Application of MDCEV to infrastructure planning in regional freight transport

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Abstract

The main objective of the paper is to develop a model capable of evaluating the societal impact of rail infrastructure investment in Argentina, using a Multiple Discrete Extreme Value Model (MDCEV) estimated on Stated and Revealed preference data. The decision modelled is the mode and port choice at a planning level, where multiple alternatives can be chosen simultaneously. The relevant variables were the *Free Alongside Ship* (FAS) price, *freight transport cost*, *travel time* and *lead time*, including non-observed heterogeneity in the modelling. As a consequence, the willingness to pay measures that are used for the cost benefit analysis become non-deterministic. To include this effect simulated WTP measurements were included and compared to a deterministic and risk based approach. Two projects were tested and both showed that the deterministic approach gives higher Benefit/Cost ratio. This paper raises the concern that if non-observed heterogeneity is not considered in project evaluation it may provide misleading results and potentially lead to wrong investment priorities for the public sector.

Keywords MDCEV, Multiple discreteness; freight choice modelling; cost benefit analysis

1. INTRODUCTION

The growth in global commerce has raised the demand for freight transport, worsening congestion, ecological externalities (Liedtke, 2009) and causing an increase in the contribution of the transportation sector to greenhouse gas emissions (Tian et al., 2014). This raise has motivated the interest to generate public policies that help decarbonize the freight transport sector, for example by inducing a shift towards less carbon intensive modes (International Energy Agency, 2013). Additionally, freight transport has a large impact on the overall competitiveness of an economy (Capka, 2008), further motivating the implementation of more efficient and cheaper modes. In order to achieve these objectives, over the last decade there was an increasing interest in developing freight transport models and understanding the transport decision making in the freight transport context (National Academy of Science, 2010; Samimi et al., 2010; Windisch et al., 2010).

One of the main modes of transport to boost the decarbonisation of the freight sector is rail transport. However, the level service that rail has to offer in order to be competitive against road transport is not easily obtained, and often requires high investments in infrastructure and rolling stock. A model capable of evaluating the impact of improvements in the level of service, comparing them to the costs can help determine investment priorities and effectiveness of the measures. Cost-benefit analysis (CBA) (Make and Preston, 1998) linked to a model that has a behavioural framework can be a useful tool to analyse investments.

A key item in CBA of the transport sector is the value of time (VOT), since time savings have often the largest shares of benefits (Gwilliam, 1997). Behavioural models created to provide inputs to CBA can provide an accurate VOT for the analysed project. Moreover, the model can provide the level of uncertainty of the estimate in order to include it for risk analysis (e.g. Salling and Leleur, 2009) The uncertainty can come from the inclusion of unobserved heterogeneity (Hess et al., 2005) or from the standard errors of the estimation. So far no other work has been found that includes the effect of unobserved heterogeneity in CBA analysis, although recent VOT studies are starting to incorporate it to estimate confidence intervals (Hess et al., 2017).

In spite of its importance, freight demand modelling has struggled to keep pace with passenger ones (Hensher and Figliozzi, 2007) and often relied on aggregate models without much behavioural content (Ellison et al., 2017; Pourabdollahi et al., 2013). Freight transport differs from passenger transport in several aspects: i) data availability (Brooks and Trifts, 2008; Rashidi and Roorda, 2018); ii) multiplicity of actors and its behaviour complexity (Arunotayanun and Polak, 2009; de Jong et al., 2013) and; iii) time period modelled (Tavasszy and de Jong, 2014).

Given the increasing complexities of the supply chains, there is a very strong need to adopt disaggregate models of logistics behaviour (Chow et al., 2010; de Jong et al., 2013; Hensher and Figliozzi, 2007). Freight transport involves multiple decision makers whose preferences and attitudes influence the choice making process. The identification and targeting of these key actors is crucial for successfully model the phenomena. In addition, the variety of products also makes the behaviour of these agents heterogeneous.

Part of the particularities of freight transport come from the period that choices cover. At an operational level (short term), the decision can be purely discrete: How to take one single shipment to a single destination. Nevertheless, at a tactical level, where some of the planning and commercial decisions are made, there can be room for choosing multiple alternatives (not always the same mode, for instance). The selection of multiple alternatives can be made to reduce risk, to obtain smoother cash flows or to have a stable inventory flow. Additionally, tariffs are negotiated at this decision level, aggregated volumes are likely to be computed making it a relevant decision stance. This type of choice is referred as multiple discrete (Hendel, 1999) and it assumes that alternatives are no longer perfect substitutes.

Although there are cases where multiple discreteness might exist, most of the choices in freight transport are modelled under the traditional discrete choice framework (Chow et al., 2010; Danielis and Marcucci, 2007; de Jong et al., 2013; Rich et al., 2009; Vellay and de Jong, 2003). Multiple discrete choices where the intensity of the decision (e.g. how many tons are allocated to each alternative) is modelled are called Multiple Discrete Continuous, with the Multiple Discrete Continuous Extreme Value Model (MDCEV) (Bhat, 2008, 2005) as the most recent expression of these models. Few applications of the MDCEV have been found in the freight literature, and all in the urban freight context (Khan and Machemehl (2017) and Rashidi and Roorda (2018).

Argentina's exports are strongly dependant of the agricultural sector. Currently around 90% of the grain is transported by road, affecting the competitiveness of the sector when compared with larger countries such as the US (Schnepf et al., 2001) and producing other externalities such as higher fuel emissions and accidents. In the last few years the Ministry of Transport has increased the investment in rail infrastructure in order to increase the rail market share, but always with a strong budget constraint. In this context the relevant question on how to measure the impact and evaluate if the investment is compensated by the overall impact to society becomes particularly relevant.

The main objective of the paper is to develop a model capable of evaluating the societal impact of rail infrastructure investment that considers the multiple discreteness of freight planning choice. The secondary objectives are: i) estimate an MDCEV model with Revealed Preference (RP) and Stated Preference (SP) data; ii) apply the MDCEV's forecasting algorithm in order to calibrate the model and evaluate different scenarios and; iii) incorporate the different impacts of the model into the infrastructure evaluation and compare it with the deterministic and traditional risk analysis. The proposed model was estimated and applied in Argentina.

The contributions of this paper are threefold. Firstly, we model the freight choices on a tactical level. This means that we abandon the traditional approach that considers freight choices to be purely discrete and study the implications of planning decisions in modal choice. Secondly, we apply and forecast the MDCEV model in the regional freight context combining SP and RP data. To our knowledge, no other work has used the MDCEV in this context of mixing several data sources of a different nature. Both contributions address and help to reduce the gap between passenger and freight transport modelling and practical applications. Finally, we consider the cost benefit analysis to be non-deterministic due to the inclusion of random parameters in the model estimation process. The increasing use of the mixed logit due to the improvements on model fit has led to the inclusion of random parameters causing that the value of time and other attributes become non-deterministic. Consequently, the investment evaluation is also non-deterministic. Nevertheless, we are not aware of other paper that includes randomness in the value of time due to non-observed heterogeneity into infrastructure evaluation.

The rest of the paper is organized as follows. Section 2 provides a description of the case study and the data collected. Section 3 describes the method adopted for model estimation, calibration and application. Section 4 presents the estimation and application results and section 5 discusses the results obtained. Finally, section 6 draws some conclusions and suggests future research.

2. CASE STUDY

This section describes the study area and logistic system of inland grain transportation in Argentina. It is then followed by the description of the Stated Preference (SP) and Revealed Preference (RP) data used for the model estimation and scenario evaluation.

2.1. Study area

Argentina´s agricultural sector is a dynamic and relevant sector in the country's economy. The exports of grains and derivatives represents 44% of the total exports (INDEC, 2018). The high share of road transport in the modal split has a large impact on the competitiveness of the agricultural sector because of the higher transport prices relative to other countries such as the United States (Schnepf et al., 2001). Some authors (Barbero, 2010; Regunaga, 2010) blamed the relatively short distances to the ports for the low share of rail transport, although the low level of service of rail will also have contributed to this (Raposo, 2014). Therefore, the Argentinian government has shifted the transport policy in an effort to increase rail share. Some of the actions involve a change in the service provided, such as the open access policy (sanctioned in 2015 and not yet implemented). Other actions involve the restoration of rail infrastructure in order to achieve better levels of service and commercial speeds. Considering the extension of the rail network and the budget constraints, some prioritization of investments needs to be made, especially considering the economic and financial constraints faced.

Argentina has three main grain exporting ports: Rosario, Bahia Blanca and Quequén. Rosario is the largest port in the country, having exported around 70% of the agricultural products in the year 2005 (Sánchez et al., 2006). It consists of several terminals located on the west Parana River bank. In this paper, the port of Rosario will be split in two parts, following the political demarcation of the Santa Fe province. The northern part is in the department of San Lorenzo and the southern part in the department of Rosario. It is located near the highest agricultural output area of the country. This separation also coincides with different rail companies arriving to each terminal.

The second largest in agricultural export and the deepest port is Bahia Blanca (BHB). It moves around 16% of the grain export movement. Because of the deepest draft, some ships are pre-loaded in Rosario and completed in BHB. It is surrounded by a relative unproductive agricultural area, that affects the port capacity of attracting cargo.

The last port with significant throughput is Quequén (QQN), exporting around 12% of the agricultural products. It is located on a river mouth, causing the draft to vary with the tide. It is surrounded by a relatively productive area, but its low port efficiency affects the port ability of gaining hinterland. This efficiency is partially reflected in a Free Alongside Ship price penalization of the port. Additionally, there are some other terminals located alongside the Paraná River. However, they are small terminals without a significant impact in the port system.

The transport system also follows an export-oriented logic since the first railroads were created. Currently, there are four main rail companies serving the country. The rail network was privatized at the beginning of the 1990ties because of the high economic deficit and low volume transported. After the privatization, transported volumes have risen but the overall market share has declined and cases of vertical integration occurred (Raposo and Cafarell, 2010).

Firstly, *Ferrosur* operates in the Southeast of the Buenos Aires Province. It mainly transports minerals from the quarries towards Buenos Aires. It is also connected to the port of Bahia Blanca (BHB). The second company, the *Ferro Expreso Pampeano* (FEPSA) serves the west of the Buenos Aires Province, East of La Pampa province and south of Santa Fe province connecting the port of BHB with Rosario. It mainly carries agricultural products. The third company is the state-owned *Belgrano Cargas y Logística*. It serves the North and Northeast of the country, carrying mainly agricultural products towards the port of Rosario. Finally, *Nuevo Central Argentino* (NCA) serves the Cordoba province, with some lines going to Tucuman. It mainly transports agricultural products (grain and industrialized) and it is linked with a major oil crusher.

For modelling purposes, the productive area of the country has been divided in to 10 zones, based on the available ports and railways attending each area. The objective was to create zones that respond to a particular hinterland and attended by one Rail Company. Zone 1 is attended by Ferrosur and is in the overlapping hinterland (area of influence) between QQN and BHB. Zone 2 is under the influence of Rosario and served marginally by NCA and FEPSA, while zone 3 is within the influences of Rosario and BHB and worked by FEPSA. Zone 4 contains the province of Cordoba and Santiago del Estero, areas supplied by NCA. Zone 5 covers the province of Santa Fe and is supplied by Belgrano Cargas.

Zones 6 to 9 are less relevant regarding agricultural production. Zone 6 corresponds to the east bank of the Paraná River, zone 7 for the North Eastern provinces, served by the Belgrano Cargas. Zone 8 is partially served by the Belgrano Cargas and NCA. Finally zone 9 corresponds to east Buenos Aires province, close to the QQN hinterland and with no freight rail service. Figure 1 shows the location of the zones and their total agricultural output in tons per km2.

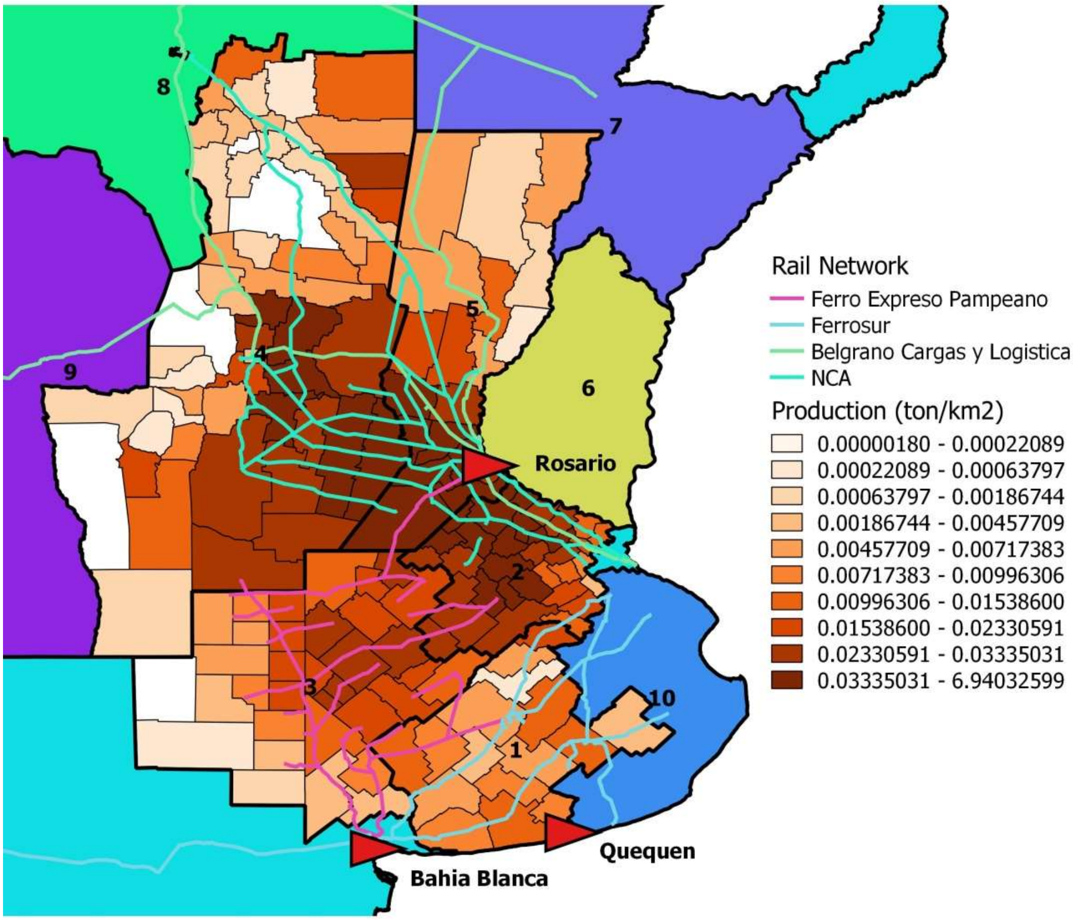


Figure 1: Study area

2.2. Logistic system

The Argentinian agricultural sector is currently a modern and innovative sector. It was transformed by the introduction of technology, genetically modified seeds, fertilizers and new ways of managing the supply chain. Figure 2 shows the main configuration, together with their main actors and their interactions.

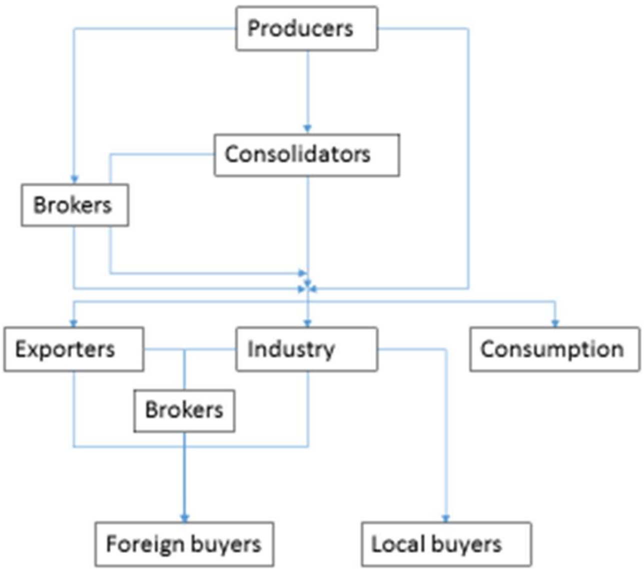


Figure 2: Agricultural supply chain source: (Instituto Nacional de Tecnología Agropecuaria, 2009)

The agricultural supply chain agents can be divided into two groups, depending on their main roles. The receivers involve exporters, industry or consumers and the senders, consisting of producers and consolidators. As seen in figure 1, producers have two options for selling their crops:

- They can sell to exporters or industry (directly for the large producers, or using brokers as intermediaries);
- or they can sell their products to a consolidator.

The brokers are agents that help to match buyers and sellers and are not directly part of the decision making process of the supply chain. Since 46% of the production is carried by a large number of small and medium producers (Regunaga, 2010), they are likely to sell through consolidators. Besides, some large producers might also need conditioning for their seeds before selling them and this is normally carried out by consolidators. Therefore, consolidators are key agents in the decision of where and how the inland transport is carried out in Argentina. Nevertheless, with the increased utilization of temporary storage facilities (*silobolsas*), producers have gained bargaining power in the supply chain because they are no longer obligated to sell at harvest time.

The buyers, especially for soybeans and sunflower, are concentrated in the ports due to the heavily export oriented nature of the production system, either for raw material (e.g. soybeans) or processed goods (e.g. soy oil). This has led to a high concentration of industries near the main exporting ports. Consequently, most of the grains produced in Argentina are destined to ports and have a common reference price, independently if it is bought for crushing or exporting. The dynamics of the interaction between buyers and sellers are normally reflected in the port's stock market, and the main reference parameter is the Free Alongside Ship price.

2.3. SP data

The SP data come from a survey conducted with the support of the Ministry of Transport of Argentina, orientated to commercial decision-makers in consolidator firms. The interviews were undertaken between June and September 2017. The commercial department of 467 consolidators located in zones 1-5 were contacted by email. From the contacted, 127 were also called to explain the survey instrument, and finally 58 valid questionnaires were obtained, a good amount for the freight context (Larranaga et al., 2017). Responses from all the study areas were obtained, resulting in a varied sample from the different areas of the country.

The SP experiment comprised 12 choice situations and presented to the interviewees as a spreadsheet sent by email. In each choice situation four mode-port alternatives were presented to the consolidator. The alternatives represent two unlabelled ports (one closer and other further away) with 2 labelled modes each (road and rail). The ports, although unlabelled, represented the 2 main ports for each consolidator, according to their location. The choice context included the following question: “Which percentage of your shipment would you send by each alternative?”

The response variable was the percentage of available cargo they would allocate to each of the four alternatives, similarly as used by (Brooks et al., 2012). The available cargo was stated in the scenarios and to fit the stated size of the company. It is expected that this method can capture small trade-offs between alternatives that are not strong enough to induce a shift to an alternative but can lead to a change in the allocation between alternatives. For example, if by changing the attributes between two scenarios the amount chosen for alternative B decreases from 90 to 80%, traditional choice surveys would not be able to register this shift because it is not large enough to change the preferred alternative. Figure 3 illustrates the choice situation presented to the respondents.

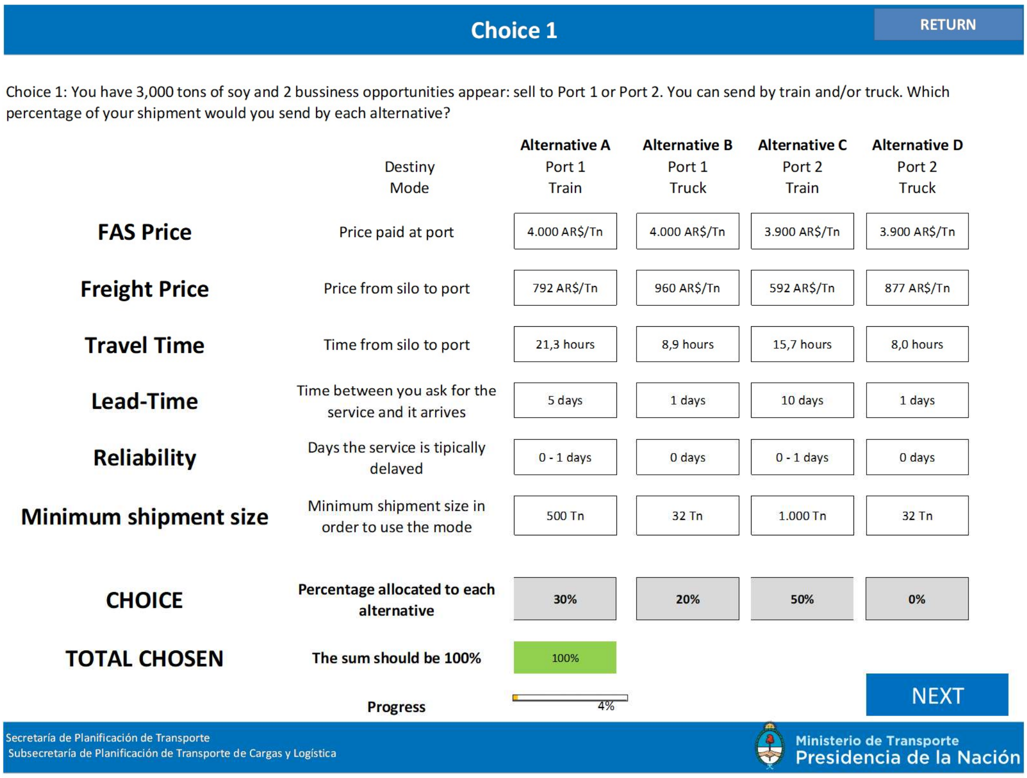


Figure 3: Choice task

The experimental design included six attributes with 3 levels each: (i) *FAS price* (Free Alongside Ship price) - the price paid at the port to the producers, (ii) *Freight transport price*, (iii) *Travel time*, (iv) *Lead time*, (v) *Reliability* and (vi) *Minimum shipment size*. The attributes were selected based on the literature review and a previous study performed in a similar context. The first four attributes were included in the previous work (Tapia et al., 2019). *Reliability* was considered in several studies (Cullinane and Toy, 2000; Feo-Valero et al., 2011; Feo et al., 2011; Hoffmann, 2003; Shinghal and Fowkes, 2002; Zamparini et al., 2011). *Minimum shipment size* was added due to compatibility with some models currently used in the Ministry of Transport. Although the number of variables tested tends to be too high for a SP experiment, all the variables were considered to be relevant for the model and its application. Independent variables with 3 levels allows the model to consider non-linearities of the preferences.

The experimental design was structured using an Efficient design (Rose and Bliemer, 2009) and implemented in NGene (ChoiceMetrics, 2014). Efficient designs allows to maximize the information obtained from the SP experiment by selecting among the possible combinations of variables the ones that could potentially provide more information to the model. Initial parameters for *FAS price*, *Freight transport price* and *Travel time* were adopted based on the previous study mentioned earlier. In the case of *Reliability*, the initial parameter value was taken from an study performed in another Latin-American country (Brazil) (Larranaga et al., 2017). Finally, a small negative amount was used for the minimum shipment size.

The values for the *FAS price* levels were based on the prices obtained for Rosario at the beginning of the survey (09/06/2017) for wheat, sunflower, maize and sorghum. The attribute levels for both ports were: the same price, with a 2.5 or 5% reduction. The price for each grain presented depended on the main production of the consolidators, which was asked in the first part of the questionnaire.

For *Freight transport price*, *Travel time*, *Lead time, Reliability* and *Minimum shipment size*, a reference value for the truck was set and then simulated values for rail. Consolidators in Argentina are used to deal with road transport and a high variation of the reference values could make the hypothetical situations unrealistic and could cause the loss of engagement of the respondent. A similar approach has been used by Tapia et al. (2019).

The reference value for truck freight price (*Freight transport price)* is the official published one (CATAC, 2017), and the *Travel time* was considered of 65 km/h. The *Freight transport price* levels for rail were set at 67.5, 75 and 82.5% of the truck prices. For train travel time (*Travel time)*, a reference travel speed of 30 km/h was taken. The other values were 90 and 110% of that travel time.

Lead time, defined as the maximum time the shipper had to wait for being attended by the road/rail service, was defined to be 0.5 days for the truck. For rail it varied between 5, 7 and 10 days. *Reliability* was defined as the number of days the loading of the train could be delayed and took values between 0, 1 and 3 days. For truck, this was set to 0.

For the *Minimum shipment size*, the minimum volume of the shipment to be carried by train, ranged between 500 tons and 1,500 tons. For truck it was considered to be a truckload (32 tons).

The option to select more than one alternative was used intensively by the respondents. 91% of the participants chose in at least one choice task more than one alternative. Regarding each choice task, 85% chose at least two alternatives, and 30% at least three and 13% of the interviewees allocated some cargo to all four alternatives. This suggests that the alternatives have some level of complementarity and are not mutually exclusive.

2.4. RP data

The RP data consists of a consignment bill (CB) database where every grain vehicle movement is registered. The data used in this paper is a national level version of the one used in (Tapia et al., 2019), so the same issues and procedures are used.

The CB has no linkage to the shipper, carrier or receiver due to confidentiality issues. The information contained by this database consists of consignment bill number, transport mode, year of harvest, origin, destination, load weight and date of unloading. The database consists of 4,6726,09 records of interregional grain transport at a national level, where 2,932,686 are from places where rail and road are both present. As the records consist of vehicle movements and not of shipments, there is the need to consolidate them in order to analyse the choice context with more accuracy. This merging of records is made under the assumption that consecutive records with the same product, origin, destination and data consists on the same shipment. The consignment bills are electronically ordered at a national level, so the above assumption is reasonable. After the merging, 1,104,243 records remain. Further filtering was done to obtain focus on departments were more than one mode was used.

To approximate rail availability and rail lead time, the data from the CB was used. In order for rail to be available in certain department, at least one shipment had to be originated from the area. Tapia et al. (2019) used an additional restriction of minimum shipment size since the railway does not serve small shipments, but in this application the volume of the shipment was used as an independent variable of the model. The lead time was computed as the minimum time between shipments to a certain region. The variable is interpreted as the capability of the rail company to provide consecutive services to a certain area.

Time between zone pairs was estimated from a GIS shapefile of currently operational railways and the main roads. With the python package ‘networkx’ (Hagberg et al., 2008) time for each O-D pair was extracted using the Dijkstra shortest path algorithm. Freight cost values were obtained from the official pricing list for trucks (CATAC, 2014) and the pricing list for the San Martin railway (Belgrano Cargas y Logistica, 2014). FAS prices were obtained from the port of Bahia Blanca's board of trade (Bolsa de Comercio de Bahia Blanca, 2016) for the ports of Rosario, Quequén and Bahia Blanca, alongside with the AR$/US$ exchange rate.

2.5. Additional data

Additional data was used for augmenting the RP database for the scenario generation. The following process was adopted in order to obtain the relevant variables for the baseline and proposed scenarios.

Time data for the calibration and the scenario generation was obtained with the same method of extracting it from the GIS shapefile. For the scenario generation, the new commercial speed and new lines are modified in the shapefile and then extracted. This was considered an easy and straightforward and replicable way of creating multiple scenarios. The volume of each choice was considered to be the same from the RP data.

The FAS prices were obtained for 2018 and used for the calibration and the forecast (FyO, 2018). This assumes that seasonality and relative prices between ports remain constant for the forthcoming years of the scenarios. The dollar price for the future scenarios is 40 AR$/US$, the value adopted for the 2019 national budget projections.

Freight prices for truck are taken from the last available price list from the truck drivers´ association (CATAC, 2017). Rail prices ceased to be published in 2016. In order to use them for 2018, the 2016 rail price list (Belgrano Cargas y Logistica, 2018) was updated by the same index as the truck prices. For the scenarios, the same prices as in 2018 were considered.

Infrastructure, operating and maintenance costs adopted for each scenario were based on COSFER (Ministerio de Transporte de la Nacion Argentina, 2017). COSFER is a cost model where with the input data of the rail line (rail gauge, terrain, maintenance type, volume, average distance, type of product, commercial speed and rail improvement), the annualized cost for infrastructure investment, operational costs and maintenance costs are returned. The discount rate adopted by the COSFER is 5% and prices are dollarized.

Additionally, the COSFER model returns the cycle of the train formations. This value provides the minimum headway the rail service can offer to a certain region and thus, being comparable with the lead time values used in the estimation. For the calibration, the headway was considered the same as in the RP data.

3. METHOD

This section presents the model estimation, calibration and the scenario generation approach using the data described before. For the model estimation and forecast, the CMC R code was used (CMC, 2017). The base model used in the paper is the MDCEV.

The attractiveness of the MDCEV framework resides in the closed form of the likelihood function and the straightforward interpretation of its parameters (Pinjari and Bhat, 2011). Mixed and nested uses have also been developed to complement the MDCEV's framework (Calastri et al., 2017). In 2018 a new MDCEV model has been introduced (Bhat, 2018).

The MDCEV framework has been used in multiple sectors and contexts. In transportation there are two main applications: time use models and vehicle choice models. In time use models the discrete dimension is which activities to participate and the continuous dimension is for how (Bhat, 2005; Bhat et al., 2006; Calastri et al., 2017; Kapur and Bhat, 2007; Shamshiripour and Samimi, 2017). Vehicle choice models treat different brands or type of vehicles as alternatives and the amount of miles driven as the continuous dimension (Bhat and Sen, 2006; Jian et al., 2017; Shin et al., 2018, 2015; You et al., 2014). In mass consumption products some of the applications were: fuel usage (Huh et al., 2018), promotions effects in alcohol consumption (Lu et al., 2017), fresh food consumption (Richards et al., 2012) and fluid milk packaging labelling (Bonnet and Bouamra-Mechemache, 2016).

There are some applications of a discrete-continuous framework in freight modelling. Some efforts have been made in modelling the joint decision of mode and shipment size (Abdelwahab and Sargious, 1992; de Jong and Ben-Akiva, 2007; Holguín-Veras, 2002; Johnson and de Jong, 2011; Mcfaden et al., 1986; Windisch et al., 2010), but not in the form of MDCEV models. The MDCEV framework has been applied in the studies performed by Khan and Machemehl (2017) and Rashidi and Roorda (2018). Rashidi and Roorda modelled freight vehicle ownership of Canadian businesses with a multivariate copula. Their approach is a direct adaptation from passenger transport modelling to freight. The paper by Khan and Machemehl applies a Multiple Discrete Continuous Probit (MDCP) for choice of time of day of freight shipments. They model the number of miles (continuous dimension) used in each time of day period (discrete dimension).

3.1. Choice Model Estimation

The model used for representing the choice of mode and port in Argentina was the MDCEV model (Bhat, 2008, 2005). The utility and likelihood (LKH) function of the MDCEV are given by equations 1 and 2.

$$U(x) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_k \left\{ \left(\frac{x_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} \tag{1}$$

$$LKH = \frac{1}{\sigma^{M-1}} * \left[\prod_{i=1}^{M} c_i \right] * \left[\sum_{i=1}^{M} \frac{1}{c_i} \right] * \left[\frac{\prod_{i=1}^{M} e^{\frac{V_k}{\sigma}}}{\left(\sum_{k=1}^{K} e^{\frac{V_k}{\sigma}} \right)} \right] * (M-1)! \tag{2}$$

Where $\psi_k = e^{V_k + \varepsilon}$, x_k is …, $c_i = \left(\frac{1-\alpha_i}{e_i + \gamma_i} \right)$, $V_k = \beta_k z_k + (\alpha_k - 1) ln \left(\frac{e_k}{\gamma_k} + 1 \right)$, $\beta_k z_k$ are vectors of coefficients and attributes, e is the amount chosen for each available alternative, M are the chosen alternatives, σ is the scale parameter of the error term and $\alpha_k$and $\gamma_k$satiation parameters.

In 2018 a new MDCEV model with its forecasting algorithm was introduced (Bhat, 2018). This model was not used here because it was only proposed for situations with an outside good, which is not the case in this paper.

The satiation parameters ($\alpha_k$and γ_k) both decrease the baseline utility ψ_k when that alternative is consumed. γ introduces satiation by translation of the utility function and allows zero consumption of the good k (Bhat, 2008). It has the restriction that it must be numerically larger than 0. To achieve this, an exponential transformation is introduced, implying that the value estimated in the model does not have any restriction. The higher the value of γ, the lower the satiation effect. This implies that an alternative with higher γ, all else being equal, would be consumed proportionately more.

The other satiation parameter, α, allows satiation by changing the marginal satiation rate. The values allowed for the parameter ranges from 1 (no satiation effect) to -∞ (immediate and full satiation) (Bhat, 2008). Since both α and γ play a similar role in the utility function, they are confounded during estimation. This indicates that they cannot be estimated simultaneously. A γ profile is estimated when α is set, and a α profile sets γ to be a constant. In this paper, a γ coefficient is used because of the more straightforward forecasting method (Pinjari and Bhat, 2011).

Part of the attractiveness of the MDCEV model is that when only one alternative is chosen (discrete choice), the Likelihood function collapses to the same utility as the MNL. This property will be used in this paper to simultaneously model the multiple discrete nature of the SP data together with the discrete nature of the choices in the RP data. In some way, the assumption is that although the RP data shows discrete choices (due to the nature of the CB), it actually reflects a multiple discrete choice.

For combining both datasets, an approach similar to the nested logit trick (Hensher et al., 2008) is used. The nested logit trick consists in separating in 'artificial' nests the alternatives from SP and RP data. In the estimation, the SP data is affected by a different scale of the error term. In the MDCEV, this error term scale is explicitly shown in the Likelihood function in the σ parameter. In the estimation the $\sigma_{RP}$is set to 1, while the $\sigma_{SP}$is estimated in the model. To our knowledge, no other work mixes RP and SP data for a

MDCEV model. Although there is a significant difference in the size of the data, the RP model estimates has been influenced when combined with the SP data.

The ASCs in the model were decomposed into the mode specific constants and the port specific constants. Although a lower goodness of fit is obtained, the calibration process is more practical, as shown in sub-section 3.2.

For all the parameters, non-linearities were tested by introducing logarithmic transformations to the independent variables. With the introduction of the transformation, the possible effect of reduced sensitivity as the value of the parameter increases is analysed (Daly, 2010). Additionally, there are several papers that highlight the importance of including non-linear variables in the freight context (Gatta and Marcucci, 2016; Marcucci et al., 2015).

Observed and unobserved heterogeneity was tested. Observed heterogeneity was tested with the interaction with attributes related to the organization for the SP model and other locational attributes (which hinterland they belong, for example) for RP and SP data (Tapia et al., 2019). Unobserved, or random, heterogeneity was included by testing uniform, log uniform and lognormal distributions with 250 Halton draws (Train, 1999). Normal distributions were not preferred because as they are unbounded distributions they can provide values with the wrong sign or issues when estimating WTP measures (Daly et al., 2012b). Although generally the inclusion of random heterogeneity improves significantly the goodness of fit, observed heterogeneity is preferred due to the behavioural insights it provides.

A separate model without any heterogeneity consideration was included in order to test the traditional CBA approach. Since the model fit will be significantly lower, and thus its ability to reflect correctly the behaviour modelled, the results of this model will be used only for WTP measures. In this paper we will refer to the estimations that come from this model as the "deterministic model" because it will be used to estimate deterministic WTP, even though it is a statistical model with an error term associated.

Correlation among alternatives were included with different combinations of error components (Train, 2003). Error terms shared among alternatives with the same mode and other error terms including alternatives with the same destination were tested.

The criteria for choosing the model were not only that the model that showed the highest Log likelihood or the lowest Bayesian Information Criterion (BIC). The parameters signs were analysed considering microeconomic theory and forecasting practicality was also taken into consideration.

3.2. Model calibration

The model had been estimated with RP data from 2014, meaning that the market shares recovered by the model refer to that year. Moreover, not all the productive zones of Argentina have been used for the estimation, bringing more bias to the actual market shares provided by the Ministry of Transport of Argentina. In order to remove the bias, the ASC had to be corrected. The ASC for alternative i in iteration l is formed by the last ASC value (iteration l-1) plus log of the quotient of the actual market share (S_i) and the market shared recovered by the model (S_i^{l-1}), as shown by equation 3 (Nugroho et al., 2016).

$$ASC_i^l = ASC_i^{l-1} + log\left(\frac{S_i}{S_i^{l-1}}\right) \quad ((3)$$

In the case of the proposed model, the ASC refer either to a mode constant (e.g. train), or to a port constant (e.g. Bahia Blanca). This has been done so because the data on aggregated modal shares and port shares are easier to find and more reliable than the composed share of the mode-port alternative. Additionally, new alternatives, such as truck to Quequén and waterway to Rosario, were introduced. The main underlying assumption is that the overall coefficients and error components hold for new alternatives, but the ASC have to be recovered in order for them to be successfully included.

All the constants were updated in each iteration. The measurement of overall error used was the square of the difference between the predicted and actual shares. Convergence was reached when the error did not improve by a significant amount (0.01) between iterations.

In order to predict the market shares of the MDCEV model, a special algorithm had to be used since, different from traditional choice models, there is no straightforward method to do so. This algorithm, described in detail and demonstrated by Pinjari and Bhat (2011), consists of non-iterative way of estimating the consumption quantities for each alternative.

The forecasting algorithm consists in simulating the random coefficients, error component terms and a Gumbel distributed error term in order to obtain the baseline utility. With the baseline utility estimated, all the alternatives are ordered in decreasing order. Since this model did not have an outside good, the alternative with the highest baseline utility is assumed to be consumed.

The following step consists in comparing the Lagrange multiplier of the utility maximization problem with the baseline utility of the next ranked alternative. If the multiplier is smaller, the next alternative is assumed to be chosen and a new Lagrange multiplier is estimated to compare it with the utility of the following alternative. This continues until the multiplier is larger than the next alternative's utility, or all available alternatives are chosen. Once the number of alternatives chosen is found, the optimal consumption is calculated. Finally, the consumptions results are averaged for each choice situation.

3.3. Scenario evaluation

The policy scenarios analysed in the paper are focussing on rail infrastructure investment. A first case of restoration and another of restoration and construction are considered.

The scenario evaluation procedure consists of the steps needed for the measurement of the impact of the infrastructure investments. The main benefits would be headway improvements, time savings, operational cost savings and emission reductions. The costs would be related to the infrastructure investments for improving the railroad. The difference in maintenance costs will be computed, but a priori is not clear whether it would imply an increase or a decrease in the overall cost.

There are two main ways for evaluating the infrastructure improvements of an infrastructure improvement (Jong and Daly, 2007). The first one consists of analysing the difference in the logsum of utilities of the logit model used before and after the intervention and the second one is the "rule of half", which is going to be used in this paper. The rule of half computes half of the benefits for the new cargo attracted by the infrastructure improvement and the whole benefits for the cargo that already chose that alternative.

All the benefits are computed for all the years of the infrastructure lifespan and transformed as an annualized benefit using a 5% per year rate. In the case of the cost attributes, a result of the COSFER model, are already projected for all the project duration and presented as an annualized amount. The metric for feasibility of the project is the Benefit/Cost (B/C) ratio.

For the operational, maintenance and infrastructure costs the COSFER model was used. Firstly, the baseline costs are established for the baseline scenario, computing the current average speed, volume and infrastructure status. Secondly, the model with the new times is run in order to estimate the overall volume and ton-km. With those results, the COSFER is run again in order to obtain the new values for the lead time. Finally, the last forecast is made in order to obtain the final volume and use it as an input for the COSFER. The registered output, for the baseline and the scenarios, are the annualized costs. The COSFER model allows four types of rail intervention: full renovation, heavy improvement, medium improvement and light improvement. The criteria used to determine the type of intervention is shown in table 1. For the new lines, an additional 15% of the COSFER rail full renovation cost is computed, following the Ministry of Transport suggestions.

Table 1: Rail intervention criteria

Average speed of the rail section	Type of intervention
1 – 25 km/h	Full renovation
26-35 km/h	Heavy improvement
36 – 45 km/h	Medium improvement
> 46 km/h	Light improvement

For the quantification of the emission reduction benefits the overall ton-km for rail and truck were compared for the baseline scenario and for the scenarios with the infrastructure improvement. The emission coefficient used for truck was 62 gCO_2/tonkm and for rail of 22 gCO_2/tonkm (ECTA, 2011). For the valuation of a metric ton of CO_2 we use 23 US$ (IAWG, 2016).

In order to quantify the impacts of the improvement of the lead time to a region and the time, measurements of the Value of Headway between services (VOH) and Value of Time (VOT) were computed. Both measurements were included in the model with a logarithmic transformation, implying that the value of the savings changes from region to region. Additionally, the inclusion of random heterogeneity in the freight cost coefficient and the time coefficient makes both coefficients, VOH and VOT, stochastic. The procedure for estimating these WTP measures consists of taking draws of the distribution of the parameters and simulating the quotient. As a consequence, the value of the savings from these attributes also becomes of a probabilistic nature, so does the result of the economic valuation. As far as we are aware, no other study has introduced the effect of random heterogeneity into infrastructure evaluation.

In order to compare with more traditional approaches of CBA the VOT and VOH are estimated with the deterministic model. In order to include risk analysis, draws from a normal distribution with mean the estimates of the VOT and VOH and as a standard deviation their estimated standard errors. For the standard errors of the VOT and VOH the delta method was used (Daly et al., 2012a). As the logarithmic transformation is not considered in the most used transformations the generic equation was adapted resulting in equation (5):

$$\Phi = \frac{\partial \Omega / \partial \beta_1}{\partial \Omega / \partial \beta_2} \tag{4}$$

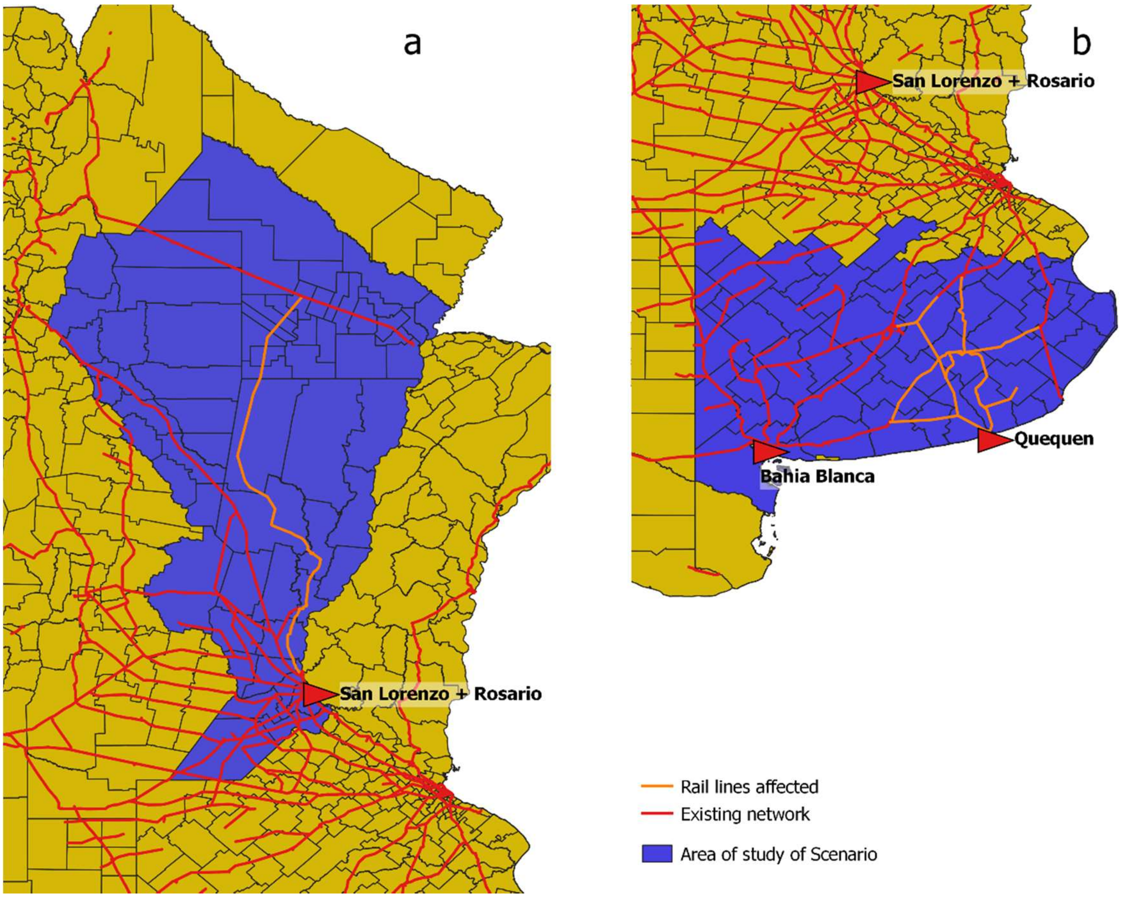
$$covariance(\Phi) = \left(\frac{\beta_1}{\beta_2 * X_1}\right)^2 * \left(\frac{\omega_{11}}{{\beta_1}^2} + \frac{\omega_{22}}{{\beta_2}^2} - \frac{2 * \omega_{12}}{\beta_1 * \beta_2}\right) \tag{5}$$

where: Ω : the utility function β_1: time or headway estimate; β_2 freight price estimate; ω_{ij} covariance of item i and j; X_1: value of time or headway.

Two scenarios were analysed in this paper. The first one consists in improving the rail tracks of the Belgrano Cargas in the Santa Fe province. This railroad is the main rail corridor for cargo coming from the north of the country. Besides the competition with the road mode, there is potential for competition with the waterways, since it runs parallel to the Paraná River. The improvement in this area would be the upgrading the tracks and replacing the railway ties with concrete ones in order to upgrade the operational speed to 50 km/h. Figure 4a shows the intervention for scenario 1.

The second scenario consists in bringing the railway network towards the port of Quequén to a good operational capacity. Currently, the rail is only used sporadically. In this case, there would be a partial renewal of the operating network (specially the one oriented towards BHB) and the construction of new rail links to improve rail availability. The area of intervention is shown in figure 4b.

Figure 4: a) Area of influence of scenario 1; b) Area of influence of scenario 2



4. RESULTS

This section will show the main results of the estimation and calibration. Additionally, the WTP measurements for the system are provided.

4.1. Model

Table 2 shows the estimation results for the combined RP and SP data model, together with the constants calibration. The SP scaling coefficient resulted to be less than 1, indicating a lower variance of the error term in relation to the RP data. This result is consistent with a planned SP experiment, where variables are controlled.

Table 2: Model estimates

	Deterministic Model			Mixed model		
	Estimation	t-value	Calibrated	Estimation	t-value	Calibrated
Scale_RP	1	NA	1	1	NA	1
Scale _SP18	4.2274	11.02	4.2274	0.4831	8.08	0.4831
Freight Transport Price (mean)[1]	-0.0895	-39.7	-0.0895	0.9001	19.59	0.9001
Travel Time (mean)[14] (distance < 500 km)	-3.0166	-37.2	-3.0166	1.181	26.92	1.181
Travel Time[4] (distance > 500 km)	-2.474	-33.4	-2.474	-3.0807	-21.6	-3.0807
Lead Time[4]	-1.9814	-14.5	-1.9814	-1.4438	-6.41	-1.4438
FAS price (mean)[2]	0.1107	52.21	0.1107	-1.5582	-51.1	-1.5582
Relative Shipment size	1.4712	46.72	1.4712	7.1321	20.8	7.1321
Gamma Train	-2.7073	-9	-2.7073	3.6923	15.31	3.6923
Gamma Truck	-3.0458	-9.86	-3.0458	3.5035	13.53	3.5035
ASC_B (SP)	-6.5895	-10.6	-6.5895	-3.2699	-7.93	-3.2699
ASC_C (SP)	-2.6924	-3.66	-2.6924	-0.4685	-3.06	-0.4685
ASC_D (SP)	-8.8703	-8.5	-8.8703	-3.7254	-7.97	-3.7254
Error comp Truck	NA	NA	NA	12.7536	15	12.7536
Travel Time (dev est)[3]	NA	NA	NA	0.4927	18.73	0.4927
Freight Price (dev est)[3]	NA	NA	NA	0.6544	9.88	0.6544
FAS price (dev est)[3]	NA	NA	NA	0.4805	8	0.4805
ASC_Rosario	-0.512	-31.2	NA	0.4864	8.66	-4.11
ASC_San Lorenzo	0.8558	51.4	NA	2.1646	39.63	-3.22
ASC_Train	1.0172	4.28	NA	-30.1875	-15.6	-43.16
ASC_Quequen	-	-				2.14
ASC_Bahia Blanca	-	-				-
ASC_Truck	-	-				-
LL (0)	-419559.3					
Final LL	- 93564.98			-88757.74		
n	144690					

1: If referring to the mixed model it is the mean of the normal distribution that generates the lognormal. The negative sign of the parameter is given externally
2: If referring to the mixed model it is the mean of the normal distribution that generates the lognormal. The positive sign of the parameter is given externally
3: standard deviation of the normal distribution that generates the lognormal
4: logarithmic transformation

Freight transport price, *Travel time*, *Lead time* and *FAS price* were significant in the mode-choice model. Non-linear effects on the utility function were added using logarithmic transformations for the *Lead time* and *Travel time*. No transformation was applied for *Freight transport price* and *FAS price*. These results are consistent of the importance of accounting for non-linear effects of attributes in the freight context (Gatta and Marcucci, 2016; Marcucci et al., 2015).

The *Travel time* coefficient was split into two separate ones, for closer and larger distances. The split difference was set to 500km in order to capture the effect of the travel time of closer ports with more detail.

Lead time and *Relative shipment size* was computed only for train-related alternatives. The negative sign of the *Lead time* coefficient implies, as expected, that the utility perceived by the decision maker for the train decreases with increase in lead time. Relative shipment size had a positive impact in the utility of the train, showing consolidators are more likely to send larger shipments sizes by rail transport.

Non-observed heterogeneity was included adopting a random coefficients specifications for *Travel time* (for ports located closer than 500km), *Freight transport price* and *FAS price.* The parameters were randomly distributed over the population assuming lognormal distributions. The adoption of lognormal distributions, although somewhat more difficult to estimate, avoids the issue of values close to zero (important for WTP measurements) and coefficient sign change (Hess et al., 2005). Correlation between alternatives was captured through an error component term within truck modes.

The gamma coefficients show the expected relative magnitudes. The gamma coefficient for train mode higher than that obtained for trucks alternatives. A higher value of gamma coefficient implies a lower satiation, consistent with larger shipments.

The ASC were estimated with a subsample that consisted of zones where more than one mode was available. The calibration was made with the complete database and recovered all the market shares within 1 percentage point.

4.2. Willingness to pay (WTP)

WTP values were computed using the parameters estimated. Draws were simulated from the distributions estimated and used to simulate the WTP measurements for time and lead time. In both cases, the logarithmic transformation of *Travel time* and *Lead time* imply that the WTP measures depend on the value of the parameter. For these cases, the mean value for each variable was used (20 days for lead time, 10 hours for truck time, 43 hours for rail time and 26 hours for the average of the system). Figure 5 shows the distribution of the WTP values.

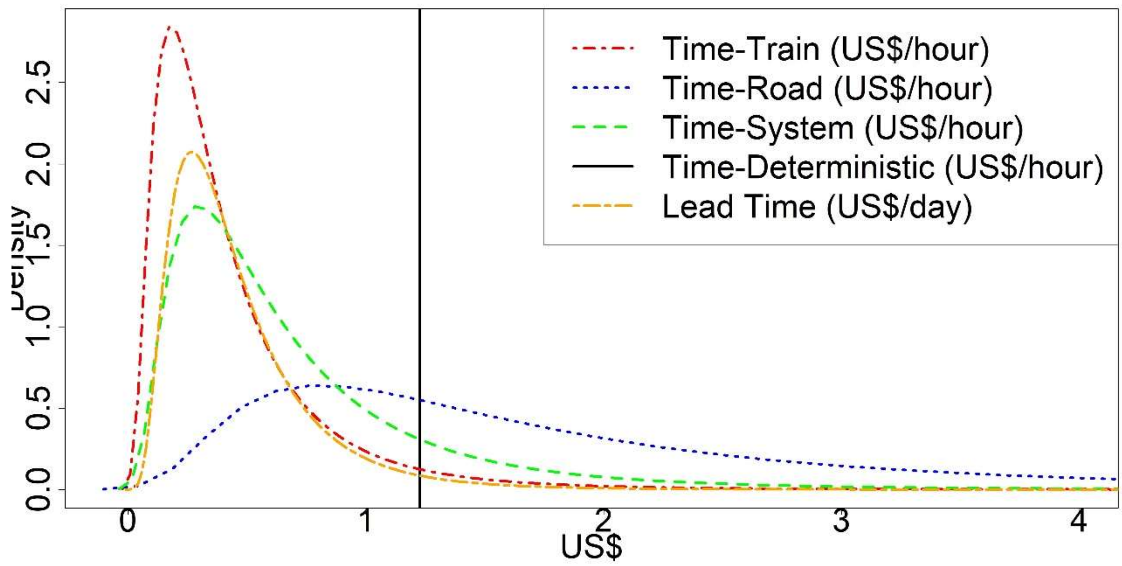


Figure 5: Willingness to pay distributions

As expected, the VOT of rail is the lowest of the three cases, followed by the system average. This corresponds to the non-linearity of the coefficient: the larger the travel time, the lower the value of the saving. The mean VOT for rail was 0.43 US$/hour*ton, for the truck 1.93 US$/hour*ton and the average of the system was 0.71 US$/hour*ton.

The WTP obtained from the deterministic model was of 1.23 US$/hour/ton, higher than the average values reported. The standard errors, mainly due to the large database, are small compared to the VOT value, ranging between 1.22 US$/hour/ton and 1.24 US$/hour/ton. Due to this, they are not shown in the figure.

The VOT obtained by the model are within range of the literature. Larranaga et al. (2017) reported ranges from the literature between 0.1 and 3.4 US$/hour/ton, and de Jong (2014) between 0.03 to 2.88

euro/ton/hour (0.1–3.4 US$/ton/hour). Tapia et al. (2019) found values for the region between QQN and BHB of around 1.49 US$/ton/hour, that are higher than the ones reported by the model presented in this paper, but still within range. In the above cases, the VOT refers to the shipper component, in the sense that it is related with the need of on-time deliveries to the client.

The mean value of WTP for *Lead time* (VOH) was 0.34 US$/day/ton and contains within its range the 0.99 US$/day/ton found by Tapia et al. (2019) for the sub region of the south east of Buenos Aires province. When estimated the deterministic value was of 1.11, and ranged between 1.09 and 1.12 US$/day/ton when considering the standard errors, a consistent estimation compared with Tapia et al. (2019).

The value can be interpreted as a proxy for having the goods for one day less within inventory. This is so because if the lead time is reduced, the consolidators can ship by train more frequently. Thus, reducing immobilized inventory.

4.3. Scenario evaluation

The models presented above were used to analyse the impact of rail infrastructure improvement and compare it with the costs of the intervention. The measure adopted to check the social feasibility of the investment was the Benefit/cost (B/C) ratio. Ratios higher than one indicate that the project is viable from the point of view of the society. Other measurements of project finance were not estimated because the purpose of the paper is to provide a framework for analysing projects and not to compare them.

The first intervention (scenario 1) is the restoration of the rail line that communicates the north of the country with the port of San Lorenzo. The intervention consists of 780 km of heavy renovation of the tracks, resulting in the annualized value of 16,143,000 US$ for 40 years (considering a 5% discount rate). The effect is a net gain of almost 50,000 tons (10% increase of the route), and the average distance of the railroad stayed roughly at 570 km. The estimated emission reduction is of 340,000 US$ per year.

Operational costs stay roughly the same 218,047, but maintenance costs go down from 1,049,228 to 3,226,997 US$ because it is assumed that concrete ties have a much lower maintenance cost than wooden ones (current situation). VOT and VOH savings were computed per region and considering the stochastic nature of its value. This results in a distribution of VOT and VOH savings and consequently resulting in a distribution in the Cost-benefit analysis. As a reference, the average value of time has also been used to generate another B/C ratio.

The second intervention (scenario 2) consists on the restoration of the 757 km rail lines around the port of QQN and the creation of an extra 430 km. The total cost of the investment is 18,692,552US$ annualized for 40 years. The expected gains are of 16,000 tons per year with an average distance of 480 km, approximately doubling the volume transported. The amount of share of the railways implied an emission reduction of 176,000 US$.

Operational costs were expected to rise in approximately 507,823 US$ and the maintenance were assumed to drop 5,288,834 US$. Figure 6 shows the B/C ratio for both projects, together with the reference deterministic value.

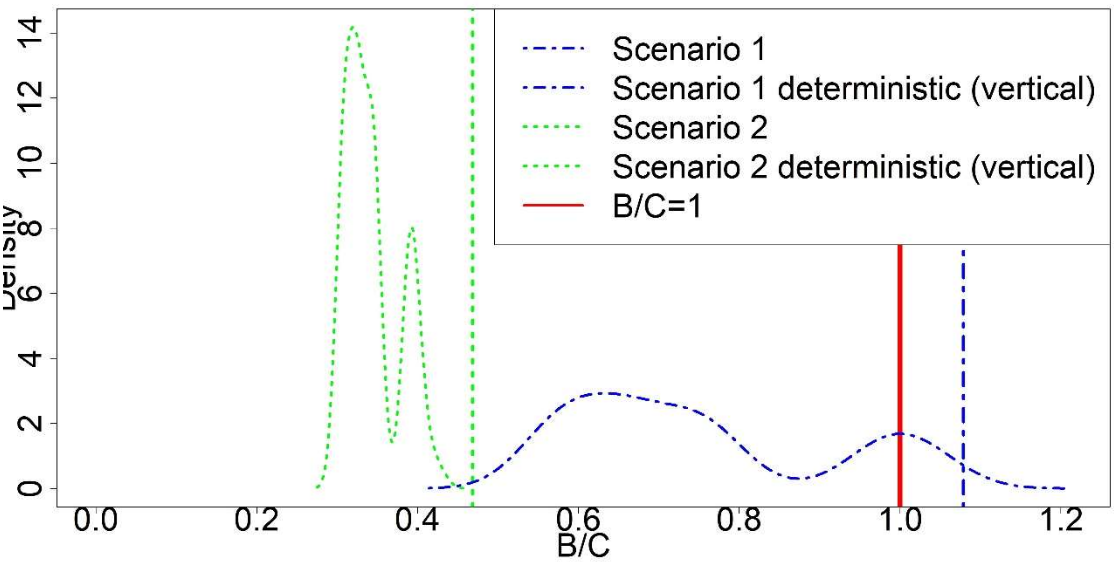


Figure 6: B/C ratio distributions

Figure 6 shows that the B/C ratio is over 1 in 12% of the cases for the scenario 1. The B/C analysis considering the variability of VOT and VOH ranges from 0.56 to 1.07 for the first intervention. For the second intervention the values ranged between 0.30 and 0.43

The deterministic B/C ratio has a value of 0.47 for the second intervention and of 1.08 for the first one. Both values are higher than the ones estimated with the WTP distributions.

5. DISCUSSION

This section presents some discussions on the results provided above. Implications of the model, scenarios and policy implications are presented.

5.1. Model

The results obtained in the model were econometrically consistent because of the sign of the variables and the relative magnitude of them. *Freight price*, *Lead time* and *Travel time* had negative signs, implying that the higher those values, the lower the attractive of the alternative. The positive sign of *FAS price* suggested that the higher the price paid at the port, the more attractive the port. Moreover, WTP measurements (relative value among variables) were within expected values.

Comparing *FAS price* and *Freight price* coefficient distributions, both have similar magnitudes, but *Freight price* coefficient was slightly higher. This was within expectations, because both variables affect directly the gross margin per ton of the sale. Nevertheless, FAS price is only received by the consolidator at least a week after it is received by the exporter, while freight price is normally paid within a smaller time frame. This, as reported previously for soy supply chain (Tapia et al., 2019), can represent an offset in the cash flows of the business involved causing that the coefficient of the freight price to be slightly higher. Such interpretation can add an extra layer in freight choice analysis, especially when tactical choices are taken into consideration. The link between the timing of sales (and consequently cash flows) is yet to be analysed and explored.

The inclusion of the relative size of the shipment as an exogenous variable only for train modes introduces shipment size as a variable in mode choice. This use apparently contradicts theory that supports that shipment size is chosen simultaneously with mode choices (de Jong and Ben-Akiva, 2007; Johnson and de Jong, 2011; Windisch et al., 2010), but it is actually consistent with that framework. The variable included in the MDCEV model is the accumulated value from different shipments from the same consolidators (see CB processing in section 2.3) representing an aggregate choice, while the values obtained from the forecast are the shipment sizes for each alternative. The latter is coherent with the literature that supports that modal choice is made simultaneously with the shipment size.

The above approach of considering different shipments in a choice is consistent with choices made as part of the tactical planning of the organization. Aggregated volumes of production are approximately known before the harvest, so the demand and transportation plans have a high correlation with actual output. This choice approach breaks the assumption of mutual alternatives exclusiveness, that fundament discrete choice models. Evidence of the non-exclusiveness of the alternatives can be found in the high use of multiple alternatives in the SP survey. This choice modelling approach enables the application of discrete-continuous frameworks as another tool for understanding and forecasting shipper's behaviour. Moreover, this model framework approach could also be extrapolated to other products and sectors. This reinterpretation of freight behaviour adds another layer to the behaviour of freight choice makers. The interaction between planning stages and the operational choices introduces additional complexities to the behaviour of the actors.

The application of the MDCEV models in freight is relatively new as far as the authors are concern. MDCEV models have the potential of considering the planning point of view of freight transport decision making by modelling aggregated choices from a disaggregate (i.e. from an individual point of view) perspectives. Moreover, no other works have been found that combined SP and RP database within the MDCEV framework.

The discrete part of the choices of the MDCEV could also be interpreted as a form of consideration set modelling. Consideration sets are a subset of all the available alternatives that are considered to be relevant to the consumer (Hensher and Ho, 2015; Wright and Barbour, 1977). The inclusion of consideration sets in choice modelling is meant to exclude irrelevant alternatives from the choice set that can bring bias into behavioural interpretations (Thill, 1992). The MDCEV model as such does not include consideration set generation in the estimation. However, when forecasting it does not allocate any consumption of the alternative if it does not reach certain threshold. Consequently, it can potentially reduce the noise generated by low utility alternatives by not allocating any consumption volume.

5.2. Policy implication

The model obtained is a useful tool to analyse the impact of rail infrastructure in rail shipments. It can provide an estimate of tonnage that would be transported before and after an intervention. With the aid of other models, such as COSFER, it can be used to generate a Cost Benefit Analysis.

The results show that the projects have to be analysed more carefully in order to analyse the social viability. The first project proved to be only partially viable and the second project proved not to be viable at all. This calls for more detailed investment alternatives that can obtain similar increase in volumes and travel speeds at a lower investment cost. Maybe by prioritizing the worse (slower) parts of the rail tracks closer to the ports, the B/C ratio could improve. This paper brings a consistent and flexible method to compare the outcomes of several types of projects.

The method provided can be easily used for evaluating other alternatives. Furthermore, other project finance indicators, such as the Net Present Value (NPV) or the Internal Rate of Return (IRR) could be used in order to prioritize the projects by impact size. This ranking becomes more important in situations where public funding might be scarce.

Nevertheless, the heterogeneity included in the modelling, through random parameters for *Freight price* and *Travel time* variables, allowed to introduce a level of uncertainty in the value of the financial evaluation metrics, accounting for the risk in the decision making of public policies. This new distribution of possible outcomes of the project may enable to develop a more sensible decision making, considering the risk aversion profile of the decision maker.

Moreover, if the randomness of the VOT is not considered, some projects might not have the expected outcome. For both projects the values reported with the deterministic WTP were higher than with the probabilistic approach. This implies that the use of deterministic appraisal might lead to taking projects into consideration that are not socially feasible.

Risk analysis is an important tool that helps understand the sensitivity of a project in an uncertain world. It is normally used by assuming that the inputs have certain distributions. In transport WTP studies, the confidence intervals are usually given, like in the Swedish (Börjesson and Eliasson, 2014), Denmark (Fosgerau et al., 2007) and UK VOT studies (Hess et al., 2017; Sanders et al., 2015) , and this paper uses the same underlying logic. Hess et al. (2017) estimates the VOT for the UK using mixed models, and characterizing the results with the mean and standard deviation in order to capture the confidence intervals of the "true" VOT. In that paper they use log uniform distributions, but they are not reported in the final report (Sanders et al., 2015).

However, the use of several VOTs can invoke the issue of equity and whether to differentiate WTP values, a discussion addressed but not solved yet in passenger transport (see Börjesson and Eliasson, (2019) for a recent discussion). Large firms normally have a larger VOT since they are more sensitive to travel time and other level of service variables. As a consequence, projects that are prioritized due to the larger time benefits could be favouring mainly the larger producers. This is sometimes solved by shadow prices (Mackie et al., 2001), that are a tool for policy makers to reduce the equity problem.

The social feasibility of a project is the first step of a project analysis. Further steps considering the economic and financial aspects have to be considered. Since private companies are operating and benefiting from the investments, they could be included in a sort of Public-Private-Partnerships (PPP). With different levels of participation of the public and private investments, an investment source configuration that is beneficial for both parties could be obtained so better infrastructure is provided. The demand forecast for the project finance could be one of the potential applications of the model.

The model could be furthered used to understand and simulate pricing policies for rail companies and to simulate the effect of revenues. The COSFER provides good reference for the costing elements of the railroad, while the model can cope with the demand side of the organization. With the interaction between both, a simulation of rail gross incomes could be done in order to understand the dynamics of the service operator.

Knowledge on rail margins can help evaluate other type of policies, such as an open access policy. This type of policies consists in the separation of the rail infrastructure provider with the infrastructure provider. Simulations on different infrastructure usage fees, transport tariffs and expected profit margin can be done in order to obtain an overall policy that benefits the whole system.

6. CONCLUSION

The study analyses the choices of mode and port of consolidators in Argentina and applies the results in order to evaluate the impacts of rail investments. An MDCEV model has been used in order to model the tactical level choice, allowing the allocation of cargo to multiple alternatives. The data used in this paper consisted in processed consignment bills as RP data and a SP survey. The model was further calibrated to reflect current shares of transportation modes and ports.

In order to apply the MDCEV in the regional freight context, the choices considered were of an aggregate nature, but at a disaggregated (individual choice) level. This implied that multiple alternatives could be chosen simultaneously, and consequently being closer to the real situation at a planning stage. This breaks the traditional assumption of discrete choice modelling that alternatives are perfect substitutes of each other.

The variables that resulted in significant coefficients for the mode and port choice were the *FAS price, freight price, travel time* and *lead time*. The first three variables followed a lognormal distribution and a logarithmic transformation was applied to the *travel time* and *lead time*. In order to understand better the effect of time, this variable was divided into two considering the distance to the port. As satiation variables for the MDCEV, mode-specific gamma parameters were estimated. The model showed lower satiation, implying larger shares, for the rail mode compared to road.

VOT (value of reducing an hour of travel time) and VOH (value of reducing a day in lead time) measurements were estimated by taking draws from the parameters' distributions. This resulted in values that averaged 0. 71 US$/hour/ton for travel time and 0.34 US$/day/ton for lead time, both values within range from the literature.

For analysing the social feasibility of a project, the cost of infrastructure, difference in operational and maintenance costs, time and lead time savings and differences in emissions were considered. The first project analysed consisted in the revitalization of a rail line that connects the port of San Lorenzo with the northern parts of Argentina, while the second one improves existing lines and expands the network around the port of Quequén. Both projects were evaluated with the B/C ratio and resulted feasible for implementation.

When compared with the results from a deterministic approach, the non-deterministic B/C ratio was lower than the deterministic ratio. This implies that the deterministic approach for infrastructure evaluation may generate misleading results. For some projects closer to the feasibility threshold this could lead to the selection of investments that will not improve overall wellbeing.

Advances in choice models have improved their explanatory power and interpretation. However, the impact that these new findings have in practice is not always analysed and applied for policy making. This paper includes two relevant contributions applied to a real case study in order to analyse their consequences.

The first one is the modelling of a tactical, rather than operational, choice for freight transport. This can potentially open a new range of models (especially MDCEV) used to understand freight choice behaviour and how strategic planning choices are made. Together with greater understanding of decision processes, more adequate policies can be designed in order to address freight externalities and impacts on the competitiveness of economies.

The second one is including the effects of non-observed heterogeneity in CBA. The use of mixed logit models has increased in the last years due to the relative ease of estimation and its large potential to improve model fit. However, the implications of the use of mixed models have not been thoroughly researched. One important implication, as it is noted in the literature, is to guarantee non negativity of WTP measurements and this has been considered in the MDCEV model presented. The second one is to incorporate the heterogeneity in WTP measure in order to quantify the benefits of the projects analysed.

Moreover, more advanced models also bring the need for more and better quality data. This paper addresses the issue by establishing methods for processing large datasets that are, after privacy issues are addressed, potentially available for the public sector.

There are several limitations related to the estimation part of this paper. First, the inland waterways were not included in any way, and this could impact the mode decision, especially for the first scenario. Nevertheless, the current shares of the barges are below 1%. Secondly, the model was estimated without the port of QQN being part of the choice set of the alternatives due to the lack of rail access and this alternative was only included in the calibration. Thirdly, during the forecasting and implementation, the data used consider the same shipment structure as present in the consignment bills and the FAS price mimic the one in 2017. During the lasts years in Argentina there has been an inflationary process, which could affect the relative prices of the transports. A paper that addresses this issue within the freight context could not been found. Finally, market or non-market actions by the truck sector were not included in the modelling. At the firsts stages of other rail improvements, trucking firms could increase the price of the short runs to and from the rail terminals, affecting the competitive position of the rail system. Moreover, there have been cases of rail facilities blocked by truck drivers.

Regarding future work, there are two main directions. The first one is about the financial project evaluation for rail investment and PPP feasibility, as the next steps for analysing the projects in order to enable their implementation. The second one has to do with the conceptual framework of freight modelling and the consideration of tactical and strategical dimension of choices.

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