinants of consumption may be used in the analysis.

The utility form borrows from the literature on block pricing schemes in telecommunication (known in this literature as multipart tariffs) (Huang, 2007; Grubb and Osborne, 2015; L. Chen, Y. Luo, and Xiao, 2019; J. Chen, Jiang, and Syed Shah, 2022).

This functional form [13] was also chosen for two other reasons. Firstly, it gives a closed-form expression for the conditional demand as a function of the model parameters. This is useful because individual demand is unobserved. Secondly, the functional form helps me compare my estimates to the literature's. Indeed, the utility function provides log-level conditional demand functions, which are widely used in the literature on the discrete-continuous choice model.

From equation 2, we can see that the only characteristics that matter in the choice are price and the difference variable, and the only source of heterogeneity is the consumer type. In other words, two consumers with the same type ω_i end up with the exact same choice. This makes the PCM presented by Berry and Pakes (2007) suitable for the analysis. We can then solve the consumer problem à la Berry and Pakes (2007) by ordering alternatives increasingly in price[14]. Given that block k is chosen, the optimal quantity is:

$$c_{ikt} = \text{argmax}_c(U(c)) = \omega_i \exp(-\alpha p_{kt}) \tag{3}$$

So the indirect utility of choosing block k is:

$$V_{ikt} = \omega_i \exp(-\alpha p_{kt}) + \delta_{kt} \tag{4}$$

where $\delta_{kt} = \beta - \alpha d_{kt} + \xi_{kt}$ is the mean utility obtained from choosing block k.

[13] Another advantage of this functional form is that it implicitly assumes no income effect on the choice. This means computing the welfare with the consumer surplus, the equivalent variation, or the compensated variation gives the same value (Willig, 1976). Therefore, solving the consumer problem with the surplus approach (Terza and Welch, 1982) or the utility approach as in this paper is equivalent.

[14] Henceforth, block k is the one with the k-th lowest price. So blocks are ordered from the last one to the first.

The consumer chooses option k if and only if $V_{ikt} > V_{ilt}$ for all l which implies [15]:

$$\underbrace{\frac{\delta_{k+1,t}-\delta_{kt}}{\exp(-\alpha p_{kt})-\exp(-\alpha p_{k+1,t})}}_{\underline{\omega}_{kt}} < \omega_i < \underbrace{\frac{\delta_{k-1,t}-\delta_{kt}}{\exp(-\alpha p_{kt})-\exp(-\alpha p_{k-1,t})}}_{\overline{\omega}_{kt}} \tag{5}$$

If $F(.)$ and $f(.)$ are the CDF and PDF of ω_i, the probability that consumer i chooses block k, given a positive consumption (henceforth conditional market shares) is then:

$$\tilde{s}_{kt} = F(\overline{\omega}_{kt}) - F(\underline{\omega}_{kt}) \tag{6}$$

if $\overline{\omega}_{kt} > \underline{\omega}_{kt}$ and 0 otherwise. Something worth mentioning is the fact that the choice of the block is entirely determined by ω_i. In this choice of the optimal block, the reaction to the marginal price may be limited to its effect on the two boundaries $\underline{\omega}_{kt}$ and $\overline{\omega}_{kt}$. This may be consistent with the idea that consumers are less sensitive to the marginal price (Ito, 2013; Ito, 2014; Borenstein, 2009).

The choice of a positive consumption: The utility obtained from consuming is then $V^*_{it} = \max_k V_{ikt}$. The consumer decides to have a non-zero consumption by comparing the utility of the inside option $V^*_{it}+\epsilon_{it}$ and the outside option $V_{i0t}+\epsilon_{i0t}$. Then, we can assume a distribution of the vector of idiosyncratic shocks $(\epsilon_{it}, \epsilon_{i0t})$ to have the probability of positive consumption. Using the Extreme Value distribution [16], we have:

$$P(i \text{ chooses a positive consumption}) = \frac{\exp(V^*_{it})}{1+\exp(V^*_{it})} \tag{7}$$

The outside option accounts for all alternatives other than using the firm's product. For example, in the empirical application on natural gas, the outside option includes other available sources of energy such as electricity. It is a common practice in energy demand analysis, especially with the instrumental variables approach, to control for those substitutes.

[15]See Appendix A.1 for more details.

[16]We normalize $V_{i0t} = 0$.

Market share : The probability for i of choosing block k:

$$P(\omega_i,\alpha,k) = P(i \text{ chooses a positive consumption}|V^*_{it} = V_{ikt}) * (F(\overline{\omega}_{kt}) - F(\underline{\omega}_{kt}))I\{\bar{\omega}_{kt} > \underline{\omega}_{kt}\} \tag{8}$$

$$P(\omega_i,\alpha,k) = \frac{\exp(\omega_i exp(-\alpha p_{kt}) + \delta_{kt})}{1+\exp(\omega_i exp(-\alpha p_{kt}) + \delta_{kt})} I\{\underline{\omega}_{kt} \leq \omega_i \leq \overline{\omega}_{kt}\} \tag{9}$$

So the market share of block k is:

$$s_{kt} = \int_{\underline{\omega}_{kt}}^{\overline{\omega}_{kt}} P(\omega_i,\alpha,k)\,dF(\omega) \tag{10}$$

Consumption: The unconditional consumption, as defined in the literature, is the expected consumption of the consumer across all blocks. The unconditional consumption can be computed from the set of conditional consumption defined in equation (3).

$$\bar{c}_{it} = \sum_k P(\omega_i,\alpha,k)\omega_i \exp(-\alpha p_{kt}) \tag{11}$$

The average consumption ($\bar{c}_t$) can be obtained by integrating equation (11) over the distribution of ω. It can be rewritten as:

$$\bar{c}_t = \sum_k \left[F(\overline{\omega}_{kt}) - F(\underline{\omega}_{kt})\right]\bar{c}_{kt} = \sum_k \tilde{s}_{kt}\bar{c}_{kt} \tag{12}$$

where $\bar{c}_{kt}$ is the observed average consumption in block k defined by:

$$\bar{c}_{kt} = \int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}} \frac{\exp(\omega_i exp(-\alpha p_{kt}) + \delta_{kt})}{1+\exp(\omega_i exp(-\alpha p_{kt}) + \delta_{kt})} c_{ikt}\,dF(\omega|\underline{\omega}_{kt} < \omega_i < \bar{\omega}_{kt}) \tag{13}$$

3.3 Price elasticity

Since there is more than one price in block rates, the definition of elasticity is less intuitive. Following Olmstead, Hanemann, and Stavins (2007), the unconditional price elasticity is the change in average consumption if all prices of the structure change at once. I define the conditional price elasticity as the elasticity of conditional demand with respect to the corresponding block marginal price. This latter type of elasticity is then the elasticity conditional on remaining on the block. It can be computed from the semi-elasticity of conditional consumption with respect to the price, i.e., $alpha$. I provide a more detailed discussion of the definition of price elasticity in Appendix B in the block pricing schedule.

The price elasticity of the average consumption with respect to the price of the block l in this setting is[17]:

$$\eta_{lt} = \frac{\partial \bar{c}_t}{\partial p_{lt}} \frac{p_{lt}}{\bar{c}_t} = \frac{p_{lt}}{\bar{c}} \sum_k \frac{\partial(\bar{c}_{kt}\tilde{s}_{kt})}{\partial p_{lt}} = \frac{p_{lt}}{\bar{c}_t} \sum_k \left(\frac{\partial \bar{c}_{kt}}{\partial p_{lt}} \tilde{s}_{kt} + \bar{c}_{kt} \frac{\partial \tilde{s}_{kt}}{p_{lt}} \right) \tag{14}$$

It accounts for switching behavior among blocks, changes in the conditional consumption of block l, and substitution with the outside good.

3.4 Case of a menu of tariffs

Sometimes, for instance in telecommunications or utilities, firms propose a menu of tariffs. Assuming each is a decreasing block pricing scheme, the previously presented model can be applied.

In an environment of J tariffs with K_j blocks each, the consumer first chooses her tariff j and then her optimal consumption given this tariff. As in section 3.2, the problem is solved backward. Given tariff j, the consumer faces K_j blocks and chooses the optimal block using the discrete-continuous approach. The optimal block in tariff j is the one whose characteristics yield the highest indirect utility.

Choice of tariff The utility obtained from consuming in tariff j is then $V^*_{ijt} = \max_k V_{ijkt}$. The consumer decides which tariff to choose by comparing the utility of consuming in each tariff $V^*_{ijt} + \epsilon_{ijt}$ and the outside option $V_{i0t} + \epsilon_{i0t}$. Then, the probability of choosing tariff j is:

$$P(i \text{ chooses consumption in tariff } j) = \frac{\exp(V^*_{ijt})}{1 + \sum_{l=1}^{J} \exp(V^*_{ilt})} \tag{15}$$

[17]See Appendix A.3 for more details

3.5 Extension of the model and further discussions

3.5.1 Another block-dependent characteristic

It may be possible to see a block-varying cost charged to the consumer in addition to the marginal price or block-specific constant β. In the empirical application, for example, the residential tariff involves a fixed fee depending on the consumption block. This constitutes a transfer from the consumer to the firm and may create notches in the budget constraint. The previously presented model can be applied by adding this new fee to the cost.

3.5.2 The two errors model à la Burtless and Hausman (1978)

In the literature, it is common to see the conditional demand of block k expressed as $c_{ikt} = \omega_i exp(\eta_i) exp(-\alpha p_{kt})$ where η_i and ω_i are usually assumed to be independent and normally distributed of parameters $(\mu_\eta = 0, \sigma_\eta)$ and $(\mu_\omega = 0, \sigma_\omega)$. The two errors play different roles in explaining the observed consumption. ω_i is the heterogeneity parameter capturing the heterogeneity in the level of consumption and, therefore, explaining why a consumer ends up in a particular block given his realization of η_i. The error η_i affects all consumers in the same way (Moffitt, 1986). This error is meant to capture all the factors contributing to a consumer having a suboptimal level of consumption (optimization errors). η_i is usually interpreted as a perception error from the consumer. Finally, the probability of choosing a particular block depends on the joint distribution of the two errors and, therefore, on the variance of the two distributions (Olmstead, 2009; Moffitt, 1990).

The two variances are separately identified by how close the consumption distribution is to what it would have been without optimization error. Without optimization errors, some bunching (resp. hole) around the kink is expected in the consumption distribution for increasing (resp. decreasing) block prices (Moffitt, 1990; Kleven, 2016). A smooth consumption distribution is, therefore, a symptom of optimization error. The smoother the distribution, the higher the variance of η compared to the variance of ω (Moffitt, 1990; Kleven, 2016). Therefore, the size of the hole or bunching can be a helpful moment to identify the two parameters separately[18].

[18] The bunching literature in labor economics, from the seminal work of Saez (2010), computes the labor elasticity from the size of the bunching mass. Recent contributions introduce some friction parameters and show that those parameters can be identified along with the elasticity under certain conditions. see Kleven (2016) for a

Unfortunately, the data available for the empirical application does not allow us to identify two different errors.

In labor literature,Kleven and Waseem (2013) proposes a method to identify both structural elasticities and optimization friction parameters with notches. Without the optimization friction, notches create both bunching and a hole in the distribution of labor supply. The size of the bunching and the hole were then used as moments for identification.

Another approach adopted by J. Chen, Jiang, and Syed Shah (2022) used moments coming from micro-data when modeling consumption of mobile plans in a three-part tariff[19]. The model includes both a perception error and a consumer type parameter. In this environment, without perception error, the consumer should consume at the level corresponding to her plan allowance. The variance of the perception error was identified from the proportion of consumers consuming between 90% and 110% of their allowance.

4 Estimation

As in Berry and Pakes (2007), the mean of ω_i was normalized to 1. So, the heterogeneity parameter is assumed to have a log-normal distribution of parameters [20] $(0, \sigma)$. The idea behind this normalization is that multiplying the vector $(\omega, \alpha, \xi_{kt})$ of the indirect utility by the same positive constant does not change the model implications. Normalizing the mean of ω_i is equivalent to expressing the parameters in terms of $E(\omega_i)$. Assuming that ω_i is a continuous variable avoids ties between blocks. The model accounts for this possibility but assumes that the weight of this kind of consumer is infinitely small. Identification relies on the conditions from Berry and Pakes (2007). The model is close to the discrete model of Song (2015), which provides a short proof of identification.

The vector to be estimated is $(\theta \equiv (\sigma, \alpha), \beta)$. Given θ, the last parameter β is recovered as the constant term of the regression of the mean utility δ on the variable $d \equiv (d_{kt})_{k,t}$ with residuals $\xi \equiv (\xi_{kt})_{t,k}$. I define $x_t \equiv (x_{kt})_k$.

review.

[19] A three-part tariff is made of an access fee, an allowance, and a marginal price for the additional units above the allowance. It can be viewed as a structure of two blocks (below and above the volume cap) with an access fee and a null marginal price in the first block.

[20] Those parameters correspond to the mean and variance of $log(\omega_i)$

4.1 Estimation procedure

The estimation procedure borrows heavily from the two-step standard procedure proposed by Berry (1994) and Song (2015). Unlike in Berry, Levinsohn, and Pakes (1995), there are no linear parameters. The mean utility δ_{kt} is a function of the second parameter α, which enters nonlinearly in the first part of the utility.

The first step in this estimation procedure is market share inversion. The idea is to solve for $\xi(\theta)$ that matches observed and predicted market shares at a given value of parameter θ. The second step consists of finding the estimate of the parameter θ, which corresponds to the minimizer of the sample counterpart of the following GMM objective function:

$$g(\theta)'Wg(\theta), \quad g(\theta) = E\left(z_{kt}^{'}\xi_{kt}(\theta)\right)$$

where W is a weighting matrix. The moment $g(\theta)$ is the interaction between the demand shock and a vector of instruments z_{kt}. This moment aims to correct the endogeneity of the price. According to the literature on piecewise budget sets, when controlling for their type of consumption ω, all consumers may be attracted by a particular block because of their characteristics or climate effect. In this analysis, I might expect the demand shock to be correlated with the price for two reasons. The first is the selection phenomenon: each block is expected to be optimal for a particular subgroup of customers, to some extent. The second reason is that this unobserved taste may be known and accounted for by the firm when choosing prices. The identification of the price coefficient α needs a set of valid instruments, as usually done in demand analysis. In particular, the instrument should be block-varying, which means there is a restriction on the type of costs that can be used[21].

Market share inversion: The goal of this step is to solve for unobserved demand shock $\xi(\theta)$ such that predicted market shares match the observed market shares for a given vector θ. To compute the market share inversion, I borrow from a suggested algorithm by Song (2015). The

[21] Another moment tested in the estimation to match is the correlation of the market shares computed with consumption and the boundaries of the block x_t. The idea is to match the observed correlation in the data with the predicted one. With the set of preferred instruments, this moment was revealed to be nonrelevant. See Appendix A.4 for simulation results using this moment.

pure characteristic model implies that market shares are discontinuous functions of the demand shock. So the usual contraction mapping used to recover mean utility in Berry, Levinsohn, and Pakes (1995) is no longer suitable (Berry and Pakes, 2007; Pang, Su, and Lee, 2015), especially in my case with the particular structure of outside-inside option choice.

The idea is to use the two subsequent choices (positive consumption and optimal block) to compute $\xi(\theta)$. Using the conditional block market shares expression in equation (6), the elements of ξ can be recovered recursively. With one random coefficient, the following analytical expression can be used:

$$\xi_{jkt}(\theta) = F^{-1}(1 - \sum_{l=1}^{k-1} \tilde{s}_{jlt})\left(\exp(-\alpha p_{j,k-1,t}) - \exp(-\alpha p_{jkt})\right) + \alpha(d_{jkt} - d_{j,k-1,t}) + \xi_{j,k-1,t}(\theta) \quad (16)$$

where $\tilde{s}_{lt}$ is the observed conditional market shares of block l. From the data, $\tilde{s}_{lt}$ is the proportion of consumers in the tariff located in block l. Since there are only $k-1$ boundaries for k unobserved shocks, the vector ξ is expressed as a function of the first blocks of unobserved shocks of each tariff $\xi = \xi(\xi_1)$. Then ξ_1 will be recovered by matching the observed and predicted inside market share. Let's illustrate this method in the case of $J = 1$ tariff with K blocks. The subscript j was dropped. For each market t for a given ω, the steps are:

1. Compute from the data conditional block market share $(\tilde{s}_{1t}, \tilde{s}_{2t}, \ldots, \tilde{s}_{Kt})$ as the ratio of the number of customers in blocks and the total number of customers in the tariff;

2. Compute the components the others $K-1$ shocks $(\xi_{kt}(\xi_{1t}))_{k=2\ldots,K}$ recursively using equation (16).

3. Finding the ξ_{1t} that matches observed vs predicted moments:

   - The observed market share for the inside options can be expressed as a function of ξ_{1t}:

$$\Gamma(\xi_{1t}) = \int \frac{\exp(max_k(\omega_i exp(-\alpha p_{kt}) + \delta_{kt}(\xi_{1t}) + \beta))}{1 + \exp(max_k(\omega_i exp(-\alpha p_{kt}) + \delta_{kt}(\xi_{1t}) + \beta))}\, dF(\omega) \quad (17)$$

The third step consists of solving a nonlinear equation with one unknown. I provide proof in Appendix A.2 of the uniqueness of the solution.

5 Monte Carlo

The estimation algorithm was tested with some Monte Carlo simulations. The exercise is performed for the model described in Section 3 with $J = 1$ tariff. Each Monte Carlo sample is generated to mimic the data from the empirical application. Therefore, like in the empirical application data, the consumption thresholds defining the blocks $(x_{kt})_{(k,t)}$ are market-invariant.

5.1 Data generation process

The key difficulty in the simulation exercise is to guarantee positive market shares for each block in every market within the samples. According to equations (6) and (9), this requires that the breakpoints $(\underline{\omega}_{kt})_k$ form a decreasing sequence in all markets. Therefore, the pricing structure [22] should be designed to be consistent with the sequence $(\underline{\omega}_{kt})_k$ being decreasing.

To solve this issue with PCM, Berry and Pakes (2007) suggested setting the price as a convex function of the mean utility[23]. This trick is not helpful in my case since the marginal price enters the utility function non-linearly. The strategy adopted in this paper is to instead solve the reverse problem, namely finding the sequence of marginal prices corresponding to a given decreasing sequence $(\underline{\omega}_{kt})_k$ (or, equivalently, a vector of nonzero conditional market shares) and given values of block thresholds $(x_{kt})_{(k)}$ and demand shocks.

Pricing structure The algorithm for the pricing structure is the following. For each market t, and $K = 8$ blocks:

1. Draw block boundaries $(x_{kt})_k$ from a discrete uniform (1,1000)
2. Generate the vector of dimension K of demand shocks ξ_t.
3. Generate the set of $(\underline{\omega}_{kt})_k$ by computing the quantile of a lognormal distribution $(0, \sigma = 2.5)$ corresponding to the conditional market shares $(\tilde{s}_{kt})_k$.

[22] The pricing structure in the market t refers to marginal prices $(p_{kt})_k$ and block thresholds $(x_{kt})_k$.

[23] In the simulation section proposed by Berry and Pakes (2007), the price of the product j was defined as $p_{jt} = \frac{\exp(\delta_{jt})}{20}$ with $\delta_{jt} = x_{jt}\beta + \xi_{jt}$, the mean utility of the product j. This was possible because the price was not included in the set of variables x_{jt}. In my case, since the parameter d_{kt} and therefore δ_{jt} are functions of price, this method did not work. see Berry and Pakes (2007) and Song (2008),Song (2007) for more details

4. Solve for the set of marginal prices corresponding to $(\underline{\omega}_k)_k = \left(\frac{(\xi_{k+1,t}-\xi_{kt})-\alpha(d_{k+1,t}-d_{kt})}{\exp(-\alpha p_k)-\exp(-\alpha p_{(k+1)})}\right)_k$. This is a system of $K-1$ equations and K unknowns[24]. The price of the last block was randomly chosen from a uniform(2,15).

In step (2), the vector of demand shock is constructed as follows. The first component of the demand shock vector is a draw from a uniform (-5,-3), and the increment between successive components is sampled from a uniform distribution over the interval (1, 2). Using these two draws, the other components are recovered recursively[25]. The variations between successive components of the vector translate into variations in the marginal prices of the corresponding blocks. The goal is to ensure sufficient variation in marginal prices within the pricing structure. In step (3), the conditional market shares are generated from a linear combination of three binomial probability mass functions of $n = K = 8$ trials[26]. The goal is to mimic the asymmetry of the distribution of customers among blocks.

I consider two variables to build the vector of instruments. The first instrument is the marginal price of the last block corresponding to the uniform draw in step (4). Because the last block is the one with the lowest price, its marginal price can be viewed as a proxy for the marginal cost. The second instrument is constructed for each market t as follows. Once the pricing structure is built, the mean utility $\delta_{kt} = -\alpha d_{kt} + \xi_{kt} + \beta$ can be computed. Given the vector δ_t, and the boundary of the block $(x_{kt})_k$, the instrument p^* is the set of prices in the absence of the unobserved shock. The vector of instruments is made up of the two variables and their second-order interactions[27].

The 5000 consumers were generated to behave as the model.

5.2 Simulation results

The simulation results are presented in Table 1. The weighting matrix used in the estimation is the identity matrix. The number of draws of the random coefficient ω for integral simulations

[24] Given the price of the last block, the other prices may be recovered recursively.

[25] The final vector is centered.

[26] The following linear combination is used: $\pi \in \{\pi_1 = 0.2, \pi_2 = 0.9, \pi_3\}, K = 8$, with π_3 drawn from a uniform $(0.4, 0.7)$: $0.1 \times \text{Bin}(\pi_1, K) + 0.2 \times \text{Bin}(\pi_2, K) + 0.7 \times \text{Bin}(\pi_3, K)$
with $\text{Bin}(\pi, K)$ the binomial mass probability of success probability π and number of trials K.

[27] Other instruments were also tested, though with less success. These include the boundary of the block $(x_{kt})_k$ and the length of the blocks.

Table 1: Simulation results

Number of markets	$\alpha = 0.5$	$\sigma = 2.5$	$\beta = 6$
12	0.500	2.555	6.003
	(0.05)	(0.588)	(0.521)
24	0.498	2.493	5.986
	(0.05)	(0.469)	(0.532)
50	0.5	2.504	6.009
	(0.046)	(0.378)	(0.488)

Notes: The numbers in brackets are standard errors of estimates across different Monte Carlo samples.

is R=5000[28]. The market share inversion (equation 17) was solved to minimize the quadratic distance between the predicted and observed market shares[29].

The model is solved with a simplex-based method (Nelder-Mead algorithm)[30]. The starting point is a draw in a range of values around the true parameters [31]. The standard errors presented are standard errors of estimates in different Monte Carlo samples[32]. The results indicate that the estimation algorithm works effectively. However, the estimators are biased in finite samples. We can conclude that this method can identify the true parameters. However, estimating with a low number of markets may introduce some bias in the random coefficient estimation.

[28]The PCM estimation is known to be less sensitive to the number of draws (Berry and Pakes (2007),Song (2008)). The same simulation exercise was performed with R = 10000 with similar results. Only the results with R=5000 are reported in the paper.

[29]A first attempt was made by solving the nonlinear equation directly with the Newton-Raphson algorithm with limited success. This method is more sensitive to the starting values, requires much more time, and yields a solution further away from the true parameter compared to the chosen method.

[30]The optimization was performed for $-5 \leq \alpha \leq 5$ and $01 \leq \sigma \leq 5$ to avoid numerical issues. The box constraint version of the BFGS-based routine gives similar results for starting points in the neighborhood of the true solution. The simplex-based routine is preferred given that the objective function may be nonsmooth. In fact, market shares may not be continuous with respect to the demand shocks (Li, 2018).

[31]For each sample, five different starting points were used. Only the results corresponding to the lowest value of the criterion function were kept.

[32]The simulation exercise is also performed without the last moment about the correlation between average consumption and block boundaries. See Appendix A2 for more details.

6 Empirical application

6.1 Presentation of the industry

I use public data on natural gas distribution from the firm Energir. Energir is the only provider for most of the province of Quebec, providing 97% of its consumption. It is regulated by the *Régie de l'énergie* using a rate-on-return type regulation. Each year, new tariffs are decided with the following process. Energir has to submit a case providing anticipated changes in costs, predicted demand, proposed pass-through rates, and proposed tariffs. This proposal is discussed in public hearings with the regulator, Energir's representatives, and consumer advocacy groups to decide on efficient costs, pass-through rates, and, therefore, new prices. Most of the information about hearings is available on the regulator's website. On September 1st each year, the new tariffs are supposed to be implemented. However, there have been instances in previous years where the implementation has been delayed due to ongoing discussions between parties. In such cases, previous tariffs are re-conducted, or more rarely, provisional tariffs may be implemented. Therefore, in the same year, there may be more than one distribution tariff covering different periods.

The firm proposes a menu of four distribution tariffs, and a consumer is assigned to a tariff depending on their consumption profile (residential or industrial usage). Each tariff involves a non-linear scheme with a decreasing marginal price. For each plan, the cost of consumption is made of a fixed fee (independent of real consumption) and the cost of real consumption.
My analysis focuses on the tariff[33] meant for industrial usage D3 and D4[34]. This tariff is particular because the consumer agrees to a volume cap with the firm. In the event of overage, additional consumption is charged at a higher rate. The pricing structure used for the volume cap is a decreasing block scheme[35]. Since the bill is based on this contracted volume, consumers get punished for choosing it suboptimally. They are overcharged for overage or pay more than their consumption if the volume cap overestimates consumption. This choice of the

[33]The firm considers the first four blocks and the last five blocks as different tariffs.

[34]The main problem with using the residential tariff is that only annual consumption is observed while consumption decisions are monthly.

[35]The fixed fee is a decreasing block pricing based on the volume cap. The second part of the cost is using a uniform price. Since the final cost is the sum of the two costs, the final pricing scheme is a decreasing block scheme where, for each block, the marginal price is the sum of the block price and uniform price.

Table 2: Studied tariffs

Tariffs	D3	D4
Number of blocks	4	5
Share in consumption (2011)	6.93%	40.80%
Share in consumption (2022)	4.52%	48.37%
Average price* (2011)	26.639	23.477
Average price* (2022)	33.675	27.639
Average relative deviation from the proposed price**	1.74%	1.70%

* The price unit is Canadian dollar cents per cubic meter
** The deviation is the absolute value of the difference divided by the proposed price.

volume cap is modeled assuming that consumers choose it optimally. This may be a restrictive assumption, given that overage seems to exist. Unfortunately, the tariffs do not register additional consumption above the volume cap. Another thing to mention is that the first block has zero market share. This block price changes periodically, but customers cannot subscribe for a volume within it. Because of the particular price structure, the marginal price of this block is similar to a transfer that each customer has to pay before consuming. This, in turn, affects the cost of consumption. This block price was added to the difference variable of the other blocks but not considered when solving the model. So, the model systematically assigned zero market share and zero consumption to this block.

6.2 Data and descriptive analysis

All data were collected on the regulator's website covering 2011-2022. For each year, I observe the total number of customers and total consumption in each tariff block, both for anticipated and realized consumption. I also observe both proposed and validated prices.

Not surprisingly, residential customers represent more than half of Energir's customers but approximately 10% of consumption, while industrial usage represents more than half in 2022 (Figure 2). The first four blocks and the last five blocks of industrial customers, the tariffs are considered to be respectively the tariff $D3$ and $D4$.

Table 2 presents some descriptive statistics from the data. Tariff D4 is meant for the heaviest consumers, and therefore the average price is lower.

Table 3: Some descriptive statistics

Variable	Average
Network maintenance interventions	20 736
Losses/Pricing basis	0.03%
Delay in implementation of price (months)	3.167

The average is the annual average throughout the period of study

Figure 2: Energir customers in 2022

Prices: Final prices faced by consumers can be divided into two parts. The distribution tariff is a decreasing block pricing scheme. The second part is a uniform price reflecting the different costs of the service (cost of the molecule, transportation to the network, storage). This second part is directly passed through to the consumer and should be added at the marginal price of each block. Since there may be more than one implemented price, the prices used in the estimation are an average[36] of all implemented prices throughout the year.[37].

The second part of the final price is set by the firm's suppliers. This price may change within the year. I used the price per unit of consumption.

Instruments Instruments used in the empirical analysis should be able to predict the price of a block while being uncorrelated to demand shocks. Cost shifters varying at the block level satisfy these conditions. However, all observed costs affect all the blocks evenly. To solve this

[36] I consider two weights for the average price: a uniform weight and consumption during the subperiod. The result used the latter weight. I provide some robustness checks in Appendix C.

[37] For example, the marginal price of the first block of the tariff D3 is the average value of the marginal price for all available versions of the tariff throughout the period. See Appendix C for more details and robustness checks.

problem, I interact observed cost shifters with the block boundaries. The block boundaries (x_k) do not vary during the study period and are assumed to be exogenous.

A first set of instruments was made of the interaction of these boundaries with some cost shifters. Available cost shifters were the planned and approved network maintenance interventions, the anticipated costs of gas losses during the production process, and the wholesale market price. With a rate-of-return type regulator, cost shifters affect implemented prices through costs. They are assumed to be mean-independent of the unobserved shock. Another instrument was made by interacting the block boundaries with the implementation delay of the new tariffs. Because firm returns are guaranteed, the later the implementation delay, the higher the price. Since the implementation date depends on the length of the discussion period, it is reasonable to assume that this period is independent of the demand shock.

The last instrument was the difference between proposed and implemented prices. This variable, reflecting the deviation from the firm's proposal, will be assumed to be independent of the demand shock. It is the closest to the simulation instruments.

A preferred set of instruments was selected based on their ability to generate the expected cost parameter sign[38]. The results are presented with the difference between proposed and implemented prices and the anticipated costs of gas losses.

It is worth mentioning that, to my knowledge, the sets of instruments previously presented were not used in the literature. Two reasons may explain this fact. First, cost shifters are not always observed, or at least are less available. Secondly, these instruments may not be helpful in identification since they are the same for all consumers in the market. Indeed, the unit of observation was individuals/geographical markets. Therefore, an instrument with low variability at the individual/geographical market level may not predict well the price faced by individuals/geographical markets.

6.3 Results

Estimation results: Table 4 presents the estimation results. In my estimation, the weighting matrix is considered to be the identity. Standard errors were computed using Bootstrap with 1000 draws. This method was used rather than the asymptotic variance of the estimator due to

[38] see Table (D.1) in Appendix D for variation in instruments

the small sample size (twelve markets). The instruments used for the estimation are similar to those used in the simulation exercise. I expected my parameters to be identified in the model. However, the 95% confidence intervals for the parameters are large. This may be explained by the small sample size. The price coefficient interval is not informative. This is consistent with the idea that consumers tend to be less sensitive to the price in a complex environment.

Table 4: Estimation results

$\hat{\alpha}$	$\hat{\sigma}$	$\hat{\beta}$
0.077	2.308	-6.624
(-0.309 0.55)*	(1.963 2.658)*	(-10.816 -3.147)*

* The confidence intervals at 95% are computed by bootstrap over 1000 replications.

Conditional elasticities: The parameter α is a semi-elasticity. The conditional elasticities for each block are reported in Table 5. The elasticities seem to decrease in absolute value with the rank of the blocks. This is consistent with the idea that heavier consumers are less sensitive to the price. The elasticities are in absolute value lower than one, implying that the demand for natural gas is inelastic. The elasticity values are in the range (in absolute value) reported for the short-run elasticity of the demand of energy goods reported by Labandeira, Labeaga, and López-Otero (2017) [39].

Substitution between blocks: It is interesting to look at the substitution effect between blocks. Table 6 shows that the price change k tends to greatly and positively affect the consumption in block k. The average consumption in the adjacent blocks and all the blocks located after $k+1$ are negatively affected. As expected (Olmstead, Hanemann, and Stavins, 2007), the blocks before $k-1$ are left unaffected.

An increase in block k price increases the difference variable, making it more costly to consume in upper blocks. Consumers in those blocks tend to react by moving to lower-rank blocks or leaving the market. Tables (B.1) and (B.2) suggest that the former is observed exclusively

[39] For their meta-analysis, the authors exclude 5% of extreme values of elasticities to get a range between -0.8 and 0.066.

Table 5: Conditional elasticity

	Block rank	Elasticity	Average marginal price
Tariff D3	1	-	30
	2	-0.174	27.89
	3	-0.159	25.53
	4	-0.154	24.55
Tariff D4	5	-0.146	23.27
	6	-0.142	22.53
	7	-0.137	21.82
	8	-0.135	21.46
	9	-0.132	20.99

The Table presents for each block the median elasticity over the period of study. The marginal price, in dollars cents per cubic meter, was averaged over the period.

in block $k+1$ and the latter is more prevalent in blocks above $k+1$. The conditional market shares of those blocks are unaffected by the change in price, unlike the market shares (see Table (B.1) and (B.2) in Appendix B). This is explained by an increase in the difference variable, which makes the outside option more attractive than the inside options. A less intuitive result is the negative effect of the price of block k on both consumption and shares of the previous blocks. In fact, increasing the price of block k moves it closer to the higher price of the previous block. This reduces for consumers in block $k-1$ the penalty of moving to higher consumption. Block k ends up receiving consumers switching from both adjacent blocks; therefore, average consumption increases in this block.

The unconditional elasticity accounts for this switching behavior among blocks and the substitution with the outside option. The average unconditional price elasticity is -0.146 during the study period. If all the prices rise by 1% then the average consumption decreases by 0.146%. Finally, if all prices rise by 1%, the firm's market share decreases by 0.76%. These elasticities indicate that increasing prices may result in the firm's loss of profit because of the loss of volumes and customers.

Table 6: Cross and own price elasticities

	Block rank	2	3	4	5	6	7	8	9
Tariff D3	1	-0.022	-0.022	-0.021	-0.007	-0.00	-0.00	-0.00	-0.00
	2	20.347	-1.688	-0.040	-0.012	-0.00	-0.00	-0.00	-0.00
	3	-18.517	8.898	-0.395	-0.034	-0.001	-0.00	-0.00	-0.00
	4	0	-7.064	3.150	-0.133	-0.002	-0.00	-0.00	-0.00
Tariff D4	5	0	0	-2.685	9.363	-0.914	-0.00	-0.00	-0.00
	6	0	0	0	-9.026	-1.171	2.743	-0.00	-0.00
	7	0	0	0	0	1.923	-14.501	17.586	-0.00
	8	0	0	0	0	0	11.545	-12.235	-1.577
	9	0	0	0	0	0	0	-5.077	1.446

Each row presents the elasticity of the block average consumption in the column with respect to the price of the block in the row. The consumers are not allowed to choose to locate in the first block; therefore, this block is not affected by any change in price. The elasticities are the median elasticity over the period of study. These elasticities take into account switching behavior both between blocks and to the outside option in addition to the consumption change conditional on remaining in the block

7 Conclusion

This paper proposes a structural demand model for a decreasing block pricing scheme with aggregate data at the block-of-consumption level. The model accounts for the discrete choice of the block and the continuous choice of the quantity while controlling for individual heterogeneity. Unlike the DCC model, identification still requires instruments for the price. This is because the self-selection problem may lead the marginal price to be correlated to demand shocks.

The model was applied to data from a natural gas distributor in Quebec. I leverage the interesting institutional background to introduce new instruments in this literature. One singularity of these instruments is that they are block-varying, which helps identify the price parameter. The results show that the conditional and unconditional price elasticities are similar to previous estimates in the literature.

Some possible extensions of the proposed model were discussed. Unfortunately, they were not added to the estimation due to insufficient relevant data. Another extension left for future research is the increasing block pricing scheme (Figure B.1). In this case, the kink may also be an optimal consumption point. However, kink optimality depends on block characteristics, which complicates analysis with aggregate data.

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Appendices

A Complement to the model

A.1 Choice probabilities

Given that blocks are ordered increasingly by the price, block k is chosen if $V_{ikt} \geq V_{ilt}$:

$$\omega_i exp(-\alpha p_{kt}) + \delta_{kt} > \omega_i exp(-\alpha p_{lt}) + \delta_{lt} \quad \Leftrightarrow \quad \begin{cases} \omega_i < (\frac{\delta_{lt}-\delta_{kt}}{(\exp(-\alpha p_{kt})-\exp(-\alpha p_{lt}))}) \text{ if } l < k \\ \omega_i > (\frac{\delta_{lt}-\delta_{kt}}{(\exp(-\alpha p_{kt})-\exp(-\alpha p_{lt}))}) \text{ if } l > k \end{cases}$$

Then block k is optimal for all ω_i belonging to the region R_t^k defined by:

$$\omega_i < min_{l\geq 1}\left(\frac{\delta_{k-l,t}-\delta_{kt}}{\exp(-\alpha p_{kt})-\exp(-\alpha p_{k-l,t})}\right) \tag{A.18}$$

$$\omega_i > max_{l\geq 1}\left(\frac{\delta_{k+l,t}-\delta_{kt}}{\exp(-\alpha p_{kt})-\exp(-\alpha p_{(k+l)t})}\right) \tag{A.19}$$

The regions R_t^k and R_t^{k+1} of the support of ω_i corresponding to the choice of option k and $k+1$ are defined respectively by equations (A.20),(A.21) :

$$\overbrace{\max_{l\geq 1}\left(\frac{\delta_{k+l,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k+l,t}\right)}\right)}^{\substack{\max\left(\frac{\delta_{k+1,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k+1,t}\right)}, \max_{l\geq 2}\frac{\delta_{k+l,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k+l,t}\right)}\right) \\ \equiv}} < \omega_i < \min_{l\geq 1}\left(\frac{\delta_{k-l,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k-l,t}\right)}\right) \tag{A.20}$$

$$\max_{l\geq 1}\left(\frac{\delta_{k+l+1,t}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{k+l+1,t}\right)}\right) < \omega_i < \underbrace{\min_{l\geq 1}\left(\frac{\delta_{k+1-l,t}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{k+1-l,t}\right)}\right)}_{\substack{\equiv \\ \min\left(\frac{\delta_{kt}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{kt}\right)}, \min_{l\geq 2}\frac{\delta_{k+1-l,t}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{k+1-l,t}\right)}\right)}} \tag{A.21}$$

From the two equations(A.20),(A.21), we can see that the regions of the support of ω_i corresponding to the choice of options are ordered. So consumers choosing $k+1$ instead of k have smaller values of ω_i.

$$\min_{l\geq 1}\left(\frac{\delta_{k+1-l,t}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{(k+1-l)t}\right)}\right)\leq \max_{l\geq 1}\left(\frac{\delta_{k+l,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{(k+l)t}\right)}\right) \tag{A.22}$$

We can show that the inequality (A.22) cannot be strict. If this inequality is strict, it means that there is a range of values of ω_i such that for each value $\tilde{\omega}_i$:

$$\min_{l\geq 1}\left(\frac{\delta_{k+1-l,t}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{k+1-l,t}\right)}\right)\leq \tilde{\omega}_i \leq \max_{l\geq 1}\left(\frac{\delta_{k+l,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k+l,t}\right)}\right)$$

For such values, we have that block k has the highest level of utility compared to the next blocks, including $k+1$, and block $k+1$ has the highest utility compared to previous blocks, including k. And this is absurd. So it should be that:

$$\begin{aligned}\min_{l\geq 1}\left(\frac{\delta_{k+1-l,t}-\delta_{k+1,t}}{\exp\left(-\alpha p_{k+1,t}\right)-\exp\left(-\alpha p_{k+1-l,t}\right)}\right) &= \max_{l\geq 1}\left(\frac{\delta_{k+l,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k+l,t}\right)}\right)\\ &= \frac{\delta_{k+1,t}-\delta_{kt}}{\exp\left(-\alpha p_{kt}\right)-\exp\left(-\alpha p_{k+1,t}\right)}\end{aligned}$$

A.2 Market shares inversion

In this appendix, I prove that the last step (step 3) of the market share inversion yields a unique solution. To do so, I show that the function described by Equation (17) is monotonic. The subscript j for the tariff has been omitted. From:

$$\begin{aligned}\Gamma(\xi_{1t}) &= \int_0^{+\infty}\frac{\exp(max_k(\omega_i exp(-\alpha p_{kt})+\delta_{kt}(\xi_{1t})))}{1+\exp(max_k(\omega_i exp(-\alpha p_{kt})+\delta_{kt}(\xi_{1t})))}\,dF(\omega)\\ \Gamma(\xi_{1t}) &= \sum_{k=1}^{K}\int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}}\underbrace{\frac{\exp(\omega_i exp(-\alpha p_{kt})+\delta_{kt}(\xi_{1t}))}{1+\exp(\omega_i exp(-\alpha p_{kt})+\delta_{kt}(\xi_{1t}))}f(\omega)}_{g(\omega)}\,d\omega = \sum_{k=1}^{K} I_{kt}(\xi_{j1t})\end{aligned}$$

And:

$$
\begin{aligned}
\xi_{kt}(\theta) \quad &= F^{-1}(1-\sum_{l=1}^{k-1}\tilde{s}_{lt})\left(\exp(-\alpha p_{k-1,t})-\exp(-\alpha p_{kt})\right)+\alpha(d_{kt}-d_{k-1,t})+\xi_{k-1,t}(\theta) \\
\xi_{kt}(\theta) &= \sum_{h=2}^{k}\left[F^{-1}(1-\sum_{l=1}^{h-1}\tilde{s}_{lt})\left(\exp(-\alpha p_{(h-1)t})-\exp(-\alpha p_{ht})\right)+\alpha(d_{ht}-d_{(h-1)t})\right]+\xi_{1t}(\theta)
\end{aligned}
$$

we have:

$$
\begin{aligned}
\frac{\partial I_{kt}}{\partial \xi_{1t}} &= \underbrace{\frac{\partial \bar{\omega}_{kt}}{\partial \xi_{kt}}}_{=0} g(\bar{\omega}_{kt}) - \underbrace{\frac{\partial \underline{\omega}_{kt}}{\partial \xi_{kt}}}_{=0} g(\underline{\omega}_{kt}) + \int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}} \frac{\partial g}{\partial \xi_{kt}}(\omega)\frac{\partial \xi_{kt}}{\partial \xi_{1t}}\, d\omega \\
\frac{\partial I_{kt}}{\partial \xi_{1t}} &= \int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}} \frac{\partial g}{\partial \xi_{kt}}(\omega)\frac{\partial \xi_{kt}}{\partial \xi_{1t}}\, d\omega = \int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}} \frac{\exp(\omega_i exp(-\alpha p_{kt})+\delta_{kt}(\xi_{1t}))}{\left(1+\exp(\omega_i exp(-\alpha p_{kt})+\delta_{kt}(\xi_{1t}))\right)^2} f(\omega)\, d\omega \geq 0
\end{aligned}
$$

Finally $\frac{df(\xi_{1t})}{d\xi_{1t}} = \sum_k \frac{\partial I_{kt}}{\partial \xi_{1t}} \geq 0$. It can easily be seen that $\lim_{\xi_{1t}\to 0}\Gamma(\xi_{1t}) = 0$ and $\lim_{\xi_{1t}\to +\infty}\Gamma(\xi_{1t}) = 1$. We can conclude, using the intermediate value theorem, that for each $a \in [0,1]$, the equation $\Gamma(\xi_{1t}) = a$ has a unique solution.

A.3 Computing the price elasticity

I define by $x_{l,t}^{\inf}$ the consumption threshold corresponding to the lowest bound of block l. The price elasticity in this setting with respect to the price of block l is:

$$
\eta_{lt} = \frac{p_{lt}}{\bar{c}_t}\frac{\partial \bar{c}_t}{\partial p_{lt}} = \frac{p_{lt}}{\bar{c}_t}\sum_k \frac{\partial(\bar{c}_{kt}\tilde{s}_{kt})}{\partial p_{lt}} = \frac{p_{lt}}{\bar{c}_t}\sum_k \left(\frac{\partial \bar{c}_{kt}}{\partial p_{lt}}\tilde{s}_{kt} + \bar{c}_{kt}\frac{\partial \tilde{s}_{kt}}{p_{lt}}\right) \tag{A.23}
$$

where:

$$\frac{\partial \bar{c}_{kt}}{\partial p_{lt}} = \begin{cases} \bar{\omega}_{kt} \exp(-\alpha p_{kt}) D_1(k) g(\bar{\omega}_{kt}) & \text{if } l = k-1 \\ \bar{\omega}_{kt} \exp(-\alpha p_{kt}) D_3(k) g(\bar{\omega}_{kt}) - \underline{\omega}_{kt} \exp(-\alpha p_{kt}) D_4(k) g(\underline{\omega}_{kt}) + \tilde{I}_k & \text{if } l = k \\ -\underline{\omega}_{kt} \exp(-\alpha p_{kt}) D_2(k) g(\underline{\omega}_{kt}) + I_{k+1} & \text{if } l = k+1 \\ I_l & \text{if } l > k+1 \\ 0 & \text{otherwise} \end{cases} \tag{A.24}$$

$$\frac{\partial \tilde{s}_{kt}}{\partial p_{lt}} = \begin{cases} D_1(k) f(\bar{\omega}_{kt}) & \text{if } l = k-1 \\ D_3(k) f(\bar{\omega}_{kt}) - D_4(k) f(\underline{\omega}_{kt}) & \text{if } l = k \\ -D_2(k) f(\underline{\omega}_{kt}) & \text{if } l = k+1 \\ 0 & \text{otherwise} \end{cases} \tag{A.25}$$

$$\frac{\partial s_{kt}}{\partial p_{lt}} = \begin{cases} D_1 g(\bar{\omega}_{kt}) & \text{if } l = k-1 \\ (F(\bar{\omega}_{kt}) - F(\underline{\omega}_{kt})) \left(D_3 g(\bar{\omega}_{kt}) - D_4 g(\underline{\omega}_{kt})\right) + \tilde{I}^S_k & \text{if } l = k \\ -D_2 g(\underline{\omega}_{kt}) + I^S_{k+1} & \text{if } l = k+1 \\ I^S_l & \text{if } l > k+1 \\ 0 & \text{otherwise} \end{cases} \tag{A.26}$$

with:

- $g(\omega) = \frac{\exp(\underline{\omega} \exp(-\alpha p_{kt}) - \alpha d_{kt} + \xi_{kt} + \beta)}{1 + \exp(\underline{\omega}_{kt} \exp(-\alpha p_{kt}) - \alpha d_{kt} + \xi_{kt} + \beta)} \frac{f(\underline{\omega})}{F(\bar{\omega}_{kt}) - F(\underline{\omega}_{kt})}$
- $D_1 = \frac{\partial \bar{\omega}_{kt}}{\partial p_{k-1,t}} = \frac{\alpha x^{\text{inf}}_{k-1,t} (\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k-1,t})) - \alpha \left[\xi_{k-1} - \xi_{kt} - \alpha x^{\text{inf}}_{k-1,t} (p_{kt} - p_{k-1,t})\right] \exp(-\alpha p_{k-1,t})}{(\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k-1,t}))^2}$
- $D_2 = \frac{\partial \underline{\omega}_{kt}}{\partial p_{k+1,t}} = \frac{\alpha x^{\text{inf}}_{k,t} (\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k+1,t})) - \alpha \left[\xi_{k+1} - \xi_{kt} + \alpha x^{\text{inf}}_{k,t} (p_{k+1,t} - p_k)\right] \exp(-\alpha p_{k+1,t})}{(\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k+1,t}))^2} = \frac{\partial \bar{\omega}_{k+1,t}}{\partial p_{k+1,t}}$
- $D_3 = \frac{\partial \bar{\omega}_{kt}}{\partial p_{kt}} = \frac{-\alpha x^{\text{inf}}_{k-1,t} (\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k-1,t})) - \alpha \left[\xi_{k-1} - \xi_{kt} + \alpha x^{\text{inf}}_{k-1,t} (p_{kt} - p_{k-1,t})\right] \exp(-\alpha p_{kt})}{(\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k-1,t}))^2}$
- $D_4 = \frac{\partial \underline{\omega}_{kt}}{\partial p_{kt}} = \frac{-\alpha x^{\text{inf}}_{k,t} (\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k+1,t})) + \alpha \left[\xi_{k+1} - \xi_{kt} + \alpha x^{\text{inf}}_{k,t} (p_{k+1,t} - p_{kt})\right] \exp(-\alpha p_k)}{(\exp(-\alpha p_{kt}) - \exp(-\alpha p_{k+1,t}))^2} = \frac{\partial \bar{\omega}_{k+1,t}}{\partial p_{kt}}$

- $\tilde{I}_k = \int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}} \frac{\omega_i \alpha \exp(\omega_i \exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt} + \beta - \alpha p_{kt})}{1 + \exp(\beta + \omega_i \exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt})} \left(\frac{\left(x_{k,t}^{\inf} - \omega_i \exp(-\alpha p_{kt})\right)}{(1 + \exp(\beta + \omega_i exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt}))} - 1 \right) dF(\omega | \underline{\omega}_{kt} < \omega < \bar{\omega}_{kt})$
- $I_l = \int_{\underline{\omega}_{kt}}^{\bar{\omega}_{kt}} \frac{\alpha\left(x_l^{\inf} - x_{l-1,t}^{\inf}\right) \exp(\beta + \omega_i \exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt})}{\left(1 + \exp(\beta + \omega_i exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt})\right)^2} \omega_i \exp(-\alpha p_{kt})\, dF(\omega | \underline{\omega}_{kt} < \omega < \bar{\omega}_{kt}) \leq 0$
- $\tilde{I}_k^S = \int_{\underline{\omega}_k}^{\bar{\omega}_k} \frac{\alpha(w_k^{\inf} - \omega_i exp(-\alpha p_{kt})) \exp(\beta + \omega_i \exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt})}{(1 + \exp(\beta + \omega_i \exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt}))^2} dF(\omega)$
- $I_l^S = \int_{\underline{\omega}_k}^{\bar{\omega}_k} \frac{\alpha\left(x_l^{\inf} - x_{l-1,t}^{\inf}\right) \exp(\beta + \omega_i \exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt})}{\left(1 + \exp(\beta + \omega_i exp(-\alpha p_k) - \alpha d_{kt} + \xi_{kt})\right)^2} dF(\omega) \leq 0$

A.4 Simulation results

Table A.1: Simulation results

Number of markets	$\alpha = 0.5$	$\sigma = 2.5$	$\beta = 6$
With correlation			
12	0.499	2.547	5.991
	(0.05)	(0.588)	(0.521)
24	0.497	2.487	5.965
	(0.05)	(0.0.474)	(0.532)
50	0.497	2.488	5.972
	(0.047)	(0.381)	(0.495)
Without correlation			
12	0.500	2.555	6.003
	(0.05)	(0.588)	(0.521)
24	0.498	2.493	5.986
	(0.05)	(0.469)	(0.532)
50	0.5	2.504	6.009
	(0.046)	(0.378)	(0.488)

The numbers in brackets are standard errors of estimates across different Monte Carlo samples.

B The price elasticity of block pricing scheme in the literature

Since there is more than one price in the block pricing scheme, the definition of price elasticity is less evident.

Instrumental variable approaches With IV-estimator approaches, the idea is to express the observed demand as a function of the price and other parameters. Then the price elasticity, as defined in the literature, is already given by/is computed from the price coefficient. As discussed earlier, this approach regresses the conditional demand on the corresponding marginal price. The estimated price elasticity is the conditional price elasticity that does not incorporate block-switching behavior. It gives an idea of how much, on average, an individual changes his (conditional) demand if the corresponding marginal price changes conditional on remaining within the same block (Olmstead, 2009; Olmstead, Hanemann, and Stavins, 2007; Hewitt and Hanemann, 1995). This price elasticity can be calculated from the parameter α in my setting.

Given that this approach misspecifies the demand function (Reiss and White, 2005; Moffitt, 1990; Hewitt and Hanemann, 1995) and that the identification may rely on weak instruments (Reiss and White (2005)), this price elasticity may be misleading. The price elasticity using this approach is known to be lower than the one yielded by the DCC model.

Case of structural approach With the DCC model, the conditional price can still be estimated. Olmstead, Hanemann, and Stavins (2007) contribute by providing the formulation of unconditional price elasticity in the case of increasing block pricing. It is defined as the relative change in the average demand ($\bar{c}$ in my setting) if all the prices of the scheme change by the same amount at once.

The increasing block case is different from decreasing block pricing mainly because of the convex nature of the budget constraint (Figure B.1). In a decreasing block pricing scheme, the nonconvex budget set makes the kink points suboptimal while allowing for multiple tangencies between the budget constraint and the indifference curves. An implication of multiple tangencies is that it is hard to predict where the consumer will end up after changing one element of the pricing structure. And the effect of a change in price on consumption may display jumps [40](Heckman and MaCurdy, 1982). A change in the price of block k may affect the probability of choosing the next blocks through the difference variable but may also affect the choice probability of the previous blocks because for k to be optimal, the utility of consuming in that block verifies that $V_{ikt} = max_l V_{ilt}$. This is not the case with increasing block pricing schemes. The

[40]Heckman and MaCurdy (1982) proposed solving this problem by setting a utility function that is monotonic in consumer heterogeneity in the level of consumption.

Figure B.1: Increasing block pricing scheme

(a) Increasing block tariff

(b) Budget set

convex nature of the budget constraint (Figure B.1) allows recovery of the optimal choice by local comparison: k is optimal if it yields the highest level of utility compared to the proximate blocks (Heckman and MaCurdy (1982)). A change in the price of block k only affects the choice probability of the kink point and leaves the decision to choose the previous block unaffected.

Following Heckman and MaCurdy (1982) suggestion, the demand function in my framework increases with the consumer type, which solves the previous problem. As in the increasing block case, the local comparison approach may be used. As a consequence, the change in the price of a block will affect only the adjacent block among the preceding ones.

In this section, I examine the effect of a change in the price on consumption and market shares. The time subscript(t) was suppressed to simplify the expressions.

Conditional market share effect: optimal block given positive consumption The conditional market share is described in equation (6) by $\tilde{s}_k = F(\overline{\omega}_k) - F(\underline{\omega}_k)$. If the price of block k, p_k, increases, only three blocks' market shares are affected: the k-th block and the two adjacent blocks. This is because the two thresholds $\bar{\omega}_k$ and $\underline{\omega}_k$ are affected. The two adjacent blocks are therefore affected since they share their boundaries with block k: $\bar{\omega}_k = \underline{\omega}_{k+1}$ and $\underline{\omega}_k = \bar{\omega}_{k-1}$. The other market shares are left unaffected, restraining the substitution between the three blocks. This is a characteristic of the PCM with only one random coefficient. The total effect is then:

$$\frac{\partial \tilde{s}_{k-1}}{\partial p_k} + \frac{\partial \tilde{s}_k}{\partial p_k} + \frac{\partial \tilde{s}_{k+1}}{\partial p_k} = f(\bar{\omega}_k)(\frac{\partial \bar{\omega}_k}{\partial p_k} - \frac{\partial \underline{\omega}_{k-1}}{\partial p_k}) + f(\underline{\omega}_k)(\frac{\partial \bar{\omega}_{k+1}}{\partial p_k} - \frac{\partial \underline{\omega}_k}{\partial p_k}) = 0$$

Unfortunately, given equations (A.24) and (A.25), the sense of variation of the affected blocks' market shares cannot be determined since the sign to $(D_l)_l$ cannot be a priori predicted. Table

Table B.1: Effect of prices on conditional market shares

	Block rank	2	3	4	5	6	7	8	9
Tariff D3	1	-	-	-	-	-	-	-	-
	8	0.847	-0.847	0	0	0	0	0	0
	7	-0.836	1.221	-0.385	0	0	0	0	0
	6	0	-0.3723	0.444	-0.072	0	0	0	0
Tariff D4	5	0	0	-0.061	0.167	-0.107	0	0	0
	4	0	0	0	-0.099	0.051	0.0486	0	0
	3	0	0	0	0	0.052	-0.166	0.114	0
	2	0	0	0	0	0	0.115	-0.096	-0.02
	1	0	0	0	0	0	0	-0.019	0.019

Each row presents the change in the block market shares in the column with respect to the price of the block in the row. The consumers are not allowed to choose to locate in the first block; therefore, this block is not affected by any change in price. The numbers represent the average effects over the period.

B.1 shows the price effect of the conditional market shares computed with observed data[41]. Each row reports the price effect of within-market shares with respect to the price of a block in the row. In general, an increase in the price of block k increases block k's market share and decreases the other two blocks' market shares. It is expected to see that consumers of block $k+1$ shift to lower consumption in k, since the higher the price of block k, the more expensive it is to consume in $k+1$. The effect on lower block conditional market shares seems to be different. The higher the price of block k, the closer it is to the price of block $k-1$ and therefore, the lower is the penalty of shifting to the next block. As expected, the effect is lower, in absolute value, as we move to upper blocks. This is consistent with the idea that heavier consumers tend to be less sensitive to the cost.

Overall effect: the inside vs outside option choice In this subsection, the effect of a price change on market share s_k is described using Equation (10) and calculations in Appendix A.3.

An increase in the price of block k negatively affects both the overall consumption and the inside goods market shares.

[41] Since the first block is designed to have a zero market share, it was suppressed from estimation. A change in the price of this block left the conditional market shares unaffected, and the share of this block is unaffected by other prices.

Table B.2: Cross and own price elasticities of market shares

	Block rank	2	3	4	5	6	7	8	9
Tariff D3	1	-0.022	-0.022	-0.021	-0.008	0	0	0	0
	2	8.369	-4.935	-0.040	-0.015	0	0	0	0
	3	-7.546	8.598	-0.964	-0.040	-0.001	0	0	0
	4	0	-3.902	2.903	-0.183	-0.003	0	0	0
Tariff D4	5	0	0	-1.903	7.750	-1.668	0	0	0
	6	0	0	0	-7.395	0.831	4.261	0	0
	7	0	0	0	0	0.699	-10.209	25.447	0
	8	0	0	0	0	0	5.873	-21.704	-5.048
	9	0	0	0	0	0	0	-3.391	4.754

Each row presents the elasticity of the block market shares in the column with respect to the price of the block in the row. The consumers are not allowed to choose to locate in the first block; therefore, this block is not affected by any change in price. The elasticities are the median elasticity over the period of study. These elasticities take into account switching behavior both between blocks and to the outside option, in addition to the consumption change conditional on remaining in the block

Increasing the price of the $k-th$ block p_k results in an increase in the difference variable of all following blocks and therefore makes it costly to consume in these blocks. Those blocks are, therefore, less attractive compared to the outside options. The consequence is a lower market share of blocks and a lower average consumption in those blocks, reduced, respectively, by I_l^S and I_l. So, with a lower probability of consuming within these blocks and a lower average consumption, the unconditional consumption will probably be lower. This is the same result as found by Olmstead, Hanemann, and Stavins (2007), consistent with the negative effect of price on the demand for normal goods. However, we expect that there will be no effect on blocks before $k-1$ since the cost of consumption in these blocks is independent of the $k-th$ block[42]. Predicting the effect on the $k-th$ block and the previous block is more difficult given the Equations (A.24), (A.25), and (A.26). But given the computed effect on conditional market shares, we can conjecture that the effect might be positive and negative, respectively, for the two blocks.

Table B.2 shows the elasticities of the market shares with respect to the block prices (in the row). The results display the expected signs. As expected, increasing the $k-th$ block negatively

[42]To solve the model à la PCM, blocks were ordered increasingly with the price. Therefore, in Equations (A.24), (A.25), and (A.26), the block $k-1$ and $k+1$ correspond respectively to the upper and lower blocks of the initial pricing structure.

affects the market shares of the blocks above k. The closer to block k, the higher is the effect.

Unconditional price elasticity I follow the method applied by Olmstead, Hanemann, and Stavins (2007) to derive the elasticity. I define the average consumption after a proportional change of γ in all prices by: $\bar{c}(\gamma) = \bar{c}(P), \quad P \equiv \gamma \times (p_k)_k$. The unconditional price elasticity is:

$$\frac{\gamma}{\bar{c}(\gamma)} \frac{d\bar{c}(\gamma)}{d\gamma}|_{\gamma=1}$$

with average consumption defined by Equation (12).

C Robustness checks

C.1 Outside option computation

The goal is to use the market size to find out how many agents choose not to consume natural gas. Since *Energir* customers are assigned to tariffs depending on their consumption profile, the idea is to find the total number of potential consumers that would have been assigned to those tariffs if they were *Energir* customers.

I assume that industrial demand is mainly from the manufacturing sector, which is a heavy user of energy in Canada. I proceed in two steps. In the first step, I look for the total number of industries in Quebec. In the second step, I evaluate the market size of the studied tariffs as the number of industries eligible for those tariffs. The number of manufacturing industries is from published reports of *Institut de la Statistique du Québec* and *STIQ*[43] (Sous-traitance industrielle Québec). Information about energy consumption by sector is public information provided by Statistics Canada.

C.2 The weight of the price

In this section, I will give more details on price calculation. Let P and $P^{'}$ two block pricing schemes applied in the period. Then, the used price is $P^{*} = (n_1 P_k + n_2 P^{'}_k)$. The weight n_i is either 1/2 (uniform weights) or the part of the consumption (consumption weights) during each

[43] An association of Quebec-based manufacturers.

tariff's application in the period's total consumption. Table C.1 gives the result estimation for $n_i = 1/2$ The results using the two chosen instruments do not seem to be close. A first analysis was done using the whole set of available instruments. This corresponds to seven-moment conditions (with the constant) for identifying two parameters. The result seems to be the same. Another check will be done with the estimates of the optimal instruments.

Table C.1: Estimation results

$\hat{\alpha}$	$\hat{\sigma}$	$\hat{\beta}$
0.066	2.813	-2.1

D Estimation

Variation in instruments The proposed prices by the firm are observed, as are the implemented prices. The proposed instrument is the difference between the two prices. The idea is to use the deviation from the proposed prices as instruments. This deviation is assumed to be mean-independent with block-varying demand shocks. Table D.1 represents some descriptive statistics on available instruments.

Table D.1: Variation in instruments

	Min	max	Coefficient of Variation
Price (10 dollars cents)	1.479	3.770	0.203
Proposed price-observed price (10 dollars cents)	-2.958	-1.384	-0.188
Tariff implementation delay (months)	0	10	2.744
Losses of gas (billions of dollars)	3.354	7.580	2.034
Number of maintenance intervention (10^3)	19.465	21.879	1.947

The coefficient of variation reported for the last four lines is computed on the interaction of the instrument with block boundaries