Consumer Welfare and Unobserved Heterogeneity in Discrete Choice Models: The Value of Alpine Road Tunnels*

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Abstract

We investigate the sensitivity of consumer surplus estimates to parametric assumptions on individual preference heterogeneity in a discrete choice framework. We compare results from a parametric random coefficients logit model and a recently proposed nonparametric mixtures estimator. In particular, we provide an assessment of the direct economic value of crossing the Alps for the European road freight sector. Using revealed preference data from a detailed survey on transalpine road freight traffic, we estimate the yearly cost of closing the Mont-Blanc Tunnel, which was closed for 3 years following a large accident in early 1999. Ultimately, our results permit the economic evaluation of security and transport policy measures affecting transalpine traffic. Our findings suggest that the way we model unobserved heterogeneity significantly affects our welfare results.

Keywords: .
JEL Classification: .

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1 Introduction

In devising well-informed policy measures, reliable estimates of the welfare implications for affected individuals and firms are crucial. Economic theory and a large econometric literature have tackled the problem of providing welfare measures and their estimation. One important econometric framework have been discrete choice models, established by Luce (1959), Marshak (1959), and McFadden (1973). Measuring consumer surplus in this framework, for example from changes in product characteristics or choice sets, has a long history going back to Small and Rosen (1981), who derive the Hicksian compensating variation in the discrete choice framework. Prominent examples of estimating welfare implications using this framework are Trajtenberg (1989), on the introduction of CT scanners, Goolsbee and Petrin (2002), on Satellite TV in the US, and Petrin (2004), on the introduction of the Minivan in the US automotive market. In this literature, much progress has been made for providing flexible ways of modeling unobserved heterogeneity. The workhorse model is the random coefficients multinomial logit model introduced by Boyd and Mellman (1980) and Cardell and Dunbar (1980).[1] Just as the above examples, most applied work has modeled unobserved heterogeneity by imposing parametric distributions on the coefficients over which individuals are assumed to have heterogeneous preferences. Standard choices of distributions are the normal or the log-normal distribution. The main reasons for their tremendous success have been computational tractability, flexibility, and the relatively convenient incorporation of instrumental variables by using the method of simulated moments.

In this paper, we provide insights into the importance of how unobserved heterogeneity is modeled when estimating welfare effects of policy measures. We do so by comparing consumer surplus estimates from a nonparametric estimator of preference distributions recently proposed by Bajari et al. (2007, 2010), henceforth BFKR, and the standard parametric random coefficients logit model. We employ revealed preference data and analyze the implications of a transport policy measure which has been debated in recent years. In particular, we consider the choice of road tunnels by transalpine freight traffic. While many applications analyze welfare effects, we are not aware of many studies exploring the role of unobserved heterogeneity in this context. Hynes et al. (2008) compare welfare implications of a random coefficients logit model and a latent class model of recreational demand. They find no significantly different welfare results from both models.

[1] See McFadden and Train (2000) for a detailed exposition.

The Alps are Europe's highest and most extensive mountain range running from Mediterranean France to southern Austria. With its extreme geography, the alpine region not only forms a natural frontier between Italy and central Europe, but provides the unique gateway for ground transport between south-eastern European regions (and beyond) and central and northern Europe. Due to the limited number of crossing points, the Alps form a natural bottleneck at the core of European economic activity. After the introduction of the European single market, the opening up of eastern Europe and the corresponding enlargement of commercial relations within the European Free Trade Association (EFTA), transalpine freight traffic has become not only an important topic in European politics but a key component of transport infrastructure planning.

Mountainous road infrastructure exhibits elevated risks for its users, among others, due to its reliance on long underground passageways. Tragic displays of this fact have been the accidents in the Mont-Blanc tunnel in 1999, the Tauern tunnel in 1999, the Gotthard tunnel in 2001, and the Frejus tunnel in 2005. The most severe of these four accidents, in the Mont-Blanc tunnel, cost 39 lives and lead to a full closure of the tunnel for three years. These events have brought about policy initiatives in various forms. For the alpine regions, additional investment in security measures at tunnels and formulating the objective of shifting freight to rail and maritime transport have been particular examples.[2] Proposed safety measures have reached as far as the closure of certain road tunnels to freight traffic.[3] Quantifying the short-term monetary loss incurred by the freight transport sector from the closure of a given tunnel is of interest to inform policy decisions for two main reasons. First, the monetary consequences of a potential closure for its users are pivotal. Second, the burden caused by unintended closures due to accidents must be known when assessing the monetary benefits of investment in safety measures.

We estimate the monetary relevance of Alpine road infrastructure to road freight in Europe on routes crossing the Western Alpine corridor. In particular, we estimate the monetary loss incurred by the freight transport sector due to the closure of the Mont-Blanc tunnel. Due to the lack of point of time information in the data, we cannot use the actual exogenous event in 1999 to identify substitution patterns or to directly estimate the loss in consumer surplus. There are little studies evaluating the accidental or deliberate closure of

[2]See, for example, the European Commission's White Paper (European Commission (2001)) and European Commission (2006).

[3]See European Parliament (2001), and articles in the LA times (http://articles.latimes.com/2002/mar/10/news/mn-32111) and the BBC (http://news.bbc.co.uk/2/hi/europe/1863245.stm).

transport infrastructure. One exception is Bilotkach et al. (2009) who exploit the collapse of a freeway interchange in the San Francisco Bay Area to analyze sensitivity of pricing behavior to demand shocks. In practice, closing an infrastructure is not as exotic a discussion as one may think, witnessed in a recent debate over the potential closure of an Expressway in the Bronx in New York City (see Dolnick, 2010). We provide conclusions as to the evaluation of a potential future closure of the Mont-Blanc road tunnel to freight traffic. Our welfare analysis should be seen in a narrow sense. Total welfare encompasses not only direct changes in consumer surplus but also changes in external effects, e.g. caused by congestion or nuisances to other travelers, as well as macroeconomic variables such as regional development or trade. That is why we coin the term user benefits in our setting, signaling the narrow definition of direct effects on freight truck operators' welfare. Estimating the total social cost, especially in the alpine regions, would need to include both the direct costs to users (changes in consumer surplus) and external effects on non-freight users (congestion, for example) and non-users of the infrastructure such as inhabitants of the respective alpine valleys. The monetary cost of injuries, property damage and business interruption should be more directly quantifiable while macro-economic effects on economic activity and/or trade are difficult to identify. Here we focus on direct short-term effects likely to be the most prevalent in the current political discussion.

Using a large-scale individual-choice data set, we start out with the simplest model in the random utility framework, the multinomial logit model. We then proceed to estimate several specifications of the random-coefficients logit model, also known as mixed logit model. We further relax parametric assumptions on the random coefficients' mixing distributions, compare parametric and non-parametric results, and discuss implications for compensating variation estimates. We find that both parametric assumptions on and the dimensionality of modeled unobserved heterogeneity have a significant impact on welfare results. We thus caution the exclusive use of standard distributional assumptions in modeling heterogeneity and encourage the use of the simple nonparametric mixtures estimator employed here.

The paper is organized as follows. Section 2 presents our data set on freight traffic in the alpine region. Section 3 presents the main framework for the analysis and derives the empirical strategy. We present our estimation results in Section 4, discuss the implied substitution patterns and welfare results in Section 5, and conclude in Section 6.

2 Alpine Freight Traffic

Our data is a large-scale cross-section from the Cross-Alpine Freight Transport (CAFT) survey done every 5 years[4]. Each respective year, trucks are stopped and surveyed at all possible Alpine crossings between Vintimille and Wechsel (see Figure 1). The survey is a joint initiative by the Austrian, French, and Swiss governments to produce a representative sample of transalpine freight transport. In 2004, Germany and Italy joined the effort emphasizing the political relevance of collecting high quality data on transalpine transport activity. The data set comprises detailed information on each truck's origin and destination regions. Regions are defined at the NUTS3 level, corresponding, for example, to departments in France, districts in Germany, counties in the US. The data further include transported commodity classes, weight, vehicle characteristics, region of registration, intermediary boarder crossings, traffic direction, and more. We merge this data with shortest distances on a direct line, data on average gas and other operating costs, road and tunnel tolls, as well as with GDP data on origin and destination regions[5]. Our sample includes all French-Italian passages and all Swiss-Italian passages (see Appendix A and Figure 1).

Table 1: Alternative-specific characteristics

	Mean	Standard Deviation
Alternative characteristics		
Price	362.7	148.1
Distance	853.2	413.5
Time	18.4	11.6
User (truck) characteristics		
Weight of goods (tons)	12.8	8.8
Per capita GDP at destination	30,788.1	11,299.7

Further: commodity type, regional variables, trip direction and borders.
285,656 observations, 35,707 choice situations. CAFT 2004.

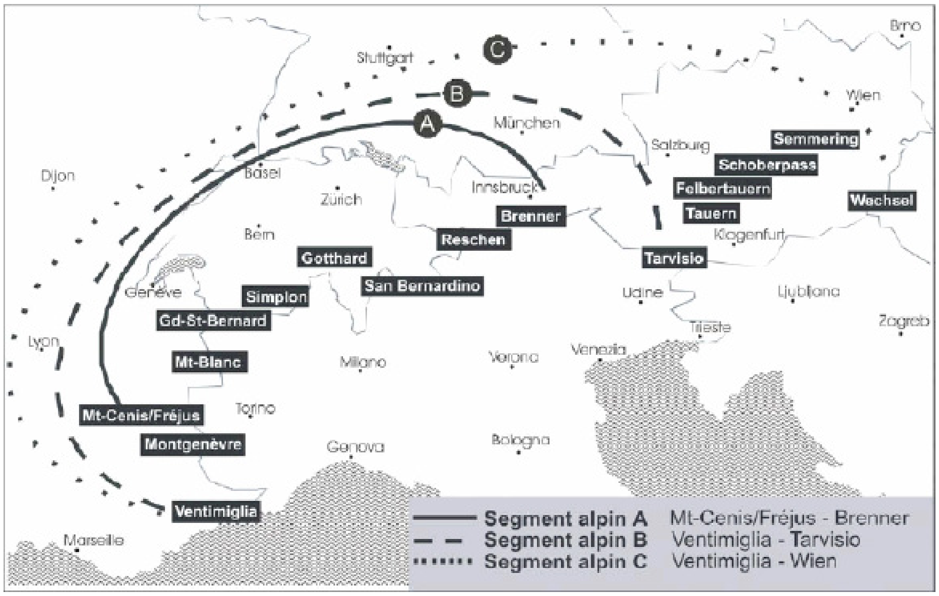
In Table 1 we present descriptive statistics of our variables. We compute *price* based on an average per kilometer cost estimated by the French *Comité National Routier* on an annual basis[7] and Alpine tunnel fees. For Swiss pas-

[4]The available waves are 1994, 1999, and 2004 with data quality increasing in each wave.

[5]We also collected data on daily weather conditions during the sample period. Unfortunately, only the French part of the sample includes observation dates and we cannot use this information. Since mainly small and high-altitude passes are negatively affected by weather, we expect the route fixed effects to capture weather effects. To some extent, we expect the same with respect to traffic volume and congestion, even though traffic data provided by the German automobile club (ADAC) does not show significant traffic jams during the sample period.

[7]See http://www.cnr.fr/grilles_couts/e-docs/00/00/00/26/document_grille_cout.phtml.

Figure 1: The Alpine corridor



Source: AlpInfo, Federal Office of Transport, Swiss Confederation.[6]

sages, we include the Heavy Vehicle Fee which is based on ton-kilometers in Switzerland. We compute *distance* in kilometers from origin to destination regions via each respective Alpine passage using Vincenty direct geographic distance calculations implemented in Stata. We also make use of information on which border-crossings were used along the way.[8] Prato (2009) provides an up-to-date survey on the challenges in working with route choice data and emphasizes that using shortest point-to-point distances increases similarity within the choice set. Thus, we expect substitutability to be over-estimated and our consumer surplus estimates to be lower bounds. We observe that the large majority of trucks choose the alternative with the minimal price and time. This is intuitive and we therefore expect a negative impact on choice probabilities in our estimation results. We do observe, however, that a small proportion does not choose the price- and time-minimizing alternative. We can think of two main reasons for this observation. First, there may be a trade-off between time and price logistics firms face and there are some who prefer a longer route to incurring the significant tunnel fees. Second, it could be the result of unobserved heterogeneity related to logistic route choice. In order to reduce fixed

[8]Our attempts to obtain shortest-link route distances from routing service providers such as Google Maps or Navteq failed, unfortunately. Thus, while we have a decent long-distance approximation based on manual checks on a small sub-sample of routes, we need to assume that no significant bias results from ignoring the fact that roads are not straight lines.

costs, logistic firms may choose to combine several loads into one truck. As a consequence, some observations may not be pure Origin-Destination relationships but only the start and end points of a more complex delivery route. Furthermore, depending on the specific good and, for example, their service contract, we expect trucks to have (unobserved) heterogenous preferences for saving money and time. Our *time* variable is based on typical truck speed and including regular compulsory stops by European law, conditional on the number of drivers per truck. We include per capita GDP of the destination region as a user characteristic to proxy for the value of a vehicle's charge, in addition to the type of commodity. The mean in our sample is closest to per capita GDP in the Netherlands in 2004.

3 Empirical Framework

We estimate the loss in user surplus from a hypothetical closure of a major transalpine road tunnel. For example, consider the problem faced by a firm located north of the Alps - say, in France - delivering its product to a downstream producer located south of the Alps - say, in Italy. By our definition, the firm faces eight mutually exclusive route options. While rail could be an option for the firm, we restrict our analysis to road freight. Even though we are forced to this restriction by our data,[9] modal choice typically depends heavily on the type of commodities and logistic specificities and is, thus, largely predetermined in our choice situations. We further motivate excluding modal choice for our setup in Section 3.3.

We adopt a discrete choice framework[10] where the choice set are eight westalpine crossings and the decision makers are individual freight trucks. In particular, user i maximizes the benefit to be obtained from a delivery trip through the Alps and faces j mutually exclusive routes. Thus, the objective function is

$$\pi_{ij} = \alpha_i(r_i - p_j) + x_j\beta_i + \xi_j + \epsilon_{ij}, \tag{1}$$

where r_i is the firm's revenue from the transaction, p_j the price for alternative j, x_j includes route characteristics, ξ_j is a constant unobserved route characteristic, and ϵ_{ij} is assumed to be independently and identically type I

[9]For the same reason, our analysis is short-term in that we employ a static choice model and do not allow for market growth or decline through an outside option.

[10]See Train (2009), McFadden and Train (2000), and Hensher and Green (2003) for in-depth treatments.

extreme value distributed. We have detailed user-specific information, such as GDP in destination and origin regions, commodity class, goods weight, vehicle type, location of vehicle ownership, and so on, allowing us to control for a range of observed user characteristics. However, we expect there are still user characteristics we cannot observe, such as *en route* pick-ups of goods, truck drivers' personal tastes, or special logistic needs that favor one route over another. It is common practice to model such unobserved heterogeneity by assuming parametric distributions for the relevant taste parameters. However, when estimating welfare measures, too strict assumptions will lead to biased results. Cherchi and Polak (2005) warn that assuming common mixing distributions such as the normal and log-normal may bias welfare estimations due to an inadequate representation of the true underlying distribution of tastes. Hensher and Greene (2003) give similar warnings and offer a range of simple ways for investigating sensible distributional assumptions.[11] BFKR propose a mixtures estimator that is nonparametric in the distribution of random coefficients. We have no good prior as to how our taste parameters should be distributed. We further would like to avoid assuming distributions that force portions of decision makers to have negative and unreasonably large coefficients, such as the normal distribution. Hence, we estimate both parametric and nonparametric specifications[12] and compare the welfare results.

3.1 Parametric Specification

We first model user heterogeneity such that taste parameters take the following form:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma \nu_i$$

where

$$\nu_i \sim \mathbb{N}(0, \mathbb{I}) \tag{2}$$

and D_i a vector of user specific characteristics in our data. User i chooses route j if and only if $U(D_i, \nu_i, p_j, x_j, \xi_j; \theta) \geq U(D_i, \nu_i, p_j, x_j, \xi_j; \theta)$ for $r = 1, ..., J$. The

[11] One straight-forward proposition is a jack-knife approach where the researcher estimates fixed coefficient logit models on sub-samples and evaluates the distributions of estimated coefficients expected to have a non-degenerate distribution.

[12] We also tried the EM algorithm proposed by Train (2008) but encountered severe convergence problems, a common problem with EM algorithms. Fosgerau and Hess (2009) also use the method of sieves to increase flexibility. They add a series expansion using Legendre Polynomials to a continuous base distribution and discrete mixtures of normal distributions.

individual choice probability for route j follows:

$$P_{ij} = \int_{\theta} \frac{exp(x_j\beta_i - p_j\alpha_i + \xi_j)}{\sum_k exp(x_k\beta_i - p_k\alpha_i + \xi_k)} f(\alpha)f(\beta)d(\alpha)d(\beta) \tag{3}$$

where we assume $f(\alpha)$ and $f(\beta)$ to be normal distributions as defined in Equation 2. We estimate the parameters θ by maximum simulated likelihood. In the multinomial logit with fixed coefficients, α and β are constant across individuals so that the index i is dropped.

3.2 Nonparametric Specification

BFKR propose a very general nonparametric mixtures estimator of unobserved heterogeneity in a wide range of economic models. Their motivating example for the random coefficients logit model lends directly to our analysis. The idea is that the researcher has some prior over the dimensionality and range of random coefficients, that is of unobserved heterogeneity in the utility function. We can then specify a grid over the assumed support of random coefficients. At each grid point, that is for each regime r, we can compute the predicted logit choice probabilities. Treating these predicted probabilities as data, a simple OLS regression where the regressors are r predicted choice probabilities yields estimates of r weights. These r weights are probability mass points representing the probability of observing regimes r in the population. Constraining the sum of probability masses to be one, we obtain a discrete distribution of our random coefficients.

The resulting implementation of the estimator is an inequality constrained ordinary least squares estimator. One drawback of this very simple form is the researcher's need to specify the support region where the random coefficients lie. If the latter is unknown, BFKR propose a location scale model that allows to both estimate the location of the support region and its scale. We have no good prior of the support region and thus proceed with the location scale model. A further practical advantage of the latter is the straight-forward inclusion of fixed coefficients. This is an open issue in BFKR's linear estimator, given that fixed coefficients are nonlinear parameters by definition in the logit model. The nonlinear estimator solves the constrained least squares problem

$$
\begin{aligned}
&\min_{a,b,\theta} \frac{1}{NJ} \sum_{i=1}^{N} \sum_{j=1}^{J} \left(y_{i,j} - \sum_{r=1}^{R} \theta^r g_j(x_i, a + b\beta^r) \right)^2 \\
&\text{subject to} \quad \sum_{r=1}^{R} \theta^r = 1 \quad \text{and} \quad \theta^r \geq 0,
\end{aligned}
\tag{4}
$$

where $a = (a_1, ..., a_K)'$ is a set of location parameters, $b = (b_1, ..., b_K)$ a set of scale parameters, θ^r the weight for the parameter vector $\beta^r = (\beta_1^r, ..., \beta_K^r)$, and

$$
g_j(x_i, a + b\beta^r) = \frac{exp\left(\sum_{k=1}^{K} x_{k,i,j}(a_k + b_k\beta_k^r)\right)}{\sum_{j=1}^{J} exp\left(\sum_{k=1}^{K} x_{k,i,j}(a_k + b_k\beta_k^r)\right)}.
$$

We estimate scale parameters b_K for random coefficients and set $b_K = 0$ for coefficients assumed to be fixed. We could allow all coefficients to be random but, as common with nonparametric estimators, we reach computational limits fast when increasing the number of random coefficients. Having reasonable starting values is important in nonlinear least squares estimation. We use the fixed coefficient logit estimates for the nonlinear parameters and $\frac{1}{R}$ for θ^r.

3.3 Identification

Given their regulated nature, tolls for individual tunnels and long-distance routes vary little across time and routes. Thus, to identify demand patterns, we use individual-level variation from users' geographic dispersion across Europe. In particular, users' origin and destination locations vary relative to the locations of alpine passages. This leads to variation both in route characteristics and individual choices. As road and tunnel tolls are not set strategically, we are confident they are not correlated with the error term. There are two factors that may affect both route choice and travel time. First, congestion may cause short-term deviation to an alternative route.[13] Second, severe weather conditions may cause deviation to alternative routes while increasing travel time. Unfortunately, we cannot fully correct for this potential problem as only parts of our data have information on the date of the choice situation.[14] Once we are

[13] Standard tunnel closures for maintenance are sporadically effective during midnight hours.

[14] We did collect daily weather conditions for the different passages but were unable to obtain the interview dates for the Swiss part of the data. This applies to congestion data analogously.

willing to assume that truck drivers form long-term expectations on potential obstacles for each route alternative[15], we think it plausible to believe that the alternative fixed effects will capture significant parts, if not all, of potential bias.

Implicitly, we assume that we observe each individual's entire choice set and that there is no outside good. While in the long run freight expeditors may switch to other modes such as air, rail, and sea or even right out stop their operations, in the short run this is very unlikely. However, in the first two columns of Table 4, showing market shares of alternatives before and after the Mont-Blanc tunnel closure in 1999, we cannot observe a remarkable shift in market shares towards any of the three rail passages in the short-run.[16] We also do not observe a downward shift in monthly tons transported after the closure, suggesting that traffic fully deviated to alternative road passages. We interpret this as evidence that modal shift is not yet as relevant as it may be in other regions. That interpretation is in line with anecdotal evidence on freight transport in France and Italy, citing specific logistic needs, the importance of geographical location, and freight terminals being major bottlenecks as just a few of many remaining problems preventing increased modal shift.[17] We conclude that observing only one mode to be a minor drawback with respect to the focus of this paper.

Bajari et al. (2009) prove nonparametric identification of the distribution of random coefficients by exploiting the logit distributional assumptions on ϵ_{ij} and without relying on large support (as compared to, for example, Berry and Haile (2010)) and monotonicity restrictions. The latter makes their identification result particularly relevant for applied work. A limitation is that their proof is valid only for continuous regressors. BFKR further survey several ways to account for endogenous regressors, which is particularly relevant where individual choice data are not available.

4 Estimation results

We begin our empirical analysis by estimating a simple multinomial logit specification and then extend the specification to the more general random coefficients logit specification, relaxing the logit's most restrictive assumption, Indepen-

[15] Deviating from a planned route is often prohibitive in terms of cost and time.

[16] Due to missing time information at the individual level, our data do not allow direct estimation of the switch to rail and alternative roads caused by the Mont Blanc tunnel closure.

[17] See Lange and Ruffini (2007), and Peter Brett Associates LLP (2010).

dence of irrelevant alternatives. The parametric estimations are done using the *mixlogit* Stata command by Hole (2007). For nonparametric estimates, elasticities, consumer surplus computations, and inference results, Matlab code is available from the authors on request.

Tables 2 and 3 show the estimated coefficients have signs as expected. In particular, price and time have negative signs. We are comforted by the fact that the price coefficient is robust throughout all our model specifications. The coefficients on the interaction term between weight of goods transported and the alternative specific constants show that heavily loaded trucks are less likely to use Swiss passages and the Montgenevre passage[18]. This corresponds to our a priori expectation that the Montgenevre pass having the highest elevation should be less attractive to heavier vehicles due to higher gas consumption and potential safety concerns.

Price coefficients are higher overall, in absolute terms, in our parametric random coefficients logit specifications than in the simple logit ones. Time has significant coefficients in all specifications. This result confirms that unobserved heterogeneity with respect to price plays an important role in our freight transport setting.

Interpreting the parametric random coefficients logit results in Table 3, where the standard deviation is not statistically different from zero, we should conclude the distribution of the time coefficient to be degenerate. In economic terms, our conclusion would be that there is no unobserved heterogeneity in preferences for time. Observing the BFKR estimates in Figure 3, however, we clearly see significant heterogeneity both in preferences over price and time.

The number of grid points is limited by sample size and computer memory. With 8GB RAM and our sample size of 35,707 choice situations, we are able to set R=274 with one and R=256 with two random coefficients. Note that, in order to use parametric methods for computing standard errors of the BFKR estimates, we need to assume that the grid points r are the true regimes that generated the data. It is obvious that, unless we can specify an almost infinite number of r, estimated probability mass points and thus their standard errors can only be approximations to the truth. We compute 95% confidence intervals, following BFKR and Gallant (1975), using standard errors from unconstrained nonlinear regression and clustering by individual choice situations. Confidence intervals are then defined as CI_{95} =

[18]The base category both for the alternative specific constants and for the interaction term with good weights is alternative 5, the Mediterranean passage at Vintimille.

Table 2: One random coefficient (1)

	Logit	RC Logit Mean	RC Logit SD	BFKR
Price	-8.478***	-9.298***	1.523***	*See Figure 2*
	(.118)	(.149)	(.079)	
Time	-.922***	-.869***		-.854***
	(.230)	(.232)		(.040)
Price × GDP$_{destination}$	1.153***	1.533***		1.096***
	(.294)	(.317)		(.001)
Mont-Blanc	4.214***	4.291***		3.969***
	(.280)	(.297)		(.243)
× Weight	.008	.010		.014***
	(.006)	(.006)		(.001)
Frejus	5.144***	5.256***		4.488***
	(.234)	(.254)		(.318)
× Weight	.020***	.023***		.026***
	(.005)	(.006)		(.002)
Montgenevre	-5.843***	-6.657***		-4.886***
	(.552)	(.657)		(.291)
× Weight	-.031***	-.036***		-.024***
	(.009)	(.010)		(.005)
Gd St-Bernard	.154	.178		.632***
	(.310)	(.332)		(.065)
× Weight	-.058***	-.063***		-.072***
	(.009)	(.010)		(.004)
Simplon	-.095	-.113		.428***
	(.310)	(.330)		(.089)
× Weight	-.047***	-.051***		-.085***
	(.010)	(.010)		(.004)
St. Gotthard	3.576***	3.730***		4.128***
	(.293)	(.312)		(.196)
× Weight	-.073***	-.076***		-.096***
	(.007)	(.007)		(.007)
San Bernadino	2.654***	2.789***		3.282***
	(.297)	(.316)		(.102)
× Weight	-.073***	-.075***		-.090***
	(.008)	(.008)		(.005)
Likelihood ratio	105342.50	130.60		
Prob > χ^2	.000	.000		
Pseudo R^2	.71			

Notes: All specifications include route dummy-commodity class and time-commodity class interaction terms as well as route dummies interacted with dummies indicating traffic connecting Italy with regions west and north of the Alps, respectively. The reference route is the Mediterranean crossing at Vintimille. Standard errors are reported in parenthesis, choice situation-clustered robust standard errors in BFKR estimation. 500 Halton draws used for simulations in parametric random coefficients logit estimations. 285,656 observations.
*** p< 0.01, ** p< 0.05, * p < 0.1

Table 3: Two correlated random coefficients (2)

	Logit	RC Logit Mean	RC Logit SD	BFKR
Price	-8.478***	-9.244***	1.273***	*See Figure 3*
	(.118)	(.148)	(.078)	
Time	-.922***	-1.504***	.271	
	(.230)	(.266)	(.291)	
Price × $GDP_{destination}$	1.153***	1.520***		1.160***
	(.294)	(.322)		(.001)
Mont-Blanc	4.214***	4.276***		5.913***
	(.280)	(.293)		(.316)
× Weight	.008	.010*		.018***
	(.006)	(.006)		(.002)
Frejus	5.144***	5.254***		6.753***
	(.234)	(.248)		(.403)
× Weight	.020***	.023***		.032***
	(.005)	(.005)		(.003)
Montgenevre	-5.843***	-6.638***		-5.318***
	(.552)	(.665)		(.319)
× Weight	-.031***	-.035***		-.013***
	(.009)	(.010)		(.003)
Gd St-Bernard	.154	.237		1.553***
	(.310)	(.332)		(.067)
× Weight	-.058***	-.065***		-.071***
	(.009)	(.010)		(.004)
Simplon	-.095	-.064		1.485***
	(.310)	(.330)		(.089)
× Weight	-.047***	-.053***		-.092***
	(.010)	(.011)		(.004)
St. Gotthard	3.576***	3.818***		5.434***
	(.293)	(.310)		(.225)
× Weight	-.073***	-.077***		-.109***
	(.007)	(.007)		(.008)
San Bernadino	2.654***	2.872***		4.509***
	(.297)	(.314)		(.115)
× Weight	-.073***	-.076***		-.102***
	(.008)	(.008)		(.006)
Likelihood ratio	105342.50	262.77		
Prob > χ^2	.000	.000		
Pseudo R^2	.71			

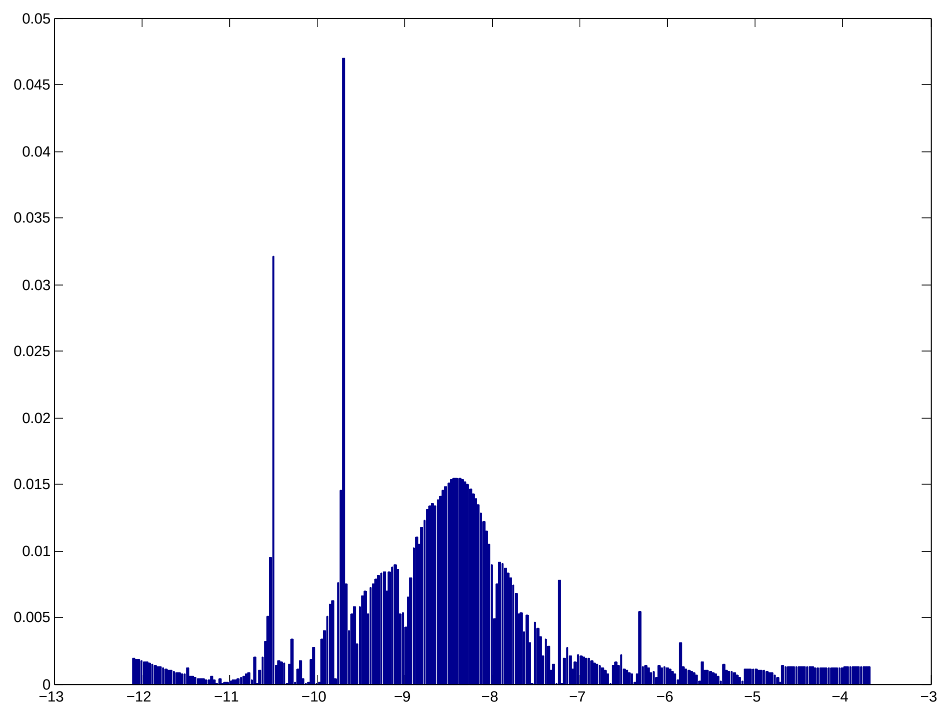
Notes: All specifications include route dummy-commodity class and time-commodity class interaction terms as well as route dummies interacted with dummies indicating traffic connecting Italy with regions west and north of the Alps, respectively. The reference route is the Mediterranean crossing at Vintimille. Standard errors are reported in parenthesis, choice situation-clustered robust standard errors in BFKR estimation. 500 Halton draws used for simulations in parametric random coefficients logit estimations. 285,656 observations.
*** p< 0.01, ** p< 0.05, * p < 0.1

$\left[\hat{\theta}^r - 1.96 \cdot SE\left(\hat{\theta}^r_{unc}\right), \hat{\theta}^r + 1.96 \cdot SE\left(\hat{\theta}^r_{unc}\right)\right] \cap [0,1]$, where $SE = \sqrt{\hat{\nu}}$ and

$$\hat{\nu} = \frac{NP}{NP-1}\left(\frac{SSE}{N-p}(J'J)^{-1}\left(\sum_{k=1}^{M}\left(\sum_{j\in G_k} u'_j \sum_{j\in G_k} u_j\right)\right)\frac{SSE}{N-p}(J'J)^{-1}\right).$$

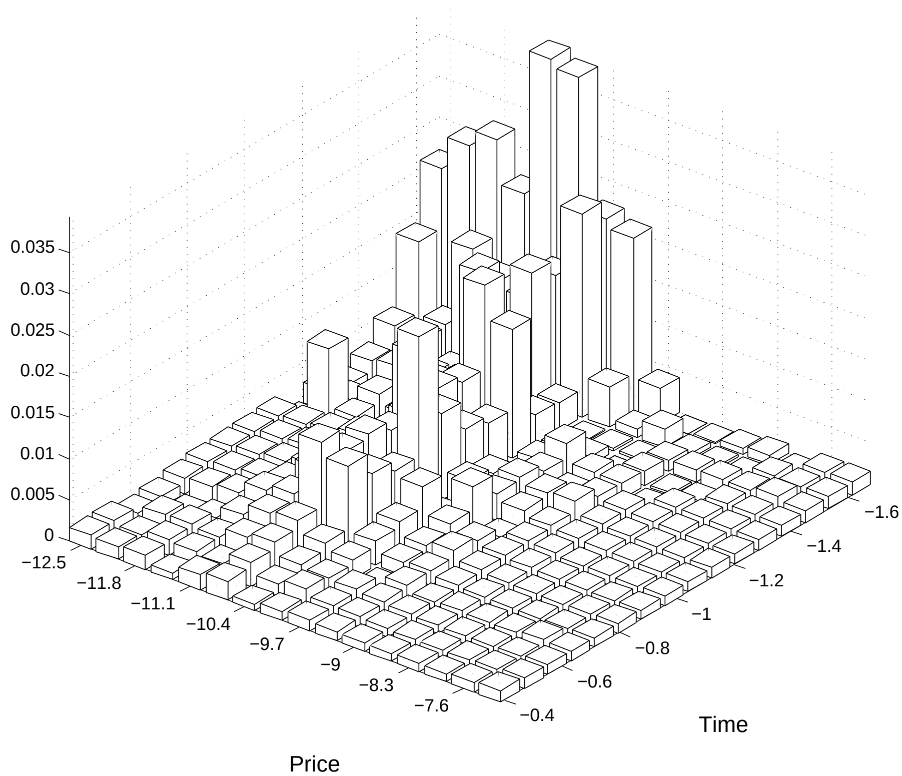
However, as do BFKR, we find these confidence intervals to be too uninformative to report. BFKR note that confidence intervals computed this way are conservative and largely over-cover. From our experience with estimations using varying grids sizes, this problem seems to get worse as the number of grid points R increases and θ are estimated closer to the zero boundary.

Figure 2: Distribution of price coefficient



Elasticities Investigating substitution patterns we see that the elasticity matrices in Tables **??** to **??** show high own-price elasticities. These elasticity levels could be explained by the cost sensitivity associated with long-distance routes. As longer routes provide a greater number of alternatives with similar characteristics (as alternatives share a larger common road network), in case of minor contingencies such as congestion on a given road a truck may readily change its preferred passage.

Figure 3: Distribution of price and time coefficients



5 Counterfactual Analysis

5.1 Diversion patterns

First, compare counterfactual shares with those observed after MB tunnel closure in 1999. Note, that road tolls and tunnel fees were not changed as a consequence of accidents. Thus, we assume there is no strategic pricing and prices remain fixed with the closure of a Tunnel. To our knowledge, congestion pricing is not employed in road transport in the region relevant for our analysis.

While the MB tunnel was closed, most traffic diverted to the nearby Frejus tunnel, bringing it to its limit of capacity. Our counterfactual results abstract from capacity constraints. IF COMPARABLE TO TABLE 4: Indicates that capacity constraints were not binding. (CHECK FOR SOURCE: HOW SEVERE WAS POTENTIAL CAPACITY CONSTRAINT?)

Table 4: Passage Market Shares - Counterfactual closure in 2004

		1999		2004	
		Open	Closed	Open	Closed
Road	Mont-Blanc	21.79		10.14	
	Frejus	27.68	44.54	32.51	32.28
	Montgenevre	1.09	3.38	0.67	3.07
	Vintimille	21.26	24.36	33.76	35.53
	Gd St-Bernard			1.19	2.07
	Simplon			1.25	1.63
	St. Gotthard			18.07	21.83
	San Bernadino			2.41	3.59
Rail	Basel (CH)	10.61	10.84		
	Modane (Frejus)	15.42	15.21		
	Vintimille	2.16	1.67		
Monthly tonnage (1000s)		4,455	4,619	4,038	

5.2 Consumer surplus

We analyze a hypothetical closure of the Mont-Blanc tunnel in 2004 and compute users' compensating variations, that is, the amount of money one would have to give to infrastructure users to maintain their ex-ante utility levels. We define the ex ante situation as the reference point, as suggested by Trajtenberg (1989). In the multinomial logit model, computation of the compensating variation is straight forward and given by the difference of the ex-post and ex ante values of the logsum measure with no unobserved taste heterogeneity:

$$CV = \frac{1}{\beta^c}\{\ln \sum_j \exp(\beta' x_j^{pre}) - \ln \sum_j \exp(\beta' x_j^{post})\} \tag{5}$$

As the random coefficients logit model introduces unobserved taste heterogeneity, each individual now may have her own valuation of product characteristics. Thus, we integrate over the estimated mixing distributions by simulation and compute the mean compensating variations for each individual n. Following Train (1998), von Haefen (2003), and Cherchi et al. (2004):

$$CV_n = \int \frac{1}{\beta^c}\{\ln \sum_j \exp(\beta' x_{nj}^{pre}) - \ln \sum_j \exp(\beta' x_{nj}^{post})\} f(\beta \mid \theta^{pre}) d(\beta) \qquad (6)$$

Equations 5 and 6 imply the assumption that the marginal utility of income, β^c, is independent of income. That is, β^c is constant with respect to and thus indirect utility additive and linear in income. While this assumption may seem restrictive, we maintain it to simplify our computations. Train (2009) points out on page 57 that the constant marginal utility assumption needs to hold only 'over the range of implicit income changes that are considered by the policy'. This means that if individual compensating variations are low relative to income, which is arguably true for our case, the assumption does not need to hold in general but only for the considered small range. We solve Equation 6 for each individual via simulation by sampling from the estimated mixing distributions. We weight the resulting sample means of compensating variations by the expansion factor provided by the CAFT 2004 data set and obtain the population mean of the change in user benefits as well as the population total by summing up.

Table 5: Welfare effects of tunnel closure

Compensating variation (in 2004 Euros)	Logit	Random Coefficients Logit		BFKR	
		(1)	(2)	(1)	(2)
Sample mean	1.11	.84	.69	1.80	1.43
Population mean	1.28	.96	.79	1.88	1.46
Population total (Mio)	4.83	3.62	2.97	7.09	5.49
Population total (%)					

Notes: 500 quasi-random draws used for simulation.

6 Conclusion

In this paper we structurally estimate the economic value for the European road freight sector of crossing the Alps. We show a considerable cost-elasticity of substitution between the different tunnels and passages.

Importantly, as a natural bottleneck for European terrestrial commerce, transalpine freight traffic is subject to tight security and environmental regulation. The results derived from our analysis permit the economic evaluation of some of these policies. In particular, the yearly cost of the closure of the Mont-Blanc road tunnel after the accident in 1999 is estimated at about XXX million Euros for the road freight sector. A further research avenue would be the analysis of potential policy initiatives such as the privatization of passageways or supply-side reactions, for example by Swiss tunnels, due to the closure of the French Mont-Blanc tunnel.

Appendix A Alpine passages

Our sample includes the following passages:

2 Mont Blanc tunnel

3 Frejus tunnel

4 Montgenevre pass

5 Vintimille expressway along the Mediterranean coast

6 Grand St-Bernard tunnel

7 Simplon pass

8 St. Gotthard tunnel

9 San Bernadino pass

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