National Technical University of Athens

School of Civil Engineering

Department of Transportation Planning and Engineering

DEVELOPMENT OF METHODS FOR ESTIMATING PUBLIC TRANSPORT SHARES UNDER COMPLEMENTARY OPERATING CONDITIONS

PhD Dissertation

Christina Milioti

Advisor: Matthew G. Karlaftis, Associate Professor

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To my family

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ABSTRACT

Development of Methods for Estimating Public Transport Shares under Complementary Operating Conditions

In this thesis demand aspects of a multimodal public transportation system are investigated using econometric methods for analyzing non-stationary data. The case of the Athens public transport system, where different modes may operate in competition or cooperation, is used as a test bed.

Demand analysis is a necessary condition for efficient decision making in a public transport system; network expansion, pricing policies, subsidy and operational decisions are based on demand analysis. Demand is expressed as a function of operational and macroeconomic factors (fare, GDP, fuel price, unemployment, car and motorcycle sales) and the impact of each factor on demand is expressed through the elasticity concept. Two different but complementary aspects of public transport demand are analyzed. Ridership of each mode and share of each mode in total ridership. The above two issues provide useful information regarding effective policy measures. Demand analysis for each mode separately allows for identifying competition and substitution effects and produces more accurate demand elasticities. The analysis of the share of each transport mode in a multimodal urban public transport system is a key factor that explains the relative position of each mode in the system. It may also be a useful index for making investment decisions concerning the public transport infrastructure and for allocating subsidies.

The econometric analysis adopted is based on cointegration and error correction techniques. This allows for treating non-stationary data, for determining short and long run elasticities and at the same time estimating the speed of adjustment towards long run equilibrium. Briefly, the method consists of the following modules: First, a unit root test is applied to test non-stationarity. Second, a cointegration test is performed to evaluate long run caused relation. Third, an error correction method is used to evaluate short run responses. Finally, in the cases that exists autocorrelation and/or autoregressive conditional heteroskedasticity on

the residuals, new error correction models are developed to account for these effects. A model with correction for autocorrelation is used to correct serial correlation on the residuals and an ARCH model is used to capture changes in variability of the time series.

According to the results, fare GDP and gasoline price are the main factors that affect PT ridership both in the short and in the long run. Of the different modes, metro and urban rail show the highest elasticities with respect to the factors examined, while bus appears to be quite inelastic. The fact that demand elasticities with respect to the explaining factors are significantly different for the different modes demonstrates the merits of demand analysis for each mode separately.

Results also indicate that fare GDP and total ridership are the main determinants of public transport mode shares. In the ridership model GDP is the factor that shows the highest elasticities, while in the shares model fare is the factor that shows the highest elasticity. This is because the substitution effects between different PT modes resulting from an increase in fares are more clearly recorded in the share models. Finally, as expected, short run elasticities appear to be lower than the long run ones both in the models explaining ridership and in the models explaining the share of each mode, because short run elasticities are governed by resistance to change.

ΠΕΡΙΛΗΨΗ

Ανάπτυξη Μεθόδων Εκτίμησης Κατανομής της Ζήτησης στα Μέσα Μαζικής Μεταφοράς σε Συνθήκες Συμπληρωματικής Λειτουργίας

Σκοπός της διατριβής είναι να διερευνηθούν οι παράγοντες που επηρεάζουν τόσο τις βραχυχρόνιες όσο και τις μακροχρόνιες μεταβολές στη ζήτηση ενός συστήματος αστικών συγκοινωνιών, το οποίο αποτελείται από πολλά συνεργαζόμενα μέσα που λειτουργούν συμπληρωματικά.

Η ανάλυση της ζήτησης σε ένα σύστημα αστικών συγκοινωνιών παρέχει χρήσιμη πληροφόρηση για την αποτελεσματική λήψη αποφάσεων που αφορούν στην λειτουργία και στην ανάπτυξη υποδομών του συστήματος. Η ζήτησή εκφράζεται ως συνάρτηση λειτουργικών και μακροοικονομικών παραγόντων (τιμή εισιτηρίου, ΑΕΠ, τιμή βενζίνης, δείκτης ανεργίας, πωλήσεις Ι.Χ.) και ο βαθμός της μεταβολής της ζήτησης λόγω μεταβολής κάποιων παραγόντων εκτιμάται μέσω του μεγέθους της ελαστικότητας της ζήτησης. Η μελέτη της ζήτησης για το κάθε μέσο μαζικής μεταφοράς του συστήματος αστικών συγκοινωνιών της πόλης των Αθηνών πραγματοποιείται με δύο προσεγγίσεις. Στην πρώτη, εξετάζονται οι παράγοντες που ερμηνεύουν την μηνιαία επιβατική κίνηση του κάθε μέσου. Στη δεύτερη, αναλύεται το ποσοστό (μερίδιο αγοράς) της συνολικής ζήτησης που καλύπτει το κάθε μέσο μαζικής μεταφοράς. Ο προσδιορισμός του μεριδίου αγοράς κάθε μέσου επιτρέπει τη λεπτομερέστερη ανάλυση σε ότι αφορά στον ειδικό ρόλο κάθε μέσου σε ένα ολοκληρωμένο σύστημα αστικών συγκοινωνιών.

Η ζήτηση κάθε μέσου χωριστά, καθώς και το μερίδιο αγοράς κάθε μέσου στο σύνολο της επιβατικής κίνησης αναλύονται εφαρμόζοντας τις οικονομετρικές μεθόδους της Συνολοκλήρωσης και Δυναμικού Υποδείγματος Διόρθωσης Λαθών, οι οποίες επιτρέπουν την ανάλυση μη στάσιμων χρονολογικών σειρών. Η μεθοδολογία αυτή απαλλάσσει από τα προβλήματα που η απλή παλινδρόμηση παράγει στην περίπτωση των μη στάσιμων χρονολογικών σειρών (φαινομενικές συσχετίσεις, μεροληπτικές εκτιμήσεις) και επιπλέον παρέχει τις βραχυχρόνιες και μακροχρόνιες ελαστικότητες, καθώς και την ταχύτητα σύγκλισης στην μακροχρόνια κατάσταση ισορροπίας.

Τα στάδια της μεθοδολογίας αποτελούν ο έλεγχος στασιμότητας των μεταβλητών, ο έλεγχος ύπαρξης συνολοκλήρωσης μεταξύ των μη στάσιμων μεταβλητών, η εκτίμηση του Υποδείγματος Διόρθωσης Λαθών και η εφαρμογή στατιστικών ελέγχων για να διαπιστωθεί αν το Υπόδειγμα Διόρθωσης Λαθών που εκτιμήθηκε είναι κατάλληλο. Τέλος, στις περιπτώσεις που παρατηρείται Αυτοσυσχέτιση (Autocorrelation) ή/και Αυτοπαλίνδρομη υπό συνθήκη Ετεροσκεδαστικότητα (Autoregressive Conditional Heteroskedasticity-ARCH) στα κατάλοιπα, εκτιμώνται καινούρια Υποδείγματα Διόρθωσης Λαθών προκειμένου να αντιμετωπιστούν οι σχετικές επιπτώσεις.

Σύμφωνα με τα αποτελέσματα, οι βασικοί παράγοντες που επηρεάζουν στατιστικώς σημαντικά την επιβατική κίνηση κάθε μέσου τόσο στην μακροχρόνια όσο και στη βραχυχρόνια περίοδο είναι το ΑΕΠ, η τιμή του εισιτηρίου και η τιμή της βενζίνης. Από τα Μέσα Μαζικής Μεταφοράς που εξετάστηκαν το μετρό και ο ηλεκτρικός σιδηρόδρομος εμφανίζουν τις μεγαλύτερες ελαστικότητες, ενώ το λεωφορείο παρουσιάζεται ιδιαίτερα ανελαστικό. Το γεγονός ότι οι ελαστικότητες της ζήτησης ως προς τους ερμηνευτικούς παράγοντες είναι σημαντικά διαφορετικές για τα διάφορα Μ.Μ.Μ. αναδεικνύει τη χρησιμότητα της ανάλυσης της ζήτησης για κάθε μέσο χωριστά.

Τα αποτελέσματα δείχνουν επίσης ότι η τιμή του εισιτηρίου, το ΑΕΠ και η συνολική επιβατική κίνηση αποτελούν τους κυριότερους παράγοντες που καθορίζουν το μερίδιο αγοράς κάθε μέσου. Οι ελαστικότητες ως προς την τιμή του εισιτηρίου παρουσιάζονται ιδιαίτερα αυξημένες στα μοντέλα των μεριδίων αγοράς σε σύγκριση με τα μοντέλα ανάλυσης της επιβατικής κίνησης, καθώς απεικονίζουν με μεγαλύτερη ευαισθησία τις υποκαταστάσεις που προκύπτουν από μια μεταβολή της τιμής του εισιτηρίου. Τέλος, όπως αναμενόταν, τόσο στα μοντέλα της επιβατικής κίνησης όσο και στα μοντέλα του μεριδίου αγοράς κάθε μέσου οι βραχυχρόνιες ελαστικότητες είναι μικρότερες από τις αντίστοιχες μακροχρόνιες, επειδή οι συνέπειες κάθε μεταβολής απαιτούν χρόνο για να φτάσουν στην πλήρη ωρίμανσή τους.

ΕΚΤΕΤΑΜΕΝΗ ΠΕΡΙΛΗΨΗ

1. Εισαγωγή - Αντικείμενο της Διατριβής

Ένα σύστημα αστικών συγκοινωνιών αποτελείται από διαφορετικά Μέσα Μαζικής Μεταφοράς (Μ.Μ.Μ.), τα οποία δύνανται να λειτουργούν συμπληρωματικά ή ανταγωνιστικά. Η συμπληρωματικότητα των μέσων μεταφοράς ως προς την παρεχόμενη εξυπηρέτηση αποτελεί αναγκαίο χαρακτηριστικό ενός ορθολογικού μεταφορικού συστήματος και επιτυγχάνεται με τη διαφοροποίηση των ρόλων των διαφόρων μέσων. Ο σωστός σχεδιασμός, η ανάπτυξη των υποδομών και η κάλυψη του λειτουργικού κόστους αποτελούν επίσης απαραίτητες προϋποθέσεις για την εύρυθμη λειτουργία ενός συστήματος αστικών συγκοινωνιών και συνήθως απαιτούν υψηλά ποσά χρηματοδότησης.

Η μελέτη της ζήτησης είναι βασική προϋπόθεση για να ληφθούν ορθολογικές αποφάσεις σχετικά με την ανάπτυξη και τη λειτουργία των αστικών συγκοινωνιών με σκοπό να εξοικονομούνται πόροι και να επιτυγχάνεται η άριστη εξυπηρέτηση. Ταυτόχρονα η μελέτη του μεριδίου αγοράς του κάθε μέσου που συμμετέχει στο συγκοινωνιακό σύστημα επιτρέπει την ορθολογική κατανομή του συνολικού ποσού επιδότησης στα διάφορα συνεργαζόμενα μέσα. Με βάση το μέγεθος και τη μορφή της ζήτησης πραγματοποιείται ο σχεδιασμός ενός συστήματος αστικών συγκοινωνιών, η επέκταση ή αναβάθμιση ενός υπάρχοντος και η αλλαγή στα λειτουργικά χαρακτηριστικά του. Πιο συγκεκριμένα, η ανάλυση της ζήτησης σε ένα σύστημα αστικών συγκοινωνιών παρέχει χρήσιμη πληροφόρηση για την αποτελεσματική λήψη αποφάσεων που αφορούν στον καθορισμό της τιμής των εισιτηρίων, του ύψους των επιδοτήσεων, καθώς επίσης, και σε αποφάσεις που αφορούν στη βέλτιστη λειτουργία, επέκταση και αναβάθμιση του συστήματος.

Ένα σύστημα αστικών συγκοινωνιών διέπεται από πολύπλοκους κανόνες λειτουργίας και η ζήτησή του επηρεάζεται τόσο από εσωτερικούς ως προς το σύστημα παράγοντες, όπως οι τιμές των εισιτηρίων και η ποιότητα της εξυπηρέτησης, όσο και από άλλους μακροοικονομικούς και δημογραφικούς παράγοντες, όπως είναι το εισόδημα του πληθυσμού που εξυπηρετείται, η τιμή της βενζίνης, ο αριθμός των κυκλοφορούντων οχημάτων, η πυκνότητα του πληθυσμού και η κυκλοφοριακή ικανότητα του οδικού δικτύου. Ο βαθμός της μεταβολής της ζήτησης λόγω μεταβολής κάποιων παραγόντων μπορεί να εκτιμηθεί μέσω του μεγέθους της ελαστικότητας της ζήτησης. Στον τομέα των δημόσιων συγκοινωνιών οι μακροχρόνιες ελαστικότητες συνδέονται κυρίως με επενδυτικές αποφάσεις, ενώ οι βραχυχρόνιες ελαστικότητες συνδέονται κυρίως με λειτουργικές αποφάσεις.

Σκοπός της διατριβής είναι να διερευνηθούν οι παράγοντες που επηρεάζουν τόσο τις βραχυχρόνιες όσο και τις μακροχρόνιες μεταβολές στη ζήτηση ενός συστήματος αστικών συγκοινωνιών το οποίο αποτελείται από πολλά συνεργαζόμενα μέσα μεταφοράς, τα οποία λειτουργούν συμπληρωματικά.

Η μελέτη της ζήτησης για το κάθε μέσο μαζικής μεταφοράς του συστήματος αστικών συγκοινωνιών της πόλης των Αθηνών πραγματοποιείται με δύο προσεγγίσεις. Στην πρώτη προσέγγιση εξετάζονται οι παράγοντες που ερμηνεύουν την μηνιαία επιβατική κίνηση του κάθε μέσου. Αυτή η προσέγγιση επιτρέπει τη λεπτομερέστερη ανάλυση των παραγόντων που επηρεάζουν την επιβατική κίνηση του κάθε μέσου του συστήματος αστικών συγκοινωνιών τόσο στη μακροχρόνια όσο και στη βραχυχρόνια περίοδο και τον προσδιορισμό των αντίστοιχων ελαστικοτήτων. Στη δεύτερη προσέγγιση αναλύεται το ποσοστό (μερίδιο) της συνολικής ζήτησης που καλύπτει το κάθε μέσο μαζικής μεταφοράς. Ο προσδιορισμός του μεριδίου αγοράς κάθε μέσου στο σύνολο της επιβατικής κίνησης επιτρέπει τη λεπτομερέστερη ανάλυση σε ότι αφορά στον ειδικό ρόλο κάθε μέσου σε ένα ολοκληρωμένο σύστημα αστικών συγκοινωνιών.

Τόσο η ζήτηση κάθε μέσου χωριστά, όσο και το μερίδιο αγοράς κάθε μέσου στο σύνολο της επιβατικής κίνησης αναλύονται εφαρμόζοντας οικονομετρικές μεθόδους που επιτρέπουν την ανάλυση μη στάσιμων χρονολογικών σειρών, και οι οποίες έχουν εφαρμοστεί κυρίως στα πλαίσια της οικονομικής θεωρίας, αλλά μέχρι σήμερα έχουν τύχει περιορισμένης χρήσης στον τομέα των μεταφορών.

Ο σκοπός της διδακτορικής διατριβής, πιο αναλυτικά, είναι:

1. Ο προσδιορισμός των παραγόντων που επηρεάζουν τη ζήτηση, για κάθε μέσο μαζικής μεταφοράς ξεχωριστά, σε ένα σύστημα αστικών συγκοινωνιών.
2. Η ανάλυση του μεριδίου αγοράς του κάθε μέσου σε ένα σύστημα αστικών συγκοινωνιών που αποτελείται από πολλά συνεργαζόμενα μέσα μεταφοράς τα οποία λειτουργούν συμπληρωματικά.
3. Η ανάπτυξη μιας μεθοδολογίας για την ανάλυση της επιβατικής κίνησης και του μεριδίου αγοράς του κάθε μέσου λαμβάνοντας υπόψη τη μη στασιμότητα των χρονολογικών σειρών που περιγράφουν τη ζήτηση.
4. Η εκτίμηση τόσο των βραχυχρόνιων όσο και των μακροχρόνιων ελαστικοτήτων, αλλά και της ταχύτητας προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας, για την επιβατική κίνηση του κάθε μέσου και για το μερίδιο αγοράς του κάθε μέσου.
5. Η εφαρμογή της μεθοδολογίας στην περίπτωση του αστικού συστήματος συγκοινωνιών τη πόλης των Αθηνών χρησιμοποιώντας μηνιαία στοιχεία χρονολογικών σειρών για την περίοδο 2002-2010.

Η διδακτορική διατριβή αποτελείται από τις εξής ενότητες (κεφάλαια): εισαγωγή, βιβλιογραφική ανασκόπηση, μεθοδολογία, ανάλυση της επιβατικής κίνησης του κάθε Μέσου Μαζικής Μεταφοράς, ανάλυση του μεριδίου αγοράς κάθε Μέσου Μαζικής Μεταφοράς και συμπεράσματα.

2. Βιβλιογραφική Ανασκόπηση

Στο δεύτερο κεφάλαιο της διατριβής πραγματοποιήθηκε βιβλιογραφική ανασκόπηση της υπάρχουσας έρευνας στο αντικείμενο της ανάλυσης της ζήτησης σε ένα σύστημα αστικών συγκοινωνιών. Στόχοι της ανασκόπησης ήταν αφενός η καταγραφή της υφιστάμενης γνώσης στο αντικείμενο της έρευνας και αφετέρου η αναζήτηση και επιλογή των μεθοδολογικών εργαλείων που θα μπορούσαν να χρησιμοποιηθούν στην εκπόνηση της έρευνας. Από πλευράς ανάλυσης της ζήτησης, το ενδιαφέρον εστιάστηκε τόσο σε μελέτες που αναλύουν τη ζήτηση για κάθε μέσο ξεχωριστά, όσο και σε μελέτες που αναλύουν το μερίδιο αγοράς του κάθε μέσου. Από πλευράς μεθοδολογίας, το ενδιαφέρον επικεντρώθηκε στις μελέτες της ζήτησης για Δημόσιες Συγκοινωνίες, οι όποιες λαμβάνουν υπόψη τη μη στασιμότητα χρονολογικών σειρών.

Η επίδραση διαφόρων παραγόντων στη ζήτηση για τα Μέσα Μαζικής Μεταφοράς έχει ερευνηθεί από πολλές μελέτες διεθνώς. Οι παράγοντες που επηρεάζουν τη ζήτηση για τα Μ.Μ.Μ. μπορούν να χωριστούν σε εσωτερικούς και εξωτερικούς ως προς το σύστημα παράγοντες. Οι κυριότεροι εσωτερικοί ως προς το σύστημα παράγοντες είναι η τιμή του εισιτηρίου και το επίπεδο εξυπηρέτησης. Οι κυριότεροι εξωτερικοί ως προς το σύστημα παράγοντες, που έχουν βρεθεί στη βιβλιογραφία να επηρεάζουν τη ζήτηση για ΜΜΜ, είναι το εισόδημα, το Ακαθάριστο Εγχώριο Προϊόν (ΑΕΠ), ο δείκτης ιδιοκτησίας ΙΧ, η τιμή της βενζίνης, οι καιρικές συνθήκες, ο δείκτης ανεργίας, ο αριθμός μεταναστών και το κόστος για παρκάρισμα.

Οι ελαστικότητες που υπολογίζονται ως προς καθένα από τους ερμηνευτικούς παράγοντες στις διάφορες μελέτες παρουσιάζουν μεγάλη διακύμανση. Η διακύμανση που παρουσιάζεται οφείλεται (Graham et al., 2009):

1. Στα Δεδομένα που χρησιμοποιούνται (π.χ. εξατομικευμένα ή όχι, δεδομένα χρονολογικών σειρών ή διαστρωματικά)
2. Στο χρονικό πλαίσιο που αναλύεται (ετήσια, μηνιαία, ημερήσια δεδομένα)
3. Στην οικονομετρική μέθοδο που εφαρμόζεται
4. Στη στατική ή δυναμική δομή του μοντέλου
5. Στον προσδιορισμό της συνάρτησης της ζήτησης
6. Στον προσδιορισμό της εξαρτημένης μεταβλητής
7. Στον αριθμό των Μεταφορικών Μέσων που συμπεριλαμβάνονται στην έρευνα

Παρόλο που έχουν πραγματοποιηθεί πολλές μελέτες διεθνώς που αναλύουν τη ζήτηση για ΜΜΜ, είναι πολύ περιορισμένος ο αριθμός των μελετών που λαμβάνουν υπόψη τη μη στασιμότητα των χρονολογικών σειρών που περιγράφουν τη ζήτηση, χρησιμοποιώντας τις τεχνικές της Συνολοκλήρωσης και του Δυναμικού Υποδείγματος Διόρθωσης Λαθών που αναπτύχτηκαν από τους Engle and Granger (1987). Η μεθοδολογία αυτή παρέχει πιο αξιόπιστα αποτελέσματα στις περιπτώσεις που η παραδοχή της στασιμότητας των σειρών στην γραμμική παλινδρόμηση παραβιάζεται (Kulendran and Stephen, 2001). O Romilly (2001) και οι Dargay και Hanly (2002) χρησιμοποίησαν την παραπάνω μεθοδολογία για να υπολογίζουν μακροχρόνιες και βραχυχρόνιες ελαστικότητες της ζήτησης του λεωφορείου στη Μεγάλη Βρετανία. Αργότερα οι Crotte κ.α. (2008) ανέλυσαν τη ζήτηση του μετρό στο Μεξικό χρησιμοποιώντας της τεχνικές της Συνολοκλήρωσης και λαμβάνοντας υπόψη τη μη στασιμότητα των χρονολογικών σειρών της επιβατικής κίνησης.

3. Μεθοδολογία

Στη τρίτο κεφάλαιο της διατριβής μελετήθηκε ενδελεχώς η θεωρία ανάλυσης μη στάσιμων χρονολογικών σειρών με σκοπό την ανάπτυξη και εφαρμογή της μεθοδολογίας για την εκτίμηση της κατανομής της ζήτησης στα Μέσα Μαζικής Μεταφοράς.

Στην παρούσα διδακτορική διατριβή χρησιμοποιήθηκε μια μεθοδολογία βασισμένη στη θεωρία της Συνολοκλήρωσης που αναπτύχθηκε από τους Engle και Granger (1987) και η οποία μπορεί να εφαρμοστεί στις περιπτώσεις που τόσο η ζήτηση όσο και οι ερμηνευτικές μεταβλητές περιγράφονται από μη στάσιμες χρονολογικές σειρές. Για την ανάπτυξη και εφαρμογή της μεθοδολογίας στον τομέα των μεταφορών χρησιμοποιήθηκαν μηνιαία στοιχεία χρονολογικών σειρών από το σύστημα αστικών συγκοινωνιών της Αθήνας. Συγκεκριμένα, για την εκτίμηση της κατανομής της ζήτησης στα Μέσα Μαζικής Μεταφοράς χρησιμοποιήθηκαν οι τεχνικές της Συνολοκλήρωσης και του Δυναμικού Υποδείγματος Διόρθωσης Λαθών (Cointegration and Error Correction Model) οι οποίες επιτρέπουν:

I. Την ανάλυση μη στάσιμων χρονολογικών σειρών, όπου οι κλασικές οικονομετρικές μέθοδοι της παλινδρόμησης παρουσιάζουν μη αξιόπιστα αποτελέσματα καθώς εμφανίζονται “φαινομενικές” συσχετίσεις (spurious correlations).
II. Τον προσδιορισμό τόσο των μακροχρόνιων όσο και των βραχυχρόνιων ελαστικοτήτων της ζήτησης ως προς καθένα από τους ερμηνευτικούς παράγοντες.
III. Την εκτίμηση της ταχύτητας προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας.

Παρακάτω, αναλύονται οι έννοιες της στασιμότητας, του βαθμού ολοκλήρωσης, της συνολοκλήρωσης και περιγράφεται η μεθοδολογία της συνολοκλήρωσης και του Δυναμικού Υποδείγματος Διόρθωσης Λαθών που αναπτύχθηκε από τους Engle and Granger.

Στασιμότητα

Μια χρονολογική σειρά χαρακτηρίζεται μη στάσιμη (non-stationary) εάν οι παράμετροί της (μέσος όρος, διακύμανση και αυτοσυνδιακύμανση των τιμών της) δεν είναι σταθεροί, αλλά μεταβάλλονται με το χρόνο. Για να είναι μια σειρά στάσιμη (stationary) πρέπει να ισχύουν ταυτόχρονα και οι τρεις παρακάτω προϋποθέσεις. Έστω και μια να μην ισχύει η σειρά χαρακτηρίζεται μη στάσιμη.

1. Σταθερός Μέσος όρος για κάθε t

$$E(X_t)=\mu \ \forall \ t \in T \quad (1)$$

2. Σταθερή Διακύμανση για κάθε t

$$Var(X_t)=E[X_t-E(X_t)]^2=\sigma^2 \ \ \forall \ t \in T \quad (2)$$

3. Η αυτοσυνδιακύμανση εξαρτάται μόνο από την χρονική υστέρηση μεταξύ δύο παρατηρήσεων

$$Cov\ (X_t, X_{t+s}) = Cov\ (X_{t+k}, X_{t+k+s})=\gamma_s \leftrightarrow$$

$$\leftrightarrow E[(X_t-\mu)(X_{t+s}-\mu)]= E[(X_{t+k}-\mu)(X_{t+k+s}-\mu)]=\gamma_s \ \ \forall \ t \in T \quad (3)$$

Βαθμός ολοκλήρωσης

Με την έννοια της στασιμότητας σχετίζεται ο βαθμός ολοκλήρωσης μιας σειράς. Μια σειρά λέγεται ότι είναι ολοκληρωμένη πρώτης τάξης (integrated of order one) και συμβολίζεται με I(1) αν μετατρέπεται σε στάσιμη λαμβάνοντας πρώτες διαφορές. Μια σειρά είναι ολοκληρωμένη d τάξεως I(d) αν μετατρέπεται σε στάσιμη παίρνοντας διαφορές d τάξεως.

Έλεγχοι μοναδιαίας ρίζας

Για τον έλεγχο στασιμότητας της σειράς αλλά και τον προσδιορισμό του βαθμού ολοκλήρωσης της εφαρμόζονται οι έλεγχοι μοναδιαίας ρίζας (unit root tests). Οι έλεγχοι μοναδιαίας ρίζας εφαρμόστηκαν πρώτη αφορά από τους Dickey-Fuller (1979). Θεωρώντας μια χρονολογική σειρά Yt εφαρμόζεται ο παρακάτω έλεγχος.

$$\Delta Y_t = a_0 + \delta Y_{t-1} + u_t \tag{4}$$

$$u_t \sim iid\,(0, \sigma^2)$$

όπου

Yt είναι η χρονολογική σειρά

u_t είναι τα κατάλοιπα

Δ είναι ο τελεστής των πρώτων διαφορών

H_0: δ=0 ↔ η Y_t είναι μη στάσιμη $I(1)$

H_1: δ<0 ↔ η Y_t στάσιμη είναι $I(0)$

Απόρριψη της μηδενικής υπόθεσης H_0 δηλώνει ότι η σειρά είναι στάσιμη, ενώ αντίστοιχα αποδοχή της H_0 δηλώνει την ύπαρξη μοναδιαίας ρίζας (μη στάσιμη χρονολογική σειρά).

Συνολοκλήρωση

Η χρήση της απλής παλινδρόμησης για την ανάλυση μη στάσιμων χρονολογικών σειρών συχνά οδηγεί στο φαινόμενο των φαινομενικών συσχετίσεων. Οι Granger and Newbold (1974) χρησιμοποίησαν τον όρο φαινομενική συσχέτιση (spurious correlation) για να εκφράσουν την περίπτωση της παλινδρόμησης μεταξύ μη στάσιμων μεταβλητών που δίνει ικανοποιητικά αποτελέσματα από πλευράς στατιστικών κριτηρίων (R^2, στατιστικό κριτήριο t) αλλά δεν εκφράζει στην ουσία καμία αιτιολογική σχέση μεταξύ των μεταβλητών. Στην περίπτωση που υπάρχει αιτιολογική σχέση μεταξύ των μη στάσιμων μεταβλητών τότε λέμε ότι οι μεταβλητές είναι συνολοκληρωμένες. Η έννοια της συνολοκλήρωσης αναπτύχθηκε από τους Engle και Granger (1987). Πιο αναλυτικά, θεωρούμε την παρακάτω εξίσωση παλινδρόμησης

$$Y_t = \alpha_0 + \beta X_t + \varepsilon_t \tag{5}$$

όπου

Y_t είναι η εξαρτημένη μεταβλητή και X_t είναι μια ανεξάρτητη εξωγενής μεταβλητή.

Αν και οι δύο μεταβλητές είναι I(1) (γίνονται στάσιμες λαμβάνοντας τις πρώτες διαφορές), αναμένεται ότι και τα κατάλοιπα $\varepsilon_t = Y_t - \alpha_0 + \beta X_t$ θα είναι επίσης I(1). Υπάρχει περίπτωση να υπάρχει ένας γραμμικός συνδυασμός των δύο μεταβλητών ο οποίος να είναι στάσιμος. Σε αυτή την περίπτωση οι μεταβλητές λέγονται συνοκληρωμένες, η εξίσωση (5) ονομάζεται εξίσωση συνολοκλήρωσης και το διάνυσμα (1, -β) διάνυσμα της συνολοκλήρωσης (cointegrated vector).Στην περίπτωση που οι μεταβλητές είναι συνολοκληρωμένες από την εξίσωση (5) προκύπτουν οι μακροχρόνιες ελαστικότητες.

Σύμφωνα με το αντιπροσωπευτικό θεώρημα των Engle και Granger (1987), όταν δύο μεταβλητές συνολοκληρώνονται τότε υπάρχει ένα Υπόδειγμα Διόρθωσης Λαθών (Εξίσωση 6) το οποίο συσχετίζει τις βραχυχρόνιες μεταβολές ΔY_t, ΔX_t με τις αποκλίσεις από την μακροχρόνια ισορροπία της προηγούμενης περιόδου (ε_{t-1})

$$\Delta Y_t = \sum_{i=1}^{q} a_{yi}\ \Delta Y_{t-i} + \sum_{i=0}^{p} a_{xi}\ \Delta X_{t-i} + a_{resid}\, \varepsilon_{t-1} + e_t \qquad (6)$$

Όπου

Δ δηλώνει τις πρώτες διαφορές

p, q ο αριθμός των υστερήσεων των ΔΧ και ΔΥ αντίστοιχα ώστε e_t ~iid $(0, \sigma^2)$

ε_{t-1} η υστέρηση των λαθών της προηγούμενης περιόδου

a_{resid} ο συντελεστής των καταλοίπων της προηγούμενης περιόδου

e_t τα κατάλοιπα

Ο συντελεστής των καταλοίπων της προηγούμενης περιόδου (a_{resid}) εκφράζει την ταχύτητα προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας. Για να υπάρχει συνολοκλήρωση μεταξύ των μεταβλητών ο συντελεστής αυτός θα πρέπει να έχει αρνητική τιμή και να είναι στατιστικά σημαντικός. Από το Δυναμικό Υπόδειγμα Διόρθωσης Λαθών προκύπτουν και οι βραχυχρόνιες ελαστικότητες.

Μεθοδολογία Engle-Granger (1987)

Η μεθοδολογία ανάλυσης μη στάσιμων χρονολογικών σειρών (Engle and Granger, 1987) που εφαρμόστηκε στην διδακτορική διατριβή πραγματοποιείται στα εξής στάδια:

I. Στο πρώτο στάδιο πραγματοποιείται ό έλεγχος μοναδιαίας ρίζας σε κάθε μια από τις μεταβλητές ώστε να βρεθεί ο βαθμός ολοκλήρωσής τους. Προϋπόθεση για την ύπαρξη συνολοκλήρωσης είναι οι μεταβλητές να έχουν τον ίδιο βαθμό ολοκλήρωσης Αν οι μεταβλητές είναι στάσιμες I(0) τότε μπορούν να εφαρμοστούν οι κλασικές οικονομετρικές μέθοδοι. Αν οι μεταβλητές είναι μη στάσιμες και έχουν τον ίδιο βαθμό ολοκλήρωσης τότε προχωράμε στο επόμενο βήμα.

II. Στο δεύτερο στάδιο πραγματοποιείται ο έλεγχος ύπαρξης συνολοκλήρωσης μεταξύ των μη στάσιμων χρονολογικών σειρών. Σε περίπτωση που οι μεταβλητές είναι συνολοκληρωμένες εκτιμάται η στάσιμη μακροχρόνια σχέση μεταξύ των μη στάσιμων μεταβλητών μέσω των εξισώσεων συνολοκλήρωσης (cointegrating regressions) και υπολογίζονται οι μακροχρόνιες ελαστικότητες της ζήτησης ως προς καθένα από τους ερμηνευτικούς παράγοντες.

III. Στο τρίτο στάδιο εκτιμάται το Δυναμικό Υπόδειγμα Διόρθωσης Λαθών. Σύμφωνα με το θεώρημα των Engle and Granger, αν οι μεταβλητές είναι συνολοκληρωμένες, η μεταξύ τους σχέση ανισορροπίας μπορεί να διατυπωθεί με ένα Υπόδειγμα Διόρθωσης Λαθών (Error Correction Model). Με το Δυναμικό Υπόδειγμα Διόρθωσης Λαθών υπολογίζονται οι βραχυχρόνιες ελαστικότητες της ζήτησης καθώς επίσης και η ταχύτητα προσαρμογής της ζήτησης στην κατάσταση της μακροχρόνιας ισορροπίας.

IV. Τέλος ελέγχεται αν το Δυναμικό Υπόδειγμα Διόρθωσης Λαθών είναι κατάλληλο εφαρμόζοντας στατιστικούς ελέγχους. Στις περιπτώσεις που παρατηρείται Αυτοσυσχέτιση (Autocorrelation) ή/και Αυτοπαλίνδρομη υπό συνθήκη Ετεροσκεδαστικότητα (Autoregressive Conditional Heteroskedasticity-ARCH) στα κατάλοιπα, εκτιμώνται καινούρια Υποδείγματα Διόρθωσης Λαθών προκειμένου να αντιμετωπιστούν οι σχετικές επιπτώσεις.

4. Ανάλυση της επιβατικής κίνησης του κάθε Μέσου Μαζικής Μεταφοράς

Εισαγωγή

Η μεθοδολογία της Συνολοκλήρωσης και του Υποδείγματος Διόρθωσης Λαθών εφαρμόστηκε για την ανάλυση της ζήτησης κάθε μέσου του συγκοινωνιακού συστήματος της Αθήνας, χρησιμοποιώντας ως βασικές ερμηνευτικές μεταβλητές την τιμή εισιτηρίου του κάθε μέσου, την τιμή της βενζίνης και το Ακαθάριστο Εγχώριο Προϊόν, το δείκτη ανεργίας, τις πωλήσεις δικύκλων και τις πωλήσεις ΙΧ. Για κάθε μέσο μαζικής μεταφοράς εκτιμήθηκαν οι μακροχρόνιες και οι βραχυχρόνιες ελαστικότητες της ζήτησης ως προς καθένα από τους ερμηνευτικούς παράγοντες, καθώς επίσης και η ταχύτητα προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας.

Η ανάλυση της ζήτησης του συγκοινωνιακού συστήματος της Αθήνας πραγματοποιήθηκε χρησιμοποιώντας δεδομένα χρονολογικών σειρών από τον Ιανουάριο του 2002 μέχρι το Δεκέμβριο του 2010. Το συγκοινωνιακό σύστημα της Αθήνας αποτελείται από πέντε μεταφορικά μέσα (μετρό, λεωφορείο, ηλεκτρικός σιδηρόδρομος τρόλεϊ και τραμ). Το τραμ δεν συμπεριελήφθηκε στην έρευνα, καθώς διαθέσιμα στοιχεία σχετικά με την επιβατική του κίνηση υπήρχαν μόνο από το 2006. Στο μεγαλύτερο μέρος του δικτύου τα μέσα αυτά λειτουργούν υπό συνθήκες συμπληρωματικής λειτουργίας, ενώ υπάρχουν και κομμάτια του δικτύου που τα μέσα λειτουργούν ανταγωνιστικά δημιουργώντας συνθήκες ανταγωνισμού και υποκατάστασης. Οι μεταβλητές που χρησιμοποιήθηκαν στην ανάλυση παρουσιάζονται στον παρακάτω πίνακα.

Πίνακας 1. Μέσος όρος και τυπική απόκλιση βασικών μεταβλητών

Μεταβλητές	Μέσος όρος	Τυπική Απόκλιση
Επιβατική κίνηση μετρό	14,295,245	2,544,766
Επιβατική κίνηση Λεωφορείου	30,338,756	3,127,397
Επιβατική κίνηση Τρόλεϊ	6,573,172	7,852,62
Επιβατική κίνηση Ηλ. Σιδηρόδρομου	9,661,460	1,526,618
Τιμή Εισιτηρίου Μετρό (€)	0.922	0.074
Τιμή Εισιτηρίου Λεωφορείου/ τρόλεϊ (€)	0.695	0.205
Τιμή Εισιτηρίου Ηλ. σιδηροδρόμου (€)	0.879	0.095
Δείκτης ανεργίας (ποσοστό)	9.076	1.752
Τιμή Βενζίνης (€)	0.799	0.143
Ακαθάριστο Εγχώριο Προϊόν (σε εκατομμύρια €)	19.768	1.657
Ακαθάριστο Εγχώριο Προϊόν ανά κάτοικο (€)	1,772	138
Πληθυσμός της Αθήνας	4,014,567	71,742
Πωλήσεις Δικύκλων	2,763.57	1,043.26
Πωλήσεις Ι.Χ.	10.755,55	3.471,38

Εξισώσεις Συνολοκλήρωσης

Στο πρώτο στάδιο της ανάλυσης ελέγχθηκε η μη στασιμότητα των μεταβλητών εφαρμόζοντας τους ελέγχους μοναδιαίας ρίζας σε καθεμιά από τις μεταβλητές (επιβατική κίνηση του κάθε μέσου, ΑΕΠ, τιμή βενζίνης, τιμή εισιτηρίου, ανεργία κτλ). Διαπιστώθηκε ότι όλες οι μεταβλητές είναι μη στάσιμες και ολοκληρωμένες πρώτης τάξης.

Στο δεύτερο στάδιο της ανάλυσης εκτιμήθηκαν οι εξισώσεις συνολοκλήρωσης από τις οποίες προέκυψαν οι μακροχρόνιες ελαστικότητες. Η εξίσωση συνολοκλήρωσης για κάθε μέσο i εκτιμήθηκε χρησιμοποιώντας την παρακάτω βασική εξίσωση.

$$\text{Επιβατική κίνηση μέσου}_i = a_0 + a_1 \text{ τιμή εισιτηρίου} + a_2 \text{ τιμή βενζίνης} + a_3 \text{ ΑΕΠ ανά κάτοικο} + \alpha_4 \text{ Πωλήσεις Δικύκλων} + u_t \quad (7)$$

Εκτιμήθηκε η εξίσωση συνολοκλήρωσης για κάθε μέσο ξεχωριστά και ελέγχτηκε αν τα κατάλοιπα u_t είναι στάσιμα ή όχι. Η στασιμότητα των καταλοίπων συνεπάγεται και την ύπαρξη συνολοκλήρωσης μεταξύ των μεταβλητών της εξίσωσης.

Πίνακας 2. Εξισώσεις Συνολοκλήρωσης
(t-statistic στην παρένθεση)

	Εξαρτημένη Μεταβλητή			
Ανεξάρτητες Μεταβλητές	**Μετρό**	**Λεωφορείο**	**Τρόλεϊ**	**Ηλεκτρικός Σιδηρόδρομος**
Σταθερός Όρος	9.21 (9.29)	17.23 (1250.95)	15.68 (1049.59)	10.33 (9.34)
Τιμή Εισιτηρίου_Μετρό	-0.23 (-1.92)			
Τιμή Εισιτηρίου_Λεωφορείου/τρόλεϊ		-0.05 (-1.83)	-0.16 (-5.18)	
Τιμή Εισιτηρίου_Ηλ, Σιδηρόδρομου				-0.33(-3.18)
ΑΕΠ ανά κάτοικο	1.03 (7.57)			0.76 (5.20)
Πωλήσεις Δικύκλων	-0.04 (-1.92)			
Τιμή Βενζίνης	0.13 (2.12)		0.08 (1.53)	
Ιούλιος	-0.23 (-6.99)	-0.07 (-2.71)	-0.09 (-3.51)	-0.25 (-6.13)
Αύγουστος	-0.69 (-20.55)	-0.29 (-11.14)	-0.37 (-14.34)	-0.47 (-11.53)
Έλεγχος Προσαρμογής R^2	0.809	0.547	0.690	0.599
Durbin-Watson stat	1.57	1.71	1.83	1.02
DF-GLS τεστ για έλεγχο μοναδιαίας ρίζας	-8.27	-7.88	-9.34	-5.41
Κριτικές τιμές του MacKinnon (5% critical level)	-4.20	-2.88	-3.39	-3.39
Αριθμός Παρατηρήσεων	108	108	108	108

Τα αποτελέσματα των εξισώσεων συνολοκλήρωσης και των ελέγχων μοναδιαίας ρίζας για κάθε ένα από τα μέσα μαζικής μεταφοράς παρουσιάζονται στον Πίνακα 2. Βασιζόμενοι στις κριτικές τιμές του Mackinnon (1991) για τους ελέγχους συνολοκλήρωσης, τα κατάλοιπα και των τεσσάρων εξισώσεων βρίσκονται να είναι μη στάσιμα I(0) βεβαιώνοντας την ύπαρξη συνολοκλήρωσης ανάμεσα στις μεταβλητές της κάθε εξίσωσης.

Η ύπαρξη συνολοκλήρωσης συνεπάγεται την ύπαρξη μιας μακροχρόνιας σχέσης ισορροπίας μεταξύ των μη στάσιμων μεταβλητών. Τα αποτελέσματα δείχνουν ότι η επιβατική κίνηση του μετρό συνολοκληρώνεται με την τιμή εισιτηρίου του μετρό, το ΑΕΠ ανά κάτοικο, την τιμή της βενζίνης και τις πωλήσεις δικύκλων. Η επιβατική κίνηση του τρόλεϊ συνολοκληρώνεται με την τιμή εισιτηρίου του και την τιμή της βενζίνης. Η επιβατική κίνηση του ηλεκτρικού σιδηρόδρομου συνολοκληρώνεται με την τιμή εισιτηρίου και το ΑΕΠ ανά κάτοικο. Τέλος, η επιβατική κίνηση του λεωφορείου συνολοκληρώνεται μόνο με την τιμή εισιτηρίου του λεωφορείου. Οι μακροχρόνιες ελαστικότητες που προέκυψαν από την ανάλυση παρουσιάζονται αναλυτικά στον Πίνακα 4. Σύμφωνα με τα αποτελέσματα το μετρό και ο ηλεκτρικός σιδηρόδρομος εμφανίζουν τις μεγαλύτερες ελαστικότητες ως προς την τιμή του εισιτηρίου και το ΑΕΠ, ενώ η ζήτηση του λεωφορείου παρουσιάζεται ιδιαίτερα ανελαστική.

Υποδείγματα Διόρθωσης Λαθών

Στο τρίτο στάδιο της ανάλυσης εκτιμήθηκαν τα Υποδείγματα Διόρθωσης Λαθών από τα οποία προέκυψαν οι βραχυχρόνιες ελαστικότητες, καθώς και η ταχύτητα προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας για κάθε Μ.Μ.Μ. Το Δυναμικό Υπόδειγμα Διόρθωσης Λαθών εκτιμήθηκε χρησιμοποιώντας την παρακάτω εξίσωση για κάθε Μ.Μ.Μ.

$$\Delta\text{επιβατική κίνηση}_t = \sum_{i=1}^{q} a_{ri}\,\Delta\,\text{επιβατική κίνηση}_{t-i} + \sum_{i=0}^{p} a_{pi}\,\Delta\text{τιμή εισιτηρίου}_{t-i} + \sum_{i=0}^{g} a_{gi}\,\Delta\,\text{τιμή βενζίνης}_{t-i} + \sum_{i=0}^{d} a_{di}\,\Delta\text{ΑΕΠ}_{t-i} + \sum_{i=0}^{m} a_{mi}\,\Delta\,\text{πωλήσεις δικύκλων}_{t-i} + a_{resid}\,u_{t-1} + e_t \tag{8}$$

Επιπλέον, σε κάθε εξίσωση περιλαμβάνονται δυαδικές μεταβλητές για κάθε μήνα ώστε να αναλυθούν οι εποχικές διακυμάνσεις της ζήτησης. Τα αποτελέσματα παρουσιάζονται στον Πίνακα 3.

Πίνακας 3. Υπόδειγμα Διόρθωσης Λαθών

	Εξαρτημένες Μεταβλητές			
Ανεξάρτητες Μεταβλητές	**Μετρό**	**Λεωφορείο**	**Τρόλεϊ**	**Ηλεκτρικός Σιδηρόδρομος**
Δ_Μετρό_Υστέρηση 1	-0.12 (-1.50)			
Δ_Λεωφορείο_ Υστέρηση1				
Δ_Τρόλεϊ_ Υστέρηση1			-0.75 (-8.66)	
Δ_Ηλ. Σιδηρόδρομος_ Υστέρηση1				-0.21 (-2.16)
Δ_Τιμή Εισιτηρίου_Μετρό	-0.04 (-0.13)			
Δ_Τιμή Εισιτηρίου_Λεωφορείου/τρόλεϊ		-0.041 (-0.31)		
Δ_Τιμή Εισιτηρίου_Ηλ. Σιδηρόδρομου				-0.18 (-0.59)
Δ_ΑΕΠ ανά κάτοικο	0.28 (1.45)			0.06 (0.27)
Δ_Πωλήσεις δικύκλων	-0.05 (-2.21)			
Δ_Τιμή βενζίνης_Υστέρηση1	0.03 (0.24)		0.06 (0.32)	
Φεβρουάριος		-0.45 (-1.92)	-0.06 (-1.72)	
Μάρτιος	0.08 (3.67)			
Αύγουστος	-0.46 (-16.99)	-0.22 (-9.52)	-0.36 (-10.72)	-0.25 (-8.27)
Ιούλιος	-0.17 (-6.83)	-0.07 (-2.99)	-0.10 (-3.32)	0.19 (-6.17)
Σεπτέμβριος	0.47 (11.36)	0.28 (11.90)		
Οκτώβριος	0.12 (2.31)	0.06 (2.86)	0.35 (7.52)	
Νοέμβριος				0.07 (2.52)
u_{t-1}	-0.55 (-5.76)	-0.88 (-8.70)	-0.25 (-1.60)	-0.32 (-3.60)
Έλεγχος Προσαρμογής R^2	0.91	0.76	0.69	0.73
Αριθμός Παρατηρήσεων	108	108	108	108
Έλεγχοι Καταλοίπων				
Breusch-Godfrey LM τεστ για αυτοσυσχέτιση καταλοίπων				
Υστέρηση1	1.63 (p=0.201)	0.53 (p=0.467)	0.05 (p=0.816)	0.57 (p=0.450)
Υστέρηση2	2.28 (p=0.320)	1.49 (p=0.474)	6.78 (p=0.034)	0.59 (p=0.745)
Υστέρηση3	4.10 (p=0.251)	2.45 (p=0.485)	7.60 (p=0.055)	1.01 (p=0.798)
Υστέρηση4	4.13 (p=0.388)	3.14 (p=0.534)	15.25 (p=0.004)	2.23 (p=0.693)
Υστέρηση5	5.04 (p=0.410)	5.37 (p=0.372)	17.76 (p=0.003)	3.26 (p=0.660)
Υστέρηση6	6.80 (p=0.339)	5.46 (p=0.486)	17.80 (p=0.007)	3.37 (p=0.761)
Υστέρηση7	6.92 (p=0.437)	5.60 (p=0.587)	17.93 (p=0.012)	4.60 (p=0.708)
Υστέρηση8	12.47 (p=0.131)	6.34 (p=0.609)	17.94 (p=0.021)	4.77 (p=0.782)
Υστέρηση9	12.76 (p=0.174)	6.35 (p=0.704)	18.44 (p=0.030)	4.96 (p=0.838)
Υστέρηση10	12.82 (p=0.234)	6.56 (p=0.766)	18.44 (p=0.048)	5.01 (p=0.891)
Υστέρηση11	13.44 (p=0.265)	6.69 (p=0.823)	18.54 (p=0.070)	5.89 (p=0.881)
Υστέρηση12	13.46 (p=0.336)	6.98 (p=0.859)	23.30 (p=0.025)	9.62 (p=0.649)
Engle' s LM τεστ για Αυτοπαλίνδρομη υπό συνθήκη Ετεροσκεδαστικότητα				
Υστέρηση1	0.01 (p=0.911)	0.81 (p=0.369)	36.88 (p=0.000)	0.34 (p=0.558)
Υστέρηση2	0.13 (p=0.936)	1.95 (p=0.377)	39.81 (p=0.000)	0.35 (p=0.841)
Υστέρηση3	0.15 (p=0.985)	2.03 (p=0.566)	40.88 (p=0.000)	0.39 (p=0.943)
Υστέρηση4	0.16 (p=0.997)	3.35 (p=0.500)	41.73 (p=0.000)	0.81 (p=0.937)
Υστέρηση5	0.45 (p=0.994)	3.36 (p=0.645).	42.94 (p=0.000)	0.92 (p=0.968)
Υστέρηση6	0.54 (p=0.997)	4.04 (p=0.672)	44.99 (p=0.000)	2.22 (p=0.898)
Υστέρηση7	0.55 (p=0.999)	4.08 (p=0.769)	45.03 (p=0.000)	3.19 (p=0.867)
Υστέρηση8	0.56 (p=0.999)	4.11 (p=0.847)	45.14 (p=0.000)	3.59 (p=0.892)
Υστέρηση9	0.58 (p=0.999)	4.22 (p=0.896)	45.15 (p=0.000)	3.85 (p=0.921)
Υστέρηση10	0.83 (p=0.999)	4.26 (p=0.935)	45.24 (p=0.000)	5.10 (p=0.884)
Υστέρηση11	1.25 (p=0.999)	4.82 (p=0.939)	45.24 (p=0.000)	5.22 (p=0.917)
Υστέρηση12	1.26 (p=0.999)	5.17 (p=0.952)	45.34 (p=0.000)	8.51 (p=0.744)

Προκειμένου να ελέγξουμε την καταλληλότητα των υποδειγμάτων πραγματοποιήθηκαν στατιστικοί έλεγχοι στα κατάλοιπα της κάθε εξίσωσης (Breusch-Godfrey LM τεστ και Engle's LM τεστ). Οι έλεγχοι υποδεικνύουν ότι στο Δυναμικό Υπόδειγμα Διόρθωσης Λαθών του τρόλεϊ εμφανίζεται αυτοσυσχέτιση και αυτοπαλίνδρομη υπό συνθήκη ετεροσκεδαστικότητα (Autoregressive Conditional Heteroskedasticity, ARCH). Για την απαιτούμενη διόρθωση αναπτύχθηκε ένα υπόδειγμα ARCH για την επιβατική κίνηση του τρόλεϊ στην βραχυχρόνια περίοδο.

Ο συντελεστής προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας (a_{resid}) είναι αρνητικός και στατιστικά σημαντικός στα Υποδείγματα Διόρθωσης Λαθών που εκτιμήθηκαν επιβεβαιώνοντας την ύπαρξη συνολοκλήρωσης μεταξύ των μεταβλητών. Ο συντελεστής αυτός μας δείχνει τον ακριβή χρόνο που χρειάζεται για να ολοκληρωθεί η πλήρης προσαρμογή στην μακροχρόνια κατάσταση ισορροπίας. Για το μεταφορικό μέσο του μετρό παίρνει την τιμή 0.55 υποδεικνύοντας ότι το 55% της προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας επιτυγχάνεται στην πρώτη περίοδο (μήνα). Η ταχύτητα προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας παρουσιάζεται ιδιαίτερα υψηλή για το λεωφορείο (0.88% της προσαρμογής επιτυγχάνεται στον πρώτο μήνα) ενώ για τα μεταφορικά μέσα του τρόλει και του ηλ σιδηρόδρομου ο συντελεστής υπολογίστηκε -0.25 και -0.32 αντίστοιχα.

<u>Ελαστικότητες</u>

Οι βραχυχρόνιες και οι μακροχρόνιες ελαστικότητες της ζήτησης ως προς καθένα από τους ερμηνευτικούς παράγοντες που προέκυψαν από τα Υποδείγματα Διόρθωσης Λαθών και τις εξισώσεις συνολοκλήρωσης αντίστοιχα παρουσιάζονται αναλυτικά στον Πίνακα 4.

Οι βραχυχρόνιες ελαστικότητες που υπολογίστηκαν για κάθε μέσο μαζικής μεταφοράς παρουσιάζονται μικρότερες από τις αντίστοιχες μακροχρόνιες καθώς οι αλλαγές στις συνήθειες των μετακινούμενων χρειάζονται χρόνο για να φτάσουν στην πλήρη ωρίμανσή τους.

Πίνακας 4. Βραχυχρόνιες και Μακροχρόνιες Ελαστικότητες

	Μακροχρόνια Περίοδος	Βραχυχρόνια Περίοδος
Μετρό		
ΑΕΠ ανά κάτοικο	1.03	0.28
Πωλήσεις Δικύκλων	-0.05	-0.05
Τιμή Εισιτηρίου_Μετρό	-0.23	-0.04
Τιμή Βενζίνης	0.13	0.03
Λεωφορείο		
Τιμή Εισιτηρίου_Λεωφορείου/τρόλεϊ	-0.05	-0.04
Ηλ. Σιδηρόδρομος		
ΑΕΠ ανά κάτοικο	0.76	0.06
Τιμή Εισιτηρίου_Ηλ. Σιδηρόδρομος	-0.33	-0.18
Τρόλεϊ		
Τιμή Εισιτηρίου_Λεωφορείου/τρόλεϊ	-0.16	-
Τιμή Βενζίνης	0.08	0.03

Η υψηλή ελαστικότητα που παρουσιάζεται για το μετρό και τον ηλεκτρικό σιδηρόδρομο ως προς το ΑΕΠ (ελαστικότητες 1.03 και 0.76 αντίστοιχα) πιθανότατα εξηγείται από το γεγονός ότι μια αύξηση στο ΑΕΠ οδηγεί στην παραγωγή περισσότερων μετακινήσεων οι οποίες απορροφώνται κυρίως από αυτά τα δύο μέσα. Οι αντίστοιχες ελαστικότητες για τα δύο αυτά μέσα στη βραχυχρόνια περίοδο εμφανίζονται πολύ μικρότερες (0.28 για το μετρό και 0.06 για τον ηλεκτρικό σιδηρόδρομο). Επιπλέον το μετρό και ο ηλεκτρικός σιδηρόδρομος παρουσιάζουν τις υψηλότερες ελαστικότητες σε σχέση με την τιμή του εισιτηρίου τόσο στην βραχυχρόνια όσο και στην μακροχρόνια περίοδο.

Η ζήτηση του λεωφορείου παρουσιάζεται ιδιαίτερα ανελαστική τόσο στην βραχυχρόνια όσο και στην μακροχρόνια περίοδο. Το αποτέλεσμα αυτό συνδέεται πιθανότατα με το γεγονός ότι το λεωφορείο αποτελεί το μοναδικό μέσο που εξυπηρετεί ορισμένα κομμάτια του δικτύου. Τέλος, μια αύξηση στην τιμή της βενζίνης αυξάνει την επιβατική κίνηση του μετρό και του τρόλεϊ.

Γενικά σε όλα τα μέσα μαζικής μεταφοράς η μικρή αρνητική τιμή της ελαστικότητας ως προς την τιμή του εισιτηρίου υποδηλώνει ότι μια αύξηση της τιμής του εισιτηρίου θα επιφέρει αύξηση των συνολικών εσόδων.

5. Ανάλυση του μεριδίου αγοράς κάθε Μέσου Μαζικής Μεταφοράς

Εισαγωγή

Ακολουθώντας την μεθοδολογική προσέγγιση της Συνολοκλήρωσης και του Δυναμικού Υποδείγματος Διόρθωσης Λαθών, στην ενότητα αύτη αναλύεται το μερίδιο αγοράς του κάθε μέσου στην συνολική ζήτηση χρησιμοποιώντας ως ερμηνευτικές μεταβλητές τη συνολική επιβατική κίνηση, την τιμή εισιτηρίου του κάθε μέσου, την τιμή της βενζίνης, τον δείκτη ανεργίας και το Ακαθάριστο Εγχώριο Προϊόν. Ο προσδιορισμός του μεριδίου αγοράς κάθε μέσου στο σύνολο της επιβατικής κίνησης επιτρέπει τη λεπτομερέστερη ανάλυση σε ότι αφορά στον ειδικό ρόλο κάθε μέσου σε ένα ολοκληρωμένο σύστημα αστικών συγκοινωνιών. Για την ανάλυση χρησιμοποιήθηκαν χρονολογικά δεδομένα από τον Ιανουάριο του 2002 ως τον Δεκέμβριο του 2010.

Εξισώσεις Συνολοκλήρωσης

Στο πρώτο στάδιο ελέγχθηκε η στασιμότητα όλων των μεταβλητών που χρησιμοποιήθηκαν στην ανάλυση και διαπιστώθηκε ότι όλες είναι μη στάσιμες και ολοκληρωμένες πρώτης τάξης. Στη συνέχεια χρησιμοποιώντας την εξίσωση συνολοκλήρωσης (9) αναλύθηκε το μερίδιο αγοράς κάθε μέσου του συγκοινωνιακού συστήματος της Αθήνας στην μακροχρόνια περίοδο.

$$\text{Μερίδιο αγοράς μέσου i} = a_0 + a_1 \ln \text{Τιμή εισιτηρίου} + a_2 \ln \text{Συνολική Επιβατική Κίνηση} + a_3 \ln \text{ΑΕΠ} + a_4 \ln \text{Τιμή βενζίνης} + u_t \qquad (9)$$

Στον Πίνακα 5 παρουσιάζονται μόνο οι μεταβλητές που βρέθηκαν να επηρεάζουν στατιστικώς σημαντικά το μερίδιο αγοράς του κάθε μέσου. Σύμφωνα με τους ελέγχους συνολοκλήρωσης που πραγματοποιήθηκαν τα κατάλοιπα της κάθε εξίσωσης είναι στάσιμα βεβαιώνοντας την ύπαρξη συνολοκλήρωσης μεταξύ των μη στάσιμων μεταβλητών.

Το μερίδιο αγοράς του μετρό, του τρόλεϊ και του ηλεκτρικού σιδηρόδρομου συνολοκληρώνονται με την τιμή του εισιτηρίου, τη συνολική επιβατική κίνηση και το ακαθάριστο εγχώριο προϊόν, ενώ το μερίδιο αγοράς του λεωφορείου συνολοκληρώνεται με την τιμή εισιτηρίου του μετρό, τη συνολική επιβατική κίνηση και την τιμή της βενζίνης.

Πίνακας 5. Εξισώσεις Συνολοκλήρωσης

	Εξαρτημένες Μεταβλητές (t-Statistic in parenthesis)			
Ανεξάρτητες Μεταβλητές[a]	**Μερίδιο Αγοράς Μετρό**	**Μερίδιο Αγοράς Λεωφορείου**	**Μερίδιο Αγοράς Τρόλεϊ**	**Μερίδιο Αγοράς Ηλ. Σιδηροδρόμου**
Σταθερός Όρος	-2.524 (-7.67)	1.939 (6.06)	0.548(4.54)	-0.711 (-2.58)
Τιμή Εισιτηρίου_Μετρό	-0.186 (-3.83)	0.166 (4.84)		
Τιμή Εισιτηρίου_Λεωφορείου/τρόλεϊ			-0.009 (-3.51)	
Τιμή Εισιτηρίου_Ηλ. Σιδηρόδρομου				-0.027 (-1.85)
Συνολική Επιβατική Κίνηση	0.103 (7.53)	-0.076 (-4.22)	-0.012 (-2.54)	0.021 (1.83)
ΑΕΠ	0.090 (4.44)		-0.022(-2.83)	0.049 (2.84)
Τιμή Βενζίνης		0.054 (2.50)		
Ενιαίο Εισιτήριο	0.047 (5.15)			
Τάση		-0.001(-6.62)		
Έλεγχος Προσαρμογής R^2	0.539	0.503	0.234	0.115
Durbin-Watson stat	1.164	1.359	1.494	1.075
ADF τεστ για έλεγχο μοναδιαίας ρίζας	-6.23	-7.25	-4.84	-6.29
Κριτικές τιμές του MacKinnon	-3.82	-3.51	-3.82	-3.82
Αριθμός Παρατηρήσεων	108	108	108	108

[a] *οι ανεξάρτητες μεταβλητές είναι σε λογαριθμική μορφή*

Υποδείγματα Διόρθωσης Λαθών

Αφού υπολογίστηκαν οι μακροχρόνιες ελαστικότητες, το επόμενο βήμα είναι η εκτίμηση των Υποδειγμάτων Διόρθωσης Λαθών για το μερίδιο αγοράς κάθε μέσου (Εξίσωση 10) προκειμένου να υπολογιστούν οι βραχυχρόνιες ελαστικότητες και ο χρόνος που απαιτείται για να επανέλθει το σύστημα στην μακροχρόνια ισορροπία.

$$\Delta \text{μερίδιο αγοράς μέσου}_t = \sum_{i=1}^{q} a_{ri}\ \Delta\text{μερίδιο αγοράς μέσου}_{t-i} + \sum_{i=0}^{p} a_{pi}\ \Delta \ln \text{τιμή εισιτηρίου}_{t-i} + \sum_{i=0}^{g} a_{gi}\ \Delta\ln\text{τιμή βενζίνης}_{t-i} + \sum_{i=0}^{d} a_{di}\ \Delta\ln\text{ΑΕΠ}_{t-i} + \sum_{i=0}^{m} a_{mi}\ \Delta\ln\text{Συνολική Επιβατική Κίνηση}_{t-i} + a_{resid}\, u_{t-1} + e_t \qquad (10)$$

Οι διαγνωστικοί έλεγχοι στα κατάλοιπα υποδεικνύουν την ύπαρξη αυτοσυσχέτισης στο Υπόδειγμα Διόρθωσης Λαθών του μεριδίου αγοράς του μετρό. Προκειμένου να διορθωθεί η αυτοσυσχέτιση στα κατάλοιπα το Υπόδειγμα Διόρθωσης Λαθών εκτιμήθηκε με τη μέθοδο της μέγιστης πιθανοφάνειας (Maximum Likelihood) λαμβάνοντας υπόψη ότι τα κατάλοιπα έχουν την παρακάτω μορφή

$$e_{it} = \rho_1 * e_{i,t-1} + \rho_2 * e_{i,t-2} + \cdots + \rho_n * e_{i,t-n} + u_{it} \qquad (11)$$

Πίνακας 6. Δυναμικό Υπόδειγμα Διόρθωσης Λαθών

	Εξαρτημένες Μεταβλητές (t-Statistic in parenthesis)			
Ανεξάρτητες Μεταβλητές[a]	**Μερίδιο Αγοράς Μετρό**	**Μερίδιο Αγοράς Λεωφορείου**	**Μερίδιο Αγοράς Τρόλεϊ**	**Μερίδιο Αγοράς Ηλ. Σιδηροδρόμου**
Δ_Μερίδιο αγοράς μετρό_Υστέρηση1	-0.124 (-1.69)			
Δ_Μερίδιο αγοράς λεωφορείου_Υστέρηση1		-0.187 (-1.94)		
Δ_Μερίδιο αγοράς Τρόλεϊ_Υστέρηση1			-0.472 (-3.57)	
Δ_Μερίδιο αγοράς Ηλ Σιδηροδρόμου_Υστέρηση1				-0.080 (-0.85)
Δ_Μερίδιο αγοράς μετρό_Υστέρηση2				
Δ_Μερίδιο αγοράς Λεωφορείου_Υστέρηση2		-0.172 (-1.87)		
Δ_Μερίδιο αγοράς Τρόλεϊ_Υστέρηση2			-0.181 (-1.72)	
Δ_Τιμή εισιτηρίου_Μετρό	-0.066 (-1.27)			
Δ_Τιμή Εισιτηρίου_Λεωφορείου/Τρόλεϊ		0.049 (0.67)	-0.001 (-0.11)	
Δ_Τιμή Εισιτηρίου_Ηλ. Σιδηρόδρομου				-0.017 (-0.41)
Δ_ΑΕΠ	-0.023 (-0.67)		-0.016 (-1.04)	0.008 (0.26)
Δ_Τιμή βενζίνης		0.028 (0.73)		
Δ_Συνολική Επιβατική Κίνηση	0.051 (-6.64)	-0.042 (-3.11)	0.002 (0.43)	-0.023 (-2.86)
Φεβρουάριος	0.010 (2.00)			
Μάρτιος			-0.003 (-1.58)	
Ιούνιος			0.005 (2.72)	
Αύγουστος	-0.021 (-3.87)			
Ιούλιος		0.011 (1.66)	0.004 (2.01)	-0.013 (-3.17)
Νοέμβριος		-0.017 (-2.26)		
Δεκέμβριος	0.017 (3.82)	-0.026 (-3.88)	-0.003 (-1.58)	0.007(1.72)
Κατάλοιπα u_{t-1}	-0.574 (-6.64)	-0.557 (-4.90)	-0.443 (-3.52)	-0.430 (-5.03)
Έλεγχος Προσαρμογής R^2	0.595	0.495	0.450	0.393
Αριθμός Παρατηρήσεων	108	108	108	108

[a] *όλες οι ανεξάρτητες μεταβλητές εκτός από τους μήνες είναι σε λογαριθμική μορφή*

	Έλεγχοι Καταλοίπων			
Breusch-Godfrey LM τεστ για αυτοσυσχέτιση καταλοίπων				
Υστέρηση1	4.37 (p=0.037)	0.11 (p=0.736)	0.07 (p=0.795)	2.02 (p=0.155)
Υστέρηση2	9.39 (p=0.009)	0.38 (p=0.826)	1.81 (p=0.404)	2.16 (p=0.339)
Υστέρηση3	9.53 (p=0.023)	1.32 (p=0.725)	2.51 (p=0.474)	2.23 (p=0.526)
Υστέρηση4	10.20 (p=0.037)	2.05 (p=0.726)	2.52 (p=0.641)	4.59 (p=0.332)
Υστέρηση5	10.20 (p=0.069)	2.18 (p=0.824)	2.87 (p=0.719)	4.86 (p=0.433)
Υστέρηση6	10.31 (p=0.112)	2.25 (p=0.895)	3.05 (p=0.802)	5.54 (p=0.477)
Υστέρηση7	10.55 (p=0.159)	2.84 (p=0.899)	3.34 (p=0.852)	7.58 (p=0.371)
Υστέρηση8	10.96 (p=0.204)	3.21(p=0.921)	3.34 (p=0.911)	8.13 (p=0.421)
Υστέρηση9	11.85 (p=0.222)	3.25 (p=0.953)	4.41(p=0.882)	8.83 (p=0.453)
Υστέρηση10	13.02 (p=0.222)	3.92 (p=0.951)	5.96 (p=0.818)	10.03 (p=0.438)
Υστέρηση11	13.04 (p=0.291)	3.98 (p=0.971)	6.44 (p=0.842)	10.36 (p=0.498)
Υστέρηση12	13.89 (p=0.307)	4.00(p=0.984)	6.54 (p=0.886)	15.52 (p=0.214)
Engle' s LM τεστ για Αυτοπαλίνδρομη υπό συνθήκη Ετεροσκεδαστικότητα				
Υστέρηση1	0.308 (p=0.579)	0.181 (p=0.670)	0.247 (p=0.619)	0.280 (p=0.597)
Υστέρηση2	0.352 (p=0.839)	0.182 (p=0.913)	0.354 (p=0.838)	0.549 (p=0.760)
Υστέρηση3	0.488 (p=0.922)	0.585 (p=0.900)	1.365 (p=0.714)	1.406 (p=0.704)
Υστέρηση4	0.524 (p=0.971)	0.616 (p=0.961)	1.411 (p=0.842)	2.008 (p=0.734)
Υστέρηση5	0.815 (p=0.976)	0.921 (p=0.969)	1.724 (p=0.886)	2.734 (p=0.741)
Υστέρηση6	0.905 (p=0.989)	1.082 (p=0.982)	1.741 (p=0.942)	3.861 (p=0.695)
Υστέρηση7	1.057 (p=0.994)	1.468 (p=0.983)	2.090 (p=0.955)	4.396 (p=0.733)
Υστέρηση8	1.220 (p=0.996)	1.554 (p=0.992)	2.131 (p=0.978)	5.658 (p=0.685)
Υστέρηση9	1.232(p=0.999)	4.759 (p=0.859)	2.378 (p=0.984)	6.307 (p=0.709)
Υστέρηση10	1.239 (p=0.999)	4.832 (p=0.902)	2.519 (p=0.991)	7. 199 (p=0.707)
Υστέρηση11	1.357(p=0.999)	5.670 (p=0.894)	5.251 (p=0.918)	7.277 (p=0.776)
Υστέρηση12	19.958(p=0.068)	6.937 (p=0.962)	5.400 (p=0.943)	12.381(p=0.416)

Οι βραχυχρόνιες και οι μακροχρόνιες ελαστικότητες που προέκυψαν από την ανάλυση παρουσιάζονται στον Πίνακα 7. Η σχέση μεταξύ των μακροχρόνιων και των βραχυχρόνιων ελαστικοτήτων καθώς επίσης και η ταχύτητα προσαρμογής στη μακροχρόνια ισορροπία δείχνουν την ευελιξία προσαρμογής του συστήματος σε κάθε επιχειρούμενη μεταβολή.

Πίνακας 7. Βραχυχρόνιες και Μακροχρόνιες Ελαστικότητες

	Μακροχρόνια Περίοδος	**Βραχυχρόνια Περίοδος**
Μετρό		
ΑΕΠ	0.39	-0.10
Τιμή Εισιτηρίου_Μετρό	-0.80	-0.28
Συνολική Επιβατική Κίνηση	0.44	0.22
Λεωφορείο		
Τιμή Εισιτηρίου_Μετρό	0.33	0.10
Τιμή Βενζίνης	0.10	0.06
Συνολική Επιβατική Κίνηση	-0.15	-0.08
Ηλ. Σιδηρόδρομος		
ΑΕΠ	0.32	0.05
Τιμή Εισιτηρίου_Ηλ. Σιδηρόδρομου	-0.17	-0.11
Συνολική Επιβατική Κίνηση	0.13	-0.14
Τρόλεϊ		
Τιμή Εισιτηρίου_Λεωφορείου/Τρόλεϊ	-0.08	-0.01
ΑΕΠ	-0.20	-0.15
Συνολική Επιβατική Κίνηση	-0.11	0.02

Ο συντελεστής προσαρμογής στην μακροχρόνια κατάσταση ισορροπίας παίρνει τιμές από -0.43 μέχρι -0.64 στα τέσσερα Υποδείγματα Διόρθωσης Λαθών υποδεικνύοντας πως η προσαρμογή στην μακροχρόνια κατάσταση ισορροπίας πραγματοποιείται σε περίπου δύο μήνες (κυμαινόμενη από 1.6 μέχρι 2.3 μήνες).

Επιπλέον, η ανάλυση δείχνει ότι το ΑΕΠ και η τιμή του εισιτηρίου είναι οι βασικοί παράγοντες που καθορίζουν τα μερίδια αγοράς των μέσων μαζικής μεταφοράς. Η θετική σχέση συνολοκλήρωσης μεταξύ του μεριδίου αγοράς του μετρό και του ΑΕΠ συνδέεται πιθανότατα με το γεγονός ότι το μετρό είναι το πιο ακριβό ΜΜΜ και ευνοείται σε περιόδους αύξησης του ΑΕΠ συγκριτικά με άλλα μέσα μαζικής μεταφοράς όπως το τρόλεϊ (αρνητική σχέση του μεριδίου αγοράς του τρόλεϊ σε σχέση με το ΑΕΠ). Επιπλέον, η θέσπιση του ενιαίου εισιτηρίου έχει ευνοήσει τη χρήση του μετρό και έχει αυξήσει το μερίδιο αγοράς του.

Τέλος, τα αποτελέσματα υποδεικνύουν πώς οι μεταβολές στη συνολική επιβατική κίνηση επηρεάζουν το μερίδιο αγοράς του κάθε μέσου ξεχωριστά. Τα μερίδια αγοράς του μετρό και του ηλεκτρικού σιδηρόδρομου αυξάνονται καθώς αυξάνεται η συνολική επιβατική κίνηση (ελαστικότητες 0.44 και 0.13 αντίστοιχα), ενώ τα μερίδια αγοράς του τρόλεϊ και του λεωφορείου μειώνονται καθώς αυξάνεται η συνολική επιβατική κίνηση στην μακροχρόνια περίοδο (ελαστικότητες -0.11 και -0.15 αντίστοιχα).

6. Συμπεράσματα

Η παρούσα Διδακτορική Διατριβή έχει ως κύριο αντικείμενο τη διερεύνηση των παραγόντων που επηρεάζουν τόσο τις βραχυχρόνιες όσο και τις μακροχρόνιες μεταβολές στη ζήτηση ενός συστήματος αστικών συγκοινωνιών το οποίο αποτελείται από πολλά συνεργαζόμενα μέσα μεταφοράς τα οποία λειτουργούν συμπληρωματικά δημιουργώντας συνθήκες ανταγωνισμού και υποκατάστασης. Η μελέτη της ζήτησης πραγματοποιείται με δύο προσεγγίσεις. Στην πρώτη προσέγγιση εξετάζονται οι παράγοντες που ερμηνεύουν την μηνιαία επιβατική κίνηση του κάθε μέσου. Στη δεύτερη προσέγγιση αναλύεται το ποσοστό (μερίδιο) της συνολικής ζήτησης που καλύπτει το κάθε μέσο μαζικής μεταφοράς.

Παρόλο που έχουν πραγματοποιηθεί πολλές μελέτες διεθνώς που αναλύουν τους παράγοντες που καθορίζουν τη ζήτηση για τα μέσα μαζικής μεταφοράς, οι περισσότερες δεν έχουν λάβει υπόψη τη μη στασιμότητα των χρονολογικών σειρών που περιγράφουν τη ζήτηση. Επιπλέον η ανάλυση του μεριδίου αγοράς του κάθε μέσου μαζικής μεταφοράς σε ένα ολοκληρωμένο σύστημα αστικών συγκοινωνιών δεν έχει διερευνηθεί κατά το παρελθόν. Η ερευνητική συμβολή της διατριβής έγκειται πρώτα στο γεγονός ότι η ανάλυση της μεταφορικής ζήτησης πραγματοποιείται με έμφαση στη μη στασιμότητα των χρονολογικών σειρών και δεύτερον στο γεγονός ότι η προσέγγιση αυτή χρησιμοποιείται για την ανάλυση του μεριδίου αγοράς του κάθε μέσου στη συνολική ζήτηση σε ένα σύστημα αστικών συγκοινωνιών που αποτελείται από συνεργαζόμενα μέσα μεταφοράς.

Η μεθοδολογία που εφαρμόστηκε στην παρούσα διδακτορική διατριβή απαλλάσσει από τα προβλήματα που η απλή παλινδρόμηση παράγει στην περίπτωση των μη στάσιμων χρονολογικών σειρών (φαινομενικές συσχετίσεις, μεροληπτικές εκτιμήσεις). Επιπλέον παρέχει τις βραχυχρόνιες και μακροχρόνιες ελαστικότητες καθώς και την ταχύτητα σύγκλισης στην μακροχρόνια κατάσταση ισορροπίας.

Οι βασικοί παράγοντες που βρέθηκε να επηρεάζουν στατιστικώς σημαντικά τη ζήτηση, τόσο στην μακροχρόνια όσο και στη βραχυχρόνια περίοδο, είναι το ΑΕΠ, η τιμή του εισιτηρίου και η τιμή της βενζίνης. Επιπλέον, διαπιστώθηκε ότι η επιρροή των παραγόντων αυτών στην επιβατική κίνηση είναι διαφορετική για κάθε μέσο μαζικής μεταφοράς. Από τα Μέσα Μαζικής Μεταφοράς που εξετάστηκαν το μετρό και ο ηλεκτρικός σιδηρόδρομος εμφανίζουν τις μεγαλύτερες ελαστικότητες, ενώ το λεωφορείο παρουσιάζεται ιδιαίτερα ανελαστικό. Το γεγονός ότι οι ελαστικότητες της ζήτησης ως προς τους ερμηνευτικούς παράγοντες είναι σημαντικά διαφορετικές για τα διάφορα Μ.Μ.Μ. αναδεικνύει τη χρησιμότητα της ανάλυσης της ζήτησης για κάθε μέσο χωριστά.

Η μελέτη του μεριδίου της ζήτησης για κάθε μέσο μαζικής μεταφοράς προσφέρει πρόσθετη πληροφόρηση για την ανάλυση της ζήτησης σε ένα σύστημα αστικών συγκοινωνιών όπου τα διάφορα μέσα λειτουργούν συμπληρωματικά, επιτρέποντας την λεπτομερέστερη ανάλυση σε ότι αφορά στον ειδικό ρόλο κάθε μέσου. Τα αποτελέσματα υποδεικνύουν πως η τιμή του εισιτηρίου, το ΑΕΠ και η συνολική επιβατική κίνηση αποτελούν τους κυριότερους παράγοντες που καθορίζουν το μερίδιο αγοράς κάθε μέσου. Οι ελαστικότητες ως προς την τιμή του εισιτηρίου παρουσιάζονται ιδιαίτερα αυξημένες στα μοντέλα των μεριδίων αγοράς σε σύγκριση με τα μοντέλα ανάλυσης της επιβατικής κίνησης, καθώς απεικονίζουν με μεγαλύτερη ευαισθησία τις υποκαταστάσεις που προκύπτουν από μια μεταβολή της τιμής του εισιτηρίου. Τέλος, όπως αναμενόταν, τόσο στα μοντέλα της επιβατικής κίνησης όσο και στα μοντέλα του μεριδίου αγοράς κάθε μέσου, οι βραχυχρόνιες ελαστικότητες είναι μικρότερες από τις αντίστοιχες μακροχρόνιες, επειδή οι συνέπειες κάθε μεταβολής απαιτούν χρόνο για να φτάσουν στην πλήρη ωρίμανσή τους.

Συμπερασματικά, η μεθοδολογία που χρησιμοποιήθηκε στη διδακτορική διατριβή παρέχει πιο αξιόπιστη ανάλυση των χρονολογικών σειρών της επιβατικής ζήτησης των Μ.Μ.Μ. και η ανάλυση του μεριδίου αγοράς κάθε μέσου προσφέρει χρήσιμη πληροφόρηση για τον άριστο τρόπο συμπληρωματικής λειτουργίας των μέσων.

TABLE OF CONTENTS

1. INTRODUCTION

In this dissertation demand aspects of a multimodal urban public transportation system are investigated using a time series approach based on cointegration and error correction techniques. This approach allows for the analysis of non stationary data and for the estimation of short and long run elasticities of the factors affecting demand. Ridership is examined for each transport mode separately. The share of each mode in total ridership is also analyzed. The Athens multimodal public transport system serves as a test bed for the developed models.

1.1. Public Transport Demand

Public transportation offers equitable and environmentally friendly services to societies and as such is an important player in sustainable transportation and mobility in urban areas. Public transportation (PT) frequently operates in a highly competitive and complex environment and its demand is affected by various socioeconomic and operational characteristics. For instance, higher incomes and lower fuel prices encourage the use of private vehicles, while suboptimal scheduling and increased fares could have a negative impact on public transport usage.

Public transport –particularly fixed track- is both expensive to built in terms of infrastructure and highly costly to run in terms of operational costs. At the same time it is largely considered as a societal good, a fact that puts pressure to keep fares as low as possible. This inevitably leads to high subsidies and raises the question of allocating these subsidies to the various public transport modes in the most effective way. The limited availability of resources and the need to reduce operating subsidies, as current economic conditions dictate, increase the complexity, but also the importance, of efficient management of public transportation systems. Demand analysis is a necessary condition for efficient decision making in a public transport system; network expansion, pricing policies, subsidy and operational decisions are based on demand analysis.

Transport demand analysis investigates how certain key factors such as fares, GDP, income, fuel prices and quality of public transport services affect transport demand. Demand variation is measured using the concept of elasticity, i.e. the ratio of the percentage change of demand to the percentage change of a factor in question. Fare is the most widely studied factor in the context of transport demand analysis because it is a controllable factor that regulates revenues and it has a distinct impact on demand. Therefore, it is a factor directly related to policy issues. The ever increasing cost of a transport system requires frequent fare increases which have to seek a compromise between the financial and the social aspect of the transport system. Fare restructuring attempts to satisfy two goals; first, to achieve a specified level of revenues which is defined after the desired level of subsidy has been defined; second, to contribute to the optimal expansion and operation of the system by reducing peak effects and by exploiting existing capacity in the best possible way. It is evident that revenue estimation resulting from a fare increase, or, a fare restructuring such as off-peak pricing can be effectively achieved through the estimation of demand elasticities with respect to fares and, that the best way to produce such elasticities is via an advanced econometric analysis.

Other factors such as income, Gross Domestic Product (GDP) although they have an important impact on demand they are not related directly to transportation policy issues. Variations in income or GDP may affect demand in conflicting ways; an increase in income level or GDP will, generally, induce more trips resulting to an increased public transport demand; but, it may also have a negative effect because it creates a shift to private cars. GDP and income are closely related so only one of the two is used in any particular study. Fuel price is directly related to the cost of car use and, thus, fuel cost usually discourages car use and positively affects public transport demand. Quality of service and parking costs are other important factors that positively affect demand for public transportation.

1.2. Motivation

In a multimodal environment different modes have differing characteristics and may operate in competition or cooperation depending on a variety of circumstances. In a multimodal public transport system that operates under common pricing policies, a variation in fares, or any relevant factor, affects in different ways demand for different public transport modes. Therefore, treating each mode of the multimodal PT system as a separate entity provides clearer information regarding the role and contribution of each mode to the system. Moreover, demand analysis for each mode separately allows for identifying substitution effects among the different modes. This is particularly useful for an effective policy differentiation taking into account the particular contribution of each mode to total demand and the manner in which the demand for each mode is affected by various factors. For example, demand mode analysis may lead to fare differentiation or to conclusions as to how a unified ticket affects demand of each mode.

In the present thesis two different but complementary aspects of public transport demand are investigated; (i) the ridership of each mode and, (ii) the share of each mode in total ridership. The above two issues provide useful information regarding effective policy measures. Demand analysis for each mode separately produces more accurate demand elasticities, while the study of the share of each mode in total public transport demand facilitates the equitable distribution of total subsidy to the various modes.

In the first part of the dissertation demand characteristics of a multimodal public transportation system are investigated using a time-series modeling approach. The aims of the analysis are: First, to quantify the effects of various factors (i.e. fare, fuel prices, income, unemployment rate, private cars, motorcycle sales) that affect the demand for different PT modes. Second, to estimate the elasticities of different modes of public transport with respect to the above factors (both in the short and in the long run), and thus analyze the trends of demand in these modes. This analysis provides useful information for the design of policy measures concerning pricing policies regarding fares and fuel prices and, also, policies for strengthening and expanding the public transport network.

In the second part of the dissertation, market shares for each public transport mode in total public transport ridership are analyzed. The analysis of the share of each transport mode in a multimodal urban public transport system is a key factor that explains the relative position of each mode in a system where, depending on the particular conditions, different modes act cooperatively or competitively. It may also be a useful index for making investment decisions concerning the public transport infrastructure and for allocating subsidies.

1.3. Methodology

A main goal of this thesis is to provide a framework for analyzing public transport demand while explicitly considering the non-stationary nature of the demand time series. Non-stationarity is a common property of many macroeconomic time series such as GDP, income, prices and so on. The use of standard regression techniques with independent, non-stationary variables can lead to spurious regressions (Granger and Newbold, 1974). In a spurious regression, fitted coefficients appear statistically significant while there is no true relationship between the dependent variable and the regressors. Thus, correlation between non stationary series may not imply the kind of causal relationship that might be inferred in the case of stationary series. However, there may exist a linear combination among non-stationary time series that yields a stationary time series. If such a combination does exist, then the variables are said to be cointegrated (Granger and Weiss, 1983). Engle and Granger (1987) formalize the idea of cointegration and provide an estimation procedure for analyzing long run as well as short run relations among non-stationary variables.

Demand elasticity is a dynamic concept; i.e. following a fare change, or -more generally- a variation on an independent variable affecting demand, demand variation does not remain constant but usually increases as time elapses. This happens because certain choices and attributes that develop following a fare change take time to reach maturity. In dynamic phenomena following a shock (a change in one of the dependent variables) the system requires some time to reach stability (the new state of equilibrium). Accurate estimation (evaluation) of the total impact of the change requires to take account not only the effect of the final state but also the transition effects. Estimating the effects resulting from the new equilibrium state requires knowledge of the long run elasticities. Estimating the effects of the transition process from the initial to the new state of equilibrium requires knowledge of the short run elasticities and the speed of adjustment (i.e. the time that takes to reach the new equilibrium state).

It is therefore useful to consider the effect that fares, GDP, gasoline prices and other relevant factors have on public transport demand both in the transition period and in the new equilibrium state by estimating short run as well as long run elasticities. In the public transport sector the long run responses are mainly associated with investment decisions, while the short run responses are associated with operational decisions. Regarding the policy measures, however, it is useful to know not only the long run effects of fares and other relevant factors on ridership as well as the time required to complete total response (Dargay and Hanly, 2002a). Cointegration techniques and error correction models help in this direction by explicitly accounting for short and long run effects as well as the speed of adjustment towards long run equilibrium.

1.4. Objectives and Contribution

Advanced econometric modeling including cointegration and error correction techniques is a field closely related to economic analysis. All the pioneering work on non-stationary time series data was developed and tested in the context of economic models. However, transportation time series data also exhibit non-stationarity. Related work in the transportation field considering non-stationary time characteristics of the variables is rather limited (Balcombe et al., 2004; Liddle, 2009). This study fills this gap by exploiting the use of advanced econometric modeling in the context of transportation demand analysis. Public transport demand analysis and public transport mode shares are analyzed using cointegration and error correction techniques in a time series analysis framework, since this methodology allows for treating non-stationary data and for determining short term and long term elasticities and the speed of adjustment towards long run equilibrium. This is a field of research that has not attracted attention in the transportation literature.

The main objectives of the dissertation are the following:

1. To analyze the share of each mode in total public transport ridership for a multimodal system where different modes may operate either in competition or cooperation.
2. To determine the impact of exogenous factors on multimodal public transport demand by treating each mode as a separate entity.
3. To provide a framework for analyzing public transport demand and public trasnsport mode shares while considering the non-stationary nature of the demand time series. The analysis is based on advanced econometric methods using cointegration techniques.
4. To capture short and long run elasticities and the speed of adjustment towards long run equilibrium for each mode's ridership and for the share of each mode in total ridership.
5. To apply the methodology in the case of the Athens multimodal public transport system using monthly data for the period 2002-2010 while explicitly accounting seasonal effects.

1.5. Thesis Outline

In chapter two, an overview of demand analysis in transportation is presented. Demand analysis procedures are characterized by the nature of the approach, the data sources, the factors chosen to explain demand and the techniques employed in the analysis. Areas that the present thesis may contribute are identified and emphasis is given on issues related to the analysis performed.

In chapter three a methodological framework related to dynamic econometric modeling is presented. The basic concepts of time series analysis including stationarity, serial correlation, Autoregressive Conditional Heteroskedasticity are discussed. Finally, a methodology for analysing non-stationary time series, based on the cointegration and error correction techniques, introduced by Engle and Granger (1987), is presented.

In chapter four a framework for analyzing demand in a multimodal public transport system is presented. The Athens Public transport system is examined as a case study. The analysis uses a cointegration and error correction time series approach. This allows for treating non stationary data, for determining short and long term elasticities and at the same time estimating the speed of convergence from the short to the long run. Autoregressive conditional Heteroskedasticity (ARCH) effects (i.e. volatility varies over time) are modeled.

In chapter five the market shares for each public transport mode in total ridership for the multimodal public transportation system of Athens are explored. Due to the non-stationary properties of the data, cointegration techniques are applied to investigate the long run equilibrium relationships and the Error Correction Models are implemented to estimate the short run dynamics as well as the speed of adjustment from the short to the long run. In addition serial correlation on the residuals, a phenomenon commonly observed in time series data, is explicitly modeled.

The last chapter summarizes the major findings of the thesis and provides the overall conclusions regarding the analysis performed. Policy recommendations based on the findings are discussed, while indications for future research are given.

2. REVIEW OF THE LITERATURE

"…competition between modes, routes or firms gives rise to a wide range of price elasticities, generally much more elastic than conventional wisdom would suggest…"

Oum, Waters and Yong (1992)

2.1. Introduction

Demand analysis procedures are characterized by the nature of the approach, the data sources, the factors chosen to explain demand and the techniques employed in the analysis. A very detailed account of almost all aspects of public transport demand analysis is presented in "The Demand for public transit: A Practical Guide" (Balcombe et al., 2004). The publication by Paulley et al. (2006) consists a condensed form of this account focusing on the effects of fares, quality of service, income and car ownership on public transport demand.

This chapter attempts to review the large body of public transport demand literature which includes a variety of methodological and modeling approaches. First a general formula for the public transport demand function is presented and the concept of elasticity is discussed. In section 2.3 public transport demand studies are classified according to the type of the data used, the nature of the study and the level of analysis. In section 2.4 a review of the main factors that have been found to affect public transport demand is presented. The factors are classified into two board categories; internal and external to the system analyzed. It should be noted that the focus on this section will be on causal aggregate studies. Finally, emphasis is given on public transport demand studies that take into account the non-stationarity of the demand time series as well as on studies that analyze multimodal public transport demand treating each mode as a separate entity.

2.2. Demand Function

The starting point of demand analysis is the assumption of an underlying demand function connecting the dependent variable (public transport demand) to the independent variables (the factors considered to affect demand).

A General Formulation for the Demand Function is given by:

$$Y = f\,(X_1, \dots \dots, \; X_n) \tag{2.1}$$

Where:

Y is the dependent variable (level of demand)

X_i ($i = 1, \dots .n$) are the independent (explanatory) variables such as travel cost, gasoline price, income and so on.

2.2.1. The Dependent Variable

In the greatest part of the literature public transport demand is modeled using travel volume as the independent variable. Travel volume is usually measured by (a) the number of trips or (b) the distance travelled. The total number of 'trips' or 'journeys' recorded is commonly used to model aggregate demand. Such data are usually derived through ticketing systems. The distance travelled, expressed in passenger kilometers, is also a measure of aggregate demand. The passenger kilometers are derived by multiplying the number of trips with the kilometers travelled. The kilometers travelled are usually measured through on-vehicle surveys or household surveys.

Mode share of public transport, tariff revenues and user expenditure are also indicators of public transport demand. Mode share of public transport and user expenditure may be used as dependent variables that indicate the importance of public transport modes in relation to one another or to other modes. However, the number of trips computed is a preferable measure of public transport demand, since it does not include aspects related to supply of service (like passenger-kms) and it is not related to pricing policies (like tariff revenues). Finally, modal choice and route choice may also represent measures of public transport demand and they are usually used in disaggregated models.

2.2.2. The Independent Variables

Independent (or explanatory) variables are factors assumed to affect Public Transport Demand. The explanatory variables may be

(a) Continuous variables such as income, GDP, fare gasoline price

(b) Discrete or categorical variables such as monthly dummies and

(c) Variables that account for dynamic effects such as lagged dependent variables

The choice of the dependent variables depends on a number of factors including scope of the analysis, data availability as well as on problems that may arise from the statistical analysis such as multicollinearity of the regressors, endogeneity issues. Concerning the data availability, there are some important factors affecting public transport demand (reliability, comfort) which are difficult to quantify in variables and thus include them in the model. Multicollinearity is a statistical phenomenon in which two or more independent variables in a multiple regression model are highly correlated. The presence of multicollinearity may affect the sign of the coefficients as well as the estimated standard errors, resulting to invalid results. In public transportation studies multicollinearity usually occurs among socioeconomic and demographic variables (for example multicollinearity may occur between income and car ownership or between population and employment). Moreover, when analyzing multimodal public transport demand, multicollinearity occurs among the fares of the different public transport modes. A loop of causality between the independent and dependent variables of a model leads to the problem of endogeneity (Gries and Redlin, 2012). In public transportation studies endogeneity usually occurs between supply and demand variables (Taylor et al., 2009).

2.2.3. Elasticity

The effect of the variation of an independent variable on the dependent variable is usually measured using the concept of elasticity. Elasticity is the ratio of the percentage variation of the dependent variable to the percentage variation of the independent variable. Let Y be the dependent variable (demand) and X the independent or explanatory variable. Relatively to a starting state, represented by the values (Y_1, X_1), a finite variation ΔX of the independent variable, causes a variation ΔY to the dependent variable, resulting to a new state represented by values (Y_2, X_2), where $Y_2=Y_1+\Delta Y$, $X_2=X_1+\Delta X$. Elasticity e_X is then defined as:

$$e_X = \frac{\text{\% change in demand}}{\text{\% change in the explanatory variable}} = \frac{\frac{\Delta Y}{Y_1}}{\frac{\Delta X}{X_1}} \qquad (2.2)$$

Where:

ΔY is the change in Demand from Y_1 to Y_2

ΔX is the change in the explanatory variable from X_1 to X_2

Y_1 is the level of demand prior to the change from X_1 to X_2

Y_2 is the level of demand after the change

2.2.3.1. Point and Arc Elasticities

Arc elasticity is the elasticity of one variable with respect to another between two given points. Taking into account the two points $P_1=(Y_1, X_1)$ and $P_2=(Y_2, X_2)$ arc elasticity can be defined as:

$$e_X^{arc} = \frac{\frac{\Delta Y}{Y1+Y2}}{\frac{\Delta X}{X1+X2}} \qquad (2.3)$$

where ΔX, ΔY are finite variations, either observed or computed via a mathematical or an estimated function, $Y=f(X)$. Arc elasticity is used when there is no general function to define the relationship of the two variables.

Assume now that there are many independent variables represented by a vector X=(X_1, $X_{2,}$ …..X_n). If there is a mathematical relation between Y and X represented by a multivariate function Y=f(X), then for arbitrarily small variation ΔY, implied by a small variation ΔX_i in X_i, elasticity can be defined in terms of the partial derivatives of f(X) of a particular point P=(Y, X) as:

$$e_{Xi}^{point} = \lim_{\Delta X_i \to 0} \left(\frac{\frac{\Delta Y}{Y}}{\frac{\Delta X_i}{X_i}} \right) = \frac{X_i}{Y} \left(\frac{\partial Y}{\partial X_i} \right) \tag{2.4}$$

This is called point elasticity because, in general, the partial derivative depends on the particular point P computed. Therefore the point elasticity refers to a particular level of demand and it can be computed only if the demand formula for the demand function is known.

2.2.3.2. Elasticities in Linear Regression

Empirically elasticity is estimated using a linear regression fitted to a series of observations (Y, X). Let β_i be the regression coefficient related to variable X_i. The exact formula of elasticity in this case depends on the way the variables are expressed. If both variables X and Y are expressed in terms of their natural logarithms (log-log model) then elasticity takes the form

$$e_{xi} = \left({}^{\Delta Y}\!/_{Y} \right) \left({}^{\Delta X_i}\!/_{Xi} \right) = {}^{\Delta(\ln Y)}\!/_{\Delta(\ln X_i)} = \beta_i \tag{2.5}$$

If Y is in terms of its original (linear) form and X in terms of its natural logarithm form (linear-log form) thrn elasticity takes the form

$$e_{xi} = \left({}^{\Delta Y}\!/_{Y} \right) \left({}^{\Delta X_i}\!/_{Xi} \right) = {}^{\Delta Y}\!/_{Y\, \Delta(\ln X_i)} = \beta_i \left(\frac{1}{X_i} \right) \tag{2.6}$$

In general if $|e|<1$ we say that the dependent variable is inelastic with respect to the independent variable (i.e. that the absolute percentage variation of the dependent variable is smaller than the percentage variation of the independent variable).

2.2.3.3. Types of Demand Elasticities

Depending on the kind of the independent variable that explains demand we may consider different types of demand elasticities. The most commonly used elasticities in public transportation studies are:

(a) Price elasticity of demand

Price (or fare) elasticity of demand measures the percentage change in quantity demanded caused by 1% change in price. This elasticity is almost always negative and it is referred to as the own-price elasticity of demand for a particular mode. In this case if demand is inelastic this means that for relatively small changes, although demand, following an increase in fare, may decrease, total revenues will increase.

(b) Cross price elasticity of demand

Cross price elasticity of demand measures the percentage change in demand for a particular good (transport mode) caused by 1% change in the price of another good (competing transport mode). When analyzing multimodal public transport demand it should be mentioned whether we refer to own or cross price elasticities. For example, the elasticity which measures the change in the demand for metro with respect to a change in metro fare is the own price elasticity, while the elasticity which measures the change in the demand for metro with respect to a change in bus fare is a cross price elasticity. In public transport analysis own price elasticities with respect to fare are expected to be negative, while cross price elasticities are expected to be either positive or negative depending on whether the other transport mode is a substitute (competitive) or a complementary one.

(c) Income elasticity of demand

Income elasticity of demand measures the percentage change in demand caused by 1% change in income. Income elasticity can be used to classify goods as normal or inferior. In case of a normal good, demand varies in the same direction as income. In case of an inferior good, demand and income move in opposite directions.

2.2.3.4. Short Long Run Elasticities

There is a set of factors that affect the size of transit elasticities; for example, elasticities tend to be higher when substitutes are available, and when consumers have more time to adjust their behavior. Therefore, the length of time period that people have to respond to price changes plays an important role; thus, demand elasticity is a dynamic concept i.e. following a fare change, more generally a variation on an independent variable affecting demand, demand variation does not remain constant but, usually increases as time elapses because certain choices and attributes that develop following a fare change take time to reach maturity. It is therefore quite useful to distinguish between short run and long run elasticities.

Demand tends to be more elastic in the long run rather than in the short run, because short run elasticities are governed by resistance to change, while long run elasticities are affected by consequential changes on behavior that take time to be realized (Mankiw, 2004). For example in the short run demand for public transport is more price inelastic as public transport users often need more time to respond and change their habits. In the long run passengers have enough time to respond to price changes switching to other modes of transport.

As a general comment, it should be noted that, in practice the elasticity value depends on the initial values of the variables and also on the magnitude of the variation considered. For example, demand elasticities with respect to fares depend on the particular fare variation. Usually a greater fare increase corresponds to a greater elasticity (proportionally greater decrease in demand). Also, demand elasticity with respect to income depends on the income level and on the income variation. Moreover, elasticities are not symmetric with respect to positive and negative variations and thus is due to different captive effects along the two directions.

2.3. Classification of Public Transport Demand Studies

Demand analysis studies may be classified into two broad categories (Taylor and Fink, 2004): (1) descriptive analysis studies that examine attitudes and perceptions about the transport system analyzed (2) causal analysis studies that examine the internal and external factors affecting the transport system analyzed. In the first class studies are mainly descriptive in nature using subjective qualitative data, while in the second class studies are mainly causal using measurable and more objective data. Figure 2.1 presents a classification of public transport demand studies. The classes presented are analyzed in the following sections, while the main advantages and disadvantages of each class are summarized in Table 2.1.

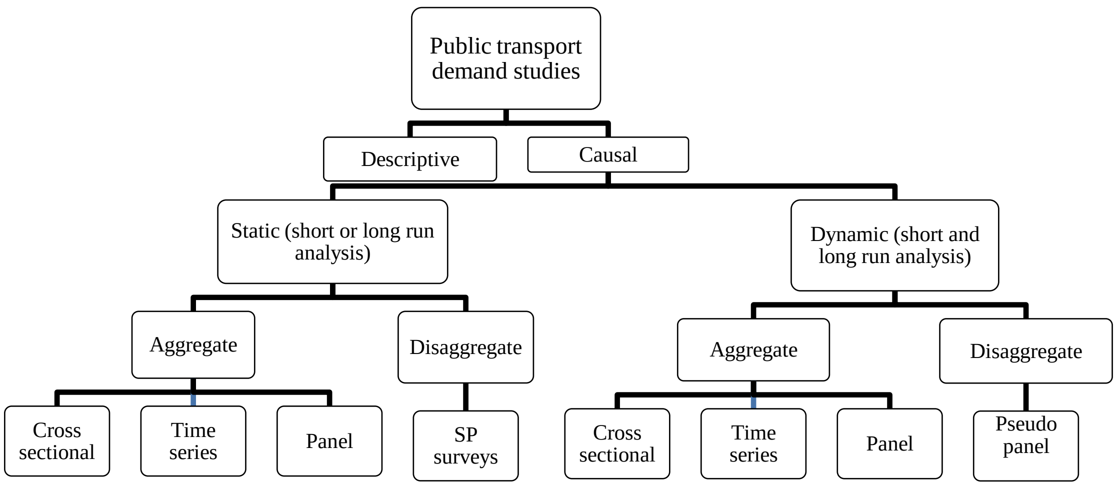

Figure 2.1. Classification of public transport demand studies

Table 2.1. Advantages and Disadvantages of PT demand Studies

	Advantages	Disadvantages
Descriptive	Analyze attitudes and perceptions	Data are highly subjective; no model structure
Causal	Empirical causal analysis; econometric models	Some variables are hard to quantify
Aggregate	Econometric models; Aggregation; Data are easier to obtain and more robust	Endogeneity, multi-collinearity problems
Disaggregate	Analyze individual choices; more precise results	Generalizability is limited; difficult to obtain the data
Cross sectional	Account for variations across cities, countries, regions	Do not account for variations across time, dynamic effects; exhibit heteroskedasticity
Time series	Examine variation in PT demand over time	Exhibit non-stationarity, autocorrelation, arch
Panel	Examine variations across units and over time	Data are more difficult to obtain;

2.3.1. Descriptive Analysis

Descriptive analysis is mainly based on the use of survey and interview data derived from well designed questionnaires addressed both to managers and transit operators, with an aim to assess perceptions of the factors affecting ridership (for example Abdel-Aty and Jovanis, 1995; Bianco et al., 1998; Brown et al., 2001; Dueker et al., 1998; Jenks, 1995; Sale, 1976). Taylor et al. (2009) report that descriptive studies usually analyze five general categories of possible actions, strategies affecting public transport demand: service improvements; fare restructuring and fare level changes; marketing and information; new planning approaches and partnerships; service quality and coordination.

2.3.2. Causal Analysis

Causal studies use measurable and more objective data than descriptive studies to quantify the factors affecting public transport demand. Causal analysis includes (a) aggregate studies that use the transit system as the unit of analysis and (b) disaggregate studies that depict individual decision–making process of travelers. Since some transport policies are based on aggregate models and some others on disaggregate models both approaches are useful in public transport demand analysis.

Small (1992) discusses the main advantages and disadvantages of aggregated as well as of disaggregated models. The main advantage of disaggregated models is that, exploiting the microeconomic theory, they can simulate with greater accuracy particular aspects of a system and thus lead to more precise policy proposals. However, aggregate models still play a basic role in transport demand analysis because they are based on data that are easier and cheaper to obtain and, in a sense, more robust. Moreover, conclusions concerning aggregate demand cannot be obtained by simply combining the results of disaggregated models (Asensio, 2000).

2.3.2.1. Disaggregated Models

The use of disaggregated modeling in transport economics and transport demand analysis has shown a considerable increase in the number of publications over the recent years. This is due to the development of discrete choice modeling. Disaggregate or behavioral demand modeling analyzes travel behavior at the level of a person or a household using (a) Stated preference (SP) data, (b) Revealed Preference (RP) data or (c) a combination of both (Louviere and Henser, 2001). Examples of disaggregated cross sectional studies in public transport demand analysis can be found in: Iseki and Taylor (2010), Henser (1998), Henser and King (1998).

2.3.2.2. Aggregated Models

Aggregate studies can be classified into three main categories according to the type of the data analyzed: (a) cross sectional data (b) time series data (c) panel data.

(a) Cross Sectional

Cross-sectional analysis refers to data collected by observing many units (such as countries, regions) at the same point in time. The distinguishing feature of cross sectional data is the independence of observations. In cross sectional data the order of the observations in the sample has no significance. Cross sectional data usually exhibit heteroskedasticity (unequal error variance across observations).

Cross sectional studies analyze public transport demand by taking into account variations across countries, across cities or across locations within a city (Wabe and Coles, 1975; Kain and Liu, 1999; Taylor and Miller, 2004; Taylor et al., 2009). In these studies, the internal factors of a transit system such as fare and service level, as well as factors outside the control of the transit system, are analyzed. Concerning the factors outside the control of the transit system, Taylor et al. (2009) found that regional geography (size of the area, population density, area of urbanization), population characteristics (percentage of immigrants, the percentage of college students) and regional economy (carless households, income) appear to have the greatest impact on public transport demand.

(b) Time Series

A time series is a collection of observations of the same phenomenon obtained through repeated measurements over time. Aggregated time series analysis implies the use of econometric models based on daily, monthly, quarterly, or annual data. The main advantage of using time series data in public transport demand analysis is that it makes possible to examine variation in public transport demand over time; using monthly or quarterly data seasonal fluctuation of transit ridership may be modeled. Moreover, time series analysis permits the dynamic model structure of demand; short run and long run elasticities can be estimated. The problems that usually arise from the analysis of time series data are: (a) non-stationarity (time-varying mean or a time-varying variance or both), (b) autocorrelation (disturbances from different time periods are correlated) and (c) autoregressive conditional heteroskedasticity (time varying error variance).

Several studies in the literature analyze aggregate public transport demand for a single area using:

- annual time series data (for example Hendrickson, 1986; FitzPoy and Smith, 1988; Kyte et al., 1988, Gomez-Ibanez, 1996; Romilly, 2001)
- quarterly time series data (Doti and Adibi, 1991)
- monthly time series data (Gaudry, 1975; Doi and Allen, 1986; Rose, 1986; Agthe and Billings, 1978; Gkritza et al., 2004; 2011; Currie and Phung, 2008; Chen et al., 2011; Chiang et al., 2011)
- daily time series data (Guo et al., 2007; Stover and McCormack, 2012)

(c) Panel Data

Panel data analysis is used when the data set has information derived from many different units (indexed by i) observed over many periods of time (indexed by t). Thus, both the time series and the cross sectional nature of the data are present. Since panel data combine both dimensions (unit and time), they have advantages comparing to pure time series and pure cross sectional data. Apart from the fact that panel data take into account heterogeneity across units, they give more informative data, fewer degrees of freedom, and fewer collinearity effects among the variables (Baltagi, 1995). Several studies have been conducted that analyze public transport demand studies using panel data (De Rus, 1990; Dargay and Hanly, 2002; Bresson et al., 2003; Crotte et al., 2008; Abrate et al., 2009; Lane, 2010; 2012).

The use of different types of data sources (time series, cross sectional, panel and stated preference data) results to different estimates of the elasticities. In particular the use of time series data, in most cases, leads to elasticities of smaller magnitude than the elasticities produced by the use of cross sectional data (Nijkamp and Pepping, 1988). Nijkamp and Pepping (1988) also report that estimated elasticities using stated preference data are higher than those estimated using cross sectional data.

2.4. Factors Analyzed

Usually explanatory factors are divided into internal and external to the system analyzed. Internal are the factors controlled by the system and external the factors exogenous to the system. However, this classification is purely schematic because some factors such as fares, which are considered internal, may be controlled by the government and thus, in such cases they are exogenous to the system (Taylor and Fink, 2004). Moreover some external factors may directly affect internal factors. Among the most important internal factors are fares and quality of service. Among the most important external factors are income, car ownership, GDP and gasoline price.

The elasticities of public transport demand with respect to a particular factor computed in various studies exhibit strong variation. According to Graham et al. (2009) most of the variation across studies is due to:

(a) Data used (aggregate or disaggregate; time series, cross sectional or panel)

(b) Time frame analyzed (yearly data, monthly data, quarterly data, daily data)

(c) Econometric method employed

(d) Static or dynamic model structure

(e) Demand specification

(f) Specification of the dependent variable (travel volume, modal choice or route choice)

(g) Number of PT modes analyzed

In this section the focus will be on aggregate demand studies. The main factors analyzed and the elasticities computed in these studies will be presented. Table 2.2 (page 38 at the end of this chapter) provides a summary of selected publications.

2.4.1. Internal Factors

2.4.1.1. Fare

Urban transport systems –particularly fixed track- require high expenditures both for infrastructure and for operating costs. On the other hand the services offered by public transport are considered a basic societal good and this fact puts pressure on keeping fares as low as possible. This usually results to an operating deficit, usually covered by appropriate subsidies. Regulating revenues by increasing fares is, therefore a problem of compromise between the social and the financial aspect of public transport. Normally, a fare increase is followed by a continuous drop of demand for some time until the level of demand reaches a steady state. As demand variation with respect to fares is, in most cases, inelastic (i.e. elasticity is between zero and one) revenues, following a fare increase, will also increase. For the above reasons public transport demand elasticity with respect to fare has been extensively studied. Many papers have appeared in the literature analyzing the following aspects of demand elasticities with respect to fares:

(a) Short and long run elasticities

As mentioned in section 2.2.3.4 the full effect of a fare change on demand occurs after some time and therefore, it is useful to distinguish between short and long run elasticities. Usually long run elasticities are higher because they reflect the full extent of the fare impact. Goodwin (1992) in his review study emphasizes the importance of analyzing both short run and long run elasticities, as this distinction has important policy implications. In the literature, long run elasticities are found to be, generally, 1.5 over 3 times higher than the short run ones (Dargay and Hanly, 1999).

(b) Elasticities of different transport modes

Different public transport modes have different elasticities with respect to the same factor. For example fare elasticities are different for the bus and the rail mode. Therefore, in a multimodal context, it is useful to analyze demand for each mode separately since it produces different results from analyzing public transport ridership as a whole. Comparing the elasticities among different transit modes, Balcombe et al. (2004) report that the total public transport price elasticity appears to be -0.40, while the price elasticities for the bus and the rail mode are -0.42 and -0.29 respectively.

(c) Cross price Elasticities

In the context of transport demand analysis fare cross elasticities indicate the way that an increase, more generally a variation, in the fares of one mode affects demand of any other mode. In a multimodal public transport system that operates under common pricing policies, a variation in fares affects in different ways demand for different public transport modes. This is partly due to the substitution effects that are present in each mode as well as to the particular service characteristics of each mode.

(d) Elasticities with respect to time of day (peak and off-peak demand elasticities)

For a particular transport mode, or transport system, demand elasticities are different during different times of the day. Usually, demand during peak hours is highly inelastic (Wabe and Coles, 1975), while demand during off-peak hours is much more elastic. This type of elasticity provides useful information either for planning purposes, when optimal capacity is under consideration, or, for designing effective time of day pricing policies with an aim to reduce peak effects. Linsalata and Pham (1991) found that peak hour fare elasticity is -0.23, while the off-peak hour elasticity is -0.42.

(e) Variations in elasticities according to level of increase and the fare level

Demand elasticity is usually a function of the fare increase. Usually higher fare increases produce higher value of elasticity (Paulley et al., 2006). The price elasticity is also related to the current fare level. When fare levels are too low relative to income, marginal changes do not affect ridership. In their study Dargay and Hanly (2002a) have found that bus ridership in London is more price elastic at higher fare levels. The elasticities computed are higher for the highest fares (ranging from -0.1 in the short run to -0.2 in the long run) and lower for the lowest fares (ranging from -0.8 in the short run to -1.4 in the long run). Bresson et al. (2003) used a random coefficient model and found that fare elasticity in England increases with fare level.

(f) Variation with the type of the area

Public transport demand is usually more elastic in rural than in urban areas, reflecting the fact that bus users are more captive in urban areas. There is evidence from the study by Dargay and Hanly (1999), where fare elasticities are higher in the shire counties in Great Britain than in the metropolitan areas, both in the short and in the long run.

(g) Variation with the type of the ticket

There is a variation in elasticities for different ticket types (single ticket, travel cards, season tickets). The effect of different types of tickets on ridership has been investigated in many studies including FitzRoy and Smith (1988), Gkritza eta al. (2011) and Garcia and Ferrer (2006). FitzRoy and Smith (1988) found that the introduction of the low cost travel cards in the German city of Freiburg resulted to the increase of both tram and bus use. Garcia and Ferrer (2006) in their study for the city of Madrid report that price and cross price elasticities differ according to the type of the ticket and the mode of transport. Generally there is evidence of an increase in fare elasticities moving from travel cards to single tickets, since travel card is a more captive form of fare. Fare integration in Italy led to a demand increase 2% and 12% in the short and in the long run respectively (Abrate et al., 2009).

2.4.1.2. Quality of Service

(a) Measures of quality of service

Quality of service includes a number of factors that affect demand in a positive or negative way. An indicative list of these factors follows:

1) Access time to boarding point
2) Quality of vehicle
3) Frequency
4) Service Reliability
5) Time spent on board
6) Interchange conditions
7) Waiting time
8) Waiting environment
9) Information provision

Some of these factors (time spent on board, waiting time, access time to boarding point) take values that can be subjected to formal measurement. Usually these factors are analyzed using revealed preference methods (RP). Some other factors (quality of vehicle, waiting environment) can only be assessed by appropriate questionnaires to operators and users and the measurement of these factors is inevitably highly subjective. These factors are usually analyzed using stated preference (SP) methods. For example quality of vehicle could include measures such as space available per pass, seating pass/total pass, but it is hard to find data and results for these variables. Disaggregated demand models is the most appropriate method for analyzing the above factors, since it is very difficult to quantify them in the aggregate level (Taylor et al., 2009).

The most common indices that can be incorporated to an aggregate demand model, as factors reflecting the quality of service are:

1) Number of vehicles in operation
2) Vehicle-kms operated
3) Vehicle hours operated

The frequency operation, as a service quality indicator, depends on the number of vehicles in use and, thus, as the number of vehicles in operation increases, the level of service is improved resulting to an increase in transit ridership. McLeod et al. (1991) used the size of bus fleet as a measure of service quality and it was found to be an important indicator of transit ridership in Honolulu.

Vehicle-kms operated is the most commonly used indicator of quality of service in aggregate public transport demand studies (Agthe and Billings, 1978; Gomez-Ibanez, 1996; Rose, 1986; Chen et al., 2011). According to Balcombe et al. (2004) bus demand elasticity with respect to vehicle kilometers is approximately 0.4 in the short run and 0.7 in the long run. For rail services elasticities are found to be greater. Rose (1986) found the long run rail demand elasticity with respect to rail service, measured in vehicle-miles, to be 1.84 in the long run.

Elasticities for PT demand have also been estimated with respect to vehicle hours operated (Yanmaz–Tuzel and Ozbay, 2010). Service levels may also be expressed in terms of passenger waiting times or in transit times (Gaudry, 1975). However, this indicator of quality of service is rarely examined in aggregate demand studies due to unavailability of data.

(b) Supply and demand

The fact that public transport demand is a function of service supply and, vice versa, service supply is a function of service demand usually leads to the problem of endogeneity. As a result the estimated parameters will be biased, when both demand and supply variables are incorporated to the same model. Many researchers have attempted to address this issue by solving the demand and supply equations separately. Taylor et al. (2009) employed two stage regression models in order to solve demand and supply equations separately and avoid endogeneity problems.

(c) Variation in service elasticities with the type or the area, the time of day

As with fare demand elasticities, demand elasticities with respect to service level depend on the type of the area (rural, urban), the time of day (off- peak, peak) and the type of the mode. Generally, elasticities tend to be higher for rural areas, off-peak journeys and the rail mode.

(d) Short and long run service elasticities

Service elasticities are different between short and long run. Kyte et al. (1988) found that service level responses range from 8 to 10 months. Service elasticities computed by Chen et al. (2011) are 0.13 in the short and 0.27 in the long run, where the long run elasticity refers to four months after a service change.

(e) Service vs fares

Some studies have found that changes in the quality of service factors are more important in attracting riders than changes in fares (Iseki and Taylor, 2010; Taylor and Miller, 2004; Litman, 2004), while others conclude that a decrease in fares will have greater impacts in ridership than an increase in service quality (McLeod et al., 1991; Chen et al., 2011).

2.4.2. External Factors

2.4.2.1. Income

The degree to which variability in income affects public transport demand has been investigated by many studies (for example Gomez Ibanez, 1996; Graham et al., 2009; Crotte et al., 2008; Dargay and Hanly, 2002a). Variations in income affect demand in conflicting ways. An increase in income level will, generally, induce more trips, but also will lead, in most cases, to an increased number of private cars. Thus, a part of the increased trips will be absorbed by public transport, and another part will be diverted to private cars. The actual split between public transport and car use will be depended on the level of the income to which the increase is applied and also to the level of service provided by public transport. Generally, the higher the level of income, the greater the shift towards private cars (Paulley et al., 2006). Indeed, some studies have found that the income has a positive effect on public transport demand because it creates additional activities that require more transport services (Romilly, 2001), while others have found that it has a negative effect because it creates a shift to private cars (Crotte et al., 2008; Dargay and Hanly 2002a). In their study Bresson et al. (2003) found that income effect on PT ridership is negative in most areas in France with the exception of Paris, where income effect is marginally positive. In most transport aggregate demand studies income is represented by GDP per capita, since since it is a more accurate value at the aggregate level (Balcombe et al., 2004). For exapmle, Clark (1997) estimated short and long run GDP bus demand elasticities for Great Britain to be 0.33 and 0.45 respectively.

2.4.2.2. Car Ownership

Private car use is a substitute for public transport use. Therefore, an increase in private cars is expected to affect negatively demand. Taylor et al. (2009) include per cent carless households in their models and found a positive significant relationship between per cent carless households and transit ridership. Gkritza et al. (2011) found that an increase in automobiles per capita increases the travel card sales in Athens, Greece. It should be noted that, income and car ownership are highly correlated. However, when they are both included in the model income is positively related to PT ridership. An example is the study of Clark (1997) in Great Britain. The long run bus demand elasticity with respect to car ownership was estimated to be -1.42, while the income long run elasticity was estimated to be 0.45. Income is negatively related to PT ridership when car ownership is not included in the model; in this case income incorporates the negative impact of car ownership on PT ridership (Paulley et al., 2006).

2.4.2.3. Employment

Several studies have proved that employment level has a positive impact on PT ridership (Hendrickson, 1986; McLeod, 1991; Doti and Adibi, 1991; Gomez Ibanez, 1996; Chung, 1997; Kuby et al., 2004). Hendrickson (1986) examined the relationship between Central Business District (CBD) employees and commuting by public transportation in 25 US metropolitan areas and found that they are intimately related. Doti and Adibi (1991) estimated the elasticity of monthly PT ridership in Orange country in California with respect to the employment level 1.74. Gomez Ibanez, (1996) show that employment level is the main determinant of transit ridership in Boston between 1970 and 1980. Some studies have found that unemployment rate is also related to transit ridership. An increase in unemployment rate increases bus ridership in Athens (Gkritza et al., 2004; 2011).

2.4.2.4. Immigrants

More recently, researchers examined the impact of the number of immigrants on transit ridership. Immigration appears to be a demographic factor that significantly affects ridership (Blumenberg and Evans, 2007; Gkritza et al., 2004; 2011; Taylor et al., 2009). Gkritza et al. (2011) found that an increase in the number of immigrants increases travel card riders. Taylor et al. (2009) conclude that population characteristics and specifically the percent of recent immigrants in population and the percent of college students in population were found to significantly affect transit ridership.

2.4.2.5. Fuel Price

Fuel price is directly related to the cost of car use. It is therefore expected, in general, that an increase in fuel price will lead to a decrease in private car use, which in turn will result to an increase in public transport. The exact extent of substitution depends on the particular level of income and other side conditions such as quality of service and road congestion. Many studies have estimated the degree to which variablitiy in transit ridership is related to fuel price and have found that transit demand elasticities with respect to fuel prices are positive and inelastic ranging from 0.08 to 0.80 (Agthe and Billings, 1978; Wang and Skinner, 1984; Doi and Allen, 1986; Yanmaz and Tuzel, 2010, Currie and Phung, 2008; Lane, 2010; 2012). In most of these studies, the estimated elasticities are small ranging from 0.10 to 0.30. This is probably explained by the fact that fuel prices represent only a small share of automobile operating costs (Taylor and Fink, 2004; Small and Van Vender, 2006).

Agthe and Billings (1978) examined the effect of gasoline prices, bus system size and other variables on bus ridership during and after the US energy crisis and estimated a gasoline price elasticity of bus rides of 0.42. Wang and Skinner (1984) analyzed the impact of fares and gasoline prices on monthly ridership in seven US cities and found that the elasticities of gasoline prices are positive and inelastic ranging from 0.08 to 0.80. Rail ridership in greater Philadelphia was modeled by Doi and Allen (1986) as a function of fares, gasoline prices, seasonal dummies and real bridge tolls for the competing automobile trips. The elasticity estimated with respect to gasoline prices was 0.11.

The full effect of a gasoline price change on demand occurs after some time and therefore it is useful to separate short and long run effects. Rose (1986) examined the effect of fares, service and gasoline prices on rail ridership using time series analysis. The estimated gasoline price elasticities are 0.11 in the short run and 0.18 in the long run. Similar values take the elasticities estimated by Chen et al. (2011) (0.11 and 0.19 in the short and in the long run respectively). Lane (2012) analyzed the presence of lagged effects of gasoline prices on rail and bus ridership and concluded that it takes time to see the full impact of gasoline prices. The estimated elasticities take values up to 0.40 for bus and up to 0.80 for rail for various gasoline price lags. Moreover, fuel price elasticities are different for different public transport modes. Haire and Machemehl (2009) have found that rail is more elastic with respect to fuel price comparing to bus.

2.4.2.6. Parking Fares

Parking cost is another factor that positively affects public transport demand. An increase in parking fares causes shifts to alternative modes including public transport. Some studies have found that policies related to increased parking fares are more effective in increasing transit ridership compared to policies of increased quality of service (Mukhija and Soup, 2006). However this factor is usually analyzed using stated preference methods (Tsamboulas, 2001; Hensher and King, 2001). TRACE (1999) based on numerous European studies provides a total cross elasticity of public transport demand with respect to parking price equal to 0.02.

2.4.2.7. Weather

A limited number of papers have examined the impacts of weather on public transport ridership. Weather conditions such as rain, snow or extreme temperatures may affect transit ridership in two ways. First, they may create a shift to other modes of transport that are more comfortable (e.g. a shift from bus to car). Second, extreme weather conditions may lead people to cancel their activities, resulting to a decreased overall ridership. Rose (1986), in order to account for weather effects on monthly rail ridership, incorporated two weather series (average daily rainfall and average daily snowfall) into a rail ridership model, but they were found to be insignificant. In their cross sectional study Kuby et al. (2004) found that cities with extreme temperatures presented reduced levels of ridership.

Guo et al. (2007) investigate the impact of five weather elements (wind, temperature, rain, snow, fog) on rail and bus ridership in Chicago. The results showed that, although good weather tends to increase ridership and bad weather tends to reduce it, extremely bad weather resulted to an increase in ridership. Comparing the two modes, they found that bus ridership is more sensitive to weather than is rail ridership. Stover and McCormack (2012) estimated separate ordinary least squares regression models for each season to examine the effects of weather conditions on bus ridership in Washington for the years 2006-2008. The results indicate that each of the four weather variables (wind, temperature, rain, snow) significantly affects ridership at least in one season. As a general conclusion, adverse weather conditions lead to a decrease in ridership.

2.4.3. Review Studies

2.4.3.1. Literature Review Studies

Since there is a great number of studies investigating the effect of different factors on the demand for public transport and also a great variation in elasticities among these studies, review papers and reports are very important in summarizing relevant findings. Several rewiew studies have been conducted (Goodwin and Williams, 1985; Goodwin, 1992; Oum et al., 1992; TRACE, 1999; TRL, 2004; Paulley et al., 2006; Litman, 2004; Taylor and Fink, 2004; Buehler and Pucher, 2012).

2.4.3.2. Meta-analysis Studies

Meta-analysis is a statistical procedure that integrates and compares the results of several independent studies focusing on similar phenomena. Meta analysis studies on public transport demand analysis offer useful information regarding the factors that should be included in the models, the mean elasticities with respect to various factors and the major influences on variations in the estimates of the mean public transport demand elasticities (Nijkamp and Pepping, 1988; Kremers et al., 2002; Holmgren, 2007; Henser, 2008).

2.5. Non-stationary Multimodal Public Transport Demand

Time series data usually suffer from non-stationarity. A time series Y_t is said to be non-stationary if its mean, its variance and the covariance between two time periods (Y_t, Y_{t-k}) depend on time t. The use of standard regression techniques with independent, non-stationary variables can lead to spurious regressions (Granger and Newbold, 1974). In a spurious regression, fitted coefficients are found to be statistically significant while there is no true relationship between the dependent variable and the regressors. Thus, correlation between non-stationary series may not imply the kind of causal relationship that might be inferred in the case of stationary series. Non-stationarity is a common property of many macroeconomic time series such as Gross Domestic Product (GDP), income, prices and so on. Transportation time series data also exhibit non-stationarity. However, there is a limited number of papers in the literature that analyze public transport demand considering the non-stationary time characteristics of the variables.

In this section the focus will be on studies that analyze public transport demand taking into account the non-stationary nature of the demand time series (Chen et al., 2011; Crotte et al., 2008; Dargay and Hanly, 2002a; 2002 b; Romilly, 2001) as well as on studies that analyze multimodal public transport demand (Garcia-Ferrer et al., 2006; Gkritza et al., 2004; 2011).

2.5.1. Cointegration and Non-stationary Time Series

Research using cointegration techniques for estimating demand elasticities in transportation is limited, with papers by Crotte et al. (2008), Dargay and Hanly (2002b) and Romilly (2001) being the exceptions. The Cointegration/Error Correction Model Approach is likely to offer much more reliable information, particularly when the stationarity assumption underlying least squares regression is violated (Kulendran and Stephen, 2001). Further, it allows for the specification of the long run equilibrium properties and the short run dynamics (via the cointegration relationships and the Error Correction Models respectively). Moreover, the estimation of the speed of adjstustment towards long run equilibrium becomes possible. Table 2.3. presents a comparison between the existing approaches for analyzing public transport demand and the proposed approaches using cointegration techniques.

Table 2.3 Comparison between existing and proposed approaches

	Existing Approaches	Proposed Approaches
Inputs	Demand characteristics; internal and external factors	Demand characteristics; Internal and external factors; Lagged "previous" residuals
Outputs	Elasticities (short or long run) Predictions	Elasticities (short and long run) Speed of adjustment Predictions
Comparison	Existing approaches are straight forward	Proposed approaches yield 1. Improved estimates 2. Unbiased elasticities 3. Short and long run elasticities 4. Speed of adjustment

Romilly's study (2001) used both system and single equation cointegration methods to determine long and short run bus demand elasticities and identify the influence of subsidy reduction on bus fares in Britain (excluding London). The study was based on 45annual observations between 1953 and 1997 on passenger journeys per capita, bus fares, motoring costs, vehicle kilometers, subsidies, income and population. All the variables were found to be non-stationary in levels and stationary after first differencing. A trend and a dummy variable that captured the effects of deregulation and subsidy reduction were also included in the model. The results from the single estimation method, in the form of autoregressive distributed lag (ARDL) estimation method, indicated that demand for bus travel, income, bus fares, motoring costs and service frequency are cointegrated. The speed of adjustment coefficient was estimated 0.37 implying that 37% of the adjustment of passenger journeys towards their long run equilibrium is occuring in the first year. The system estimation method using Johansen Maximum Likelihood (JML) approach gave poor results in terms of coefficient significance both on the variables included on the model and the error correction term (speed of adjustment coefficient).

Crotte et al. (2008) estimated time series and panel cointegration models to determine the effect that fares, income, quality of service, and fuel prices have on the demand for the Mexico City metro ridership. Using annual data from 1980 to 2005, they found that all the variables were non-stationary. In order to deal with non-stationarity of the data they estimated cointegrating regressions based on three models: (1) OLS static model (Engle Granger two step procedure, 1987) (2) the Phillips and Hansen (1990) fully-modified OLS (FMOLS) model and (3) the Saikkonen (1991) Dynamic OLS (DOLS) model. In the time series analysis, they found that the metro ridership is cointegrated with income and quality of service. The three models suggest similar results. The estimated long run income elasticities derived from the three cointegrating regressions range from -0.78 to -0.82 and the long run service elasticities range from 0.35 to 0.40. The short run elasticities were estimated via the Error Correction Models (ECM). Short run income elasticities were 3 to 4 times lower in the short run, while service elasticities were only 1.5 times lower in the short run.

Dargay and Hanly (1999) estimated both a partial adjustment model and an error correction model to analyze bus demand in English metropolitan areas and compared the two approaches. They noted that the error correction model was more appropriate given the fact that the data were found to be non-stationary. The speed of adjustment coefficient was estimated -0.68 and -0.32 for the error correction and the partial adjustment model respectively. This work is presented in two papers published by Dargay and Hanly (2000a, b).

The paper by Dargay and Hanly (2002a) is based on a dynamic econometric model relating per capita bus partonage to fares, income and service level combibing time series (1987-1996) and cross sectional data (46 English counties). A dynamic partial adjustment model was developed and two specifications were estimated; a fixed effects model and a random effects model. The results indicate that bus partonage is relatively fare-sensitive and that long run elasticities are at least twice those of short-run elasticities.

The results from the cointegration models are presented in the paper by Dargay and Hanly (2002b). The evidence of non-stationarity of the variables (using augmented Dickey–Fuller tests) suggests that cointegration techniques are appropriate. Applying the Engle–Granger two-step procedure the long run elasticities were estimated via the cointegrating regressions and the short run elasticities and the speed of adjustment were derived via the Error Correction Model (ECM). Two datasets were analyzed; (a) data at national level (Great Britain as a whole) from 1975 to 1996 (b) data at regional level (Greater London, English metropolitan counties, English shire counties, Wales, Scotland) from 1986 to 1996. Results at the national level relate bus demand (journeys per capita, passenger kilometers) with income and fare (fare index, cost per journey). Both bus fare variables (fare index, cost per journey) yield similar short-run fare elasticities (about −0.3 for journeys and −0.2 for passenger kilometers), but show a greater variation in long-run elasticities (−0.6 to −0.9 for journeys and −0.4 and −0.7 for passenger kilometers).

Table 2.4. Summary of the elasticities comptuted in cointegration studies

Cointegration and ECM	**Country**	**Fare**		**Income**		**Service**		**Motoring Costs**		**Speed of adjustment**
		SR	LR	SR	LR	SR	LR	SR	LR	
Romilly (2001)	Britain	-0.38	-1.03	0.22	0.61	0.3	0.52	0.16	0.45	-0.37
Dargay and Hanly (2002b)	Britain	−0.3	-0.54	-0.81	-1.47	0.23	0.28			-0.68
Crote et al. (2008)	Mexico	-	-	-0.17	-0.78	0.29	0.35	-	-	-0.25

Table 2.4 summarizes the elasticities computed in the above studies estimated using cointegration and error correction techniques. The fact that there are some important differences between these studies with respect to the short and long run bus elasticities and particularly with income elasticity reflects the sensitivity of Error Correction Models to data and model spesifications (TRL, 2004).

2.5.2. Monthly Ridership and Non-stationary Data

All the above studies were based on annual time series data and their analyses using cointegration techniques did not model seasonality of public transport demand. This suggests that these studies may have missed important dynamics connecting the explanatory factors with demand on a monthly time frame. On the contrary, Chen et al. (2011) used monthly data from January 1996 to February 2009 to investigate the impacts of various factors in rail ridership. In order to deal with the seasonality and non-stationarity issues, they estimated a dynamic ARFIMA (Autoregressive Fractionally Integrated Moving Average) model developed by Granger and Joyeux (1980). The time series ARFIMA model allows a fractional integration to force the series to become stationary. Moreover it makes possible to test lead and lag effects of various factors on ridership. However, this method uses first differences of the time series to achieve stationarity and thus throws away useful information about the long run conditions and about the speed of adjustment towards long run equilibrium.

The results indicate that fare, gasoline price, service level and employment level are the main determinants of rail ridership in New Jersey. Short and long run elasticities with respect to these factors were calculated and transit fare was found to exert the strongest impact both in the sort and in the long run (elasticities of 0.13 and 0.27 respectively). Gasoline price had a lag effect of 13 months and employment level a lag effect of 4 months. Transit demand is influenced by transit supply with zero and four month lag.

2.5.3. Multimodal Pubic Transport Demand

There are few papers investigating the factors affecting multimodal public transportation system ridership (Garcia-Ferrer et al., 2006; Gkritza et al., 2004; 2011; Lane, 2010; 2012; Gilbert and Jalilian, 1991; Glaister, 2001). Using time series data, Gkritza et al. (2004; 2011) investigated the factors that affect public transport ridership by mode for the multi-modal public transport system of Athens through seemingly unrelated regression equations. Although these papers estimate elasticities for multimodal transport demand, they do not consider the non-stationary nature of the demand time series.

Garcia-Ferrer et al. (2006) investigated user response to changes in prices and to the characteristics of the service for Madrid’s multimodal public transport system. Due to the unavailability of the data only two modes (metro and bus) of the multimodal public transport system of Madrid were included in the study. Two different approaches capable of dealing with the non-stationarity and strong seasonality of the data were developed; Dynamic Harmonic Regression (DHR) model developed by Young et al. (1999) and Dynamic Transfer Function Causal Model developed using intervation analysis (Box and Tiao, 1975). Although these models take into account the non-stationarity of the time series they are not capable of estimating both short and long run elasticities. The results indicate a great variation in the price elasticites computed; ranging from -0.52 to -2.17 according to the type of the ticket (travel card or single ticket) and the transport mode (metro or bus).

Table 2.2. Summary of selected aggregate public transport demand elasticity studies

Study	Data	Modes of Transport	Indicator of demand	Independent variables	Method of estimation	Results-Elasticities
Cross sectional Data						
Kuby et al. (2004). Factors influencing light-rail station boardings in the United States.	Cross sectional (261 stations in 11 metropolitan areas)	Light rail	Average weekdays boardings	Five categories (1) land use (2) intermodal connection (3) citywide (4) network structure (5) socioeconomic (6) weather (degree-days)	Regression analysis	• Employment, population, percent renters within walking distance, bus lines, park-and-ride spaces, and centrality, were significant. • Dummy variables for terminal and transfer stations, and international borders were all positive and significant.
Taylor et al. (2009) Nature and /or nurture? Analyzing the determinants of transit ridership across US urbanized areas	Cross sectional (265 US urbanized areas for the year 2000)	Public Transport	Total Transit ridership/transit ridership per capita	(1) Fares (2) Service (3) Population density (4) Population in college (5) Carless households (6) Gas price (7) Immigrants	Regression analysis with two stage simultaneous equation regression models	• Most of the variation in PT ridership across urbanized areas is explained by factors outside the control of PT system • Public transit use is strongly correlated with urbanized area size. • 26% of the variance in transit patronage is explained by service and frequency levels.
Souche (2010) Measuring the structural determinants of urban travel demand	Cross sectional (1995) 100 world's cities	Car Public transport	Number of daily PT trips per person Number of daily car trips per person	(1) Average cost of a car trip (2) Average cost of a PT trip (3) GDP per capita (4) Urban density (5) Length of roads/inhabitants (6) PT Vehicle Km per capita/surface area of the city	Regression (OLS, 2SLS, 3SLS)	• Statistically significant variables: cost of the transport mode and urban density • Urban car travel increases when the average user cost of a car and the urban density fall • An increase in these two variables combined with a reduction in the average user cost of public transport encourages public transport use.

Time Series Data						
Gaudry (1975) An aggregate time series analysis of urban transit demand: the Montreal case	Monthly data from 1956 to 1971, Montreal	Public Transport	Number of trips	(1) Fare (2) Car index (3) Waiting time (4) In transit time (5) Car in transit time (6) Weather (7) Income (8) Employment	Linear regression in conjunction with Box-Jenkins procedures for the specification of the R^{th}-order autoregressive process of the error terms.	Elasticities of monthly PT ridership with respect to : Fare (0.15) Car index (0.10) Waiting time (0.54) In transit time (0.27) Car in transit time (-0.42) Income(-0.08)
Agthe and Billings (1978) The impact of gasoline prices on urban bus ridership.	Monthly data from 1973 to 1976	Bus	Number of Bus passengers per month	(1) Gasoline prices, (2) Service (total miles) (3) energy crisis dummy variable (4) student use dummy variable	Multiple regression models ✓ linear and ✓ logarithmic function	• Elasticities of monthly transit ridership with respect to Gasoline prices (0.42) Improvements in bus service (0.50) • Energy crisis and student use increased bus demand
FitzRoy and Smith (1988) Public transport demand in Freiburg: why did patronage double in a decade?	Yearly data from 1969-1995 Freiburg	Public Transport	Number of passenger trips	(1) Fare (2) Real Income per capita (3) Service (Frequency, Route length) (4) Lagged dependent variable (5) Low cost travel cards	Ordinary Least Squares Regression	• The introduction of the low cost travel cards and the improvements in the network resulted to the increase of both tram and bus use
Doi and Allen (1986) A time series analysis of monthly ridership for an urban rail rapid transit line	Monthly data from 1978 to 1984	Rail	Number of passengers	(1) Fare (2) Gasoline price (3) Toll (4) Seasonal dummies	Time series multiple regression models ✓ linear and ✓ logarithmic form	•Elasticities of monthly PT ridership with respect to : real gasoline price (0.113/0.112) real transit fare (-0.233/-0.245) real bridge tolls for the competing automobile trips (0.167/0.185) •Seasonal variations of ridership are around -6.20 for summer period and 4.70 for October period.
Rose (1986) Transit passenger response: Short and long term elasticities using time series analysis	Monthly data from 1970 to 1981	Rail	Unlinked passenger trips	(1) Fare (2) Service (train miles) (3) Gas price (4) Cost of car trips (5) Weather effects (average daily rainfall, snowfall) (6) Lagged values of the explanatory variables	Box and Jenkins (ARIMA) Time series analysis Multivariate regression models	• Short run (SR) and long run (LR) elasticities of monthly PT ridership with respect to : gas prices (SR:0.11, LR:0.18) rail service (SR:0.00, LR:1.84) fare are zero both in the short and in the long run

Hendrickson (1986). A note on trends in transit commuting in the united states relating to employment in the central business district.	Annual data from 1960 to 1980 in 25 US cities	PT (rail, bus, taxi)	Number of commuters	(1) Central Business District (CBD) employees (2) Workers	Ordinary Least Squares regression	• PT increases whenever CBD increases • CDB Employment is more highly correlated to transit commuting than overall metropolitan size.
Kyte et al. (1988) A time series analysis of public transit ridership in Portland, Oregon,	time-series from 1971 to 1982, Portland.	Public Transport (System level, sector level, route level)	Total originating riders (transfer passengers excluded)	(1) Fare (2) Service level (3) Employment (4) Gasoline Price (5) Seasonal factors (6) Lagged variables	✓ Box and Jenkins Time series analysis ✓ forecasting	•The effect of fare changes can be measured for up to 3 months •Service level responses range from 8 to 10 months •Employment and Gasoline price do have immediate effects
McLeod et al. (1991) Multivariate time series model of transit ridership based on historical, aggregated data: the past, present and future of Honolulu.	Annual data from 1958 to 1986 Honolulu	Public Transport	Revenue trips Linked trips	(1) Fare (2) Income per capita (3) Employment (4) Size of bus fleet (5) Dummy for strikes	✓Multiple linear regression techniques ✓forecasting	•Fare elasticities -0.56 and -0.61 •Service elasticities 0.25 and 0.28. •The income elasticities are negative indicating mass transit is an inferior good.
Doti and Adibi (1991). A model for forecasting public transit	Quarterly data from 1974 to 1988	Public Transport	Total number of passengers	(1) Total wage and salary employment (2) Transit vehicle service/total population (3) Fares/gasoline prices (4) Seasonal factors (5) External shocks	✓ Multiple linear regression model ✓ Cochrane and Orcutt to remove autocorrelation ✓ Forecasting	•Elasticities of monthly PT ridership with respect to : employment (1.74) public transit service (0.37) price of public transit (-0.31) •Seasonal variation
Gomez_Ibanez (1996). Big city transit rider snip, deficits and Politics: Avoiding Reality in Boston	Annual data from 1970 to 1990 Boston	(bus, street car and rapid transit services)	Annual Ridership	(1) Income (2) Employment (3) Trend (4) Lagged Fare (5) Lagged vehicle miles	Regression with first order serial correction of the error term	• External factors (employment, income) have a greater impact on ridership than internal factors (service level, fares)

Romilly (2001) Subsidy and Local Bus Service Deregulation in Britain: A re-evaluation	Annual data from 1953 to 1997, Britain Non-stationary time series	Bus	Passenger journeys per person	(1) Fare (2) Income (3) Vehicle-kms (4) Motoring costs (5) Operating costs (6) Subsidies (7) Population (8) Fleet structure (9) Deregulation (dummy variable)	✓ Single equation estimation (ARDL estimation method) ✓ System estimation: Johansen maximum likelihood method ✓ Forecasting	• The positive effects of deregulation on fares and passenger trips are cancelled out by the negative effects of subsidy reduction. • Short run (SR) and long run (LR) elasticities of bus ridership with respect to: Bus fare (SR:-0.38, LR:-1.03) Income (SR:0.22, LR:0.61) Motoring costs (SR:0.16, LR:0.45) Service level (SR:0.3, LR:0.52) Speed of adjustment coefficient 0.37
Gkritza et al. (2004) Estimating Elasticities for Multi-modal public Transport Demand: A time series Approach	Monthly data from 1995 to 2001 Athens	Metro Bus Electric bus	Total Bus Riders Electric Bus Riders, Metro Riders (ticket sales travel cards)	(1) Ticket price and Travel card price (per mode) (2) Monthly hours of strikes (3) Vehicle Kms (per mode) (4) Income per capita (5) Unemployment (6) Fuel price (7) Automobile ownership (8) Immigrants	SURE model	• Different transit modes have different elasticities • PT demand is inelastic with respect to fares • Travel card sales seem to be more sensitive in comparison to ticket sales
Garcia-Ferrer et al. (2006) Demand Forecast and Elasticities Estimation of Public Transport	Monthly data from 1987 to 2000 Madrid Non stationary time series	Metro Bus	Trip tickets	(1) Fare (single ticket–travel card) (2) Changes in fares (3) Changes in service (4) Strikes	✓ Dynamic Harmonic regression Model ✓ Transfer Function causal Model ✓ Forecasting	• Price and cross price elasticities differ according to the type of the ticket and the transport mode • With the exception of travel cards tickets show significant negative own price elasticities
Guo et al. (2007) The impact of weather on transit ridership in Chicago	Daily data Monthly from 2001 to 2004 Chicago	Bus Rail	Bus and rail passenger trips	(1) wind (2) temperature (3) Rain (4) Snow (5) Fog (6) Seasonal dummies	Ordinary Least Squares Regression	• Good weather tends to increase ridership while bad weather tends to reduce it. Extremely bad weather may increase ridership. • Bus ridership is more sensitive to weather than is rail. • Weekend ridership is more sensitive to weather than is weekday ridership.
Yanmaz –Tuzel and Ozbay (2010). Impacts of Gasoline prices on New Jersey Transit ridership	Monthly data from 2005 to 2008 Yearly data from 1980 to 2008 New Jersey	Public Transport	Transit ridership	(1) Transit fare (2) Gasoline prices (3) Lagged Gasoline prices (4) Service (vehicle hours) (5) Employment (6) economic growth factor (7) seasonal dummies	Time-series regression models	• Several months elapse before travelers respond to gasoline price changes. • Elasticity values with respect to gasoline prices are quite low ranging from 0.12 to 0.22 (short term) and from 0.03 to 0.18 (medium term). • Service rate, economic growth, and transit fares are found to affect ridership

Stover and McCormack (2011) The impact of weather on bus ridership in Pierce Country, Washington	Daily data from 2006-2008, Washington	Bus	Unlinked bus passenger trips	(1) Wind, Temperature, Rain, Snow (2) Gas price (3) Unemployment (4) Fare (5) Service (6) Seasonal dummies	Multiple regression Ordinary least squares estimator	• Cold temperatures led to decreases in ridership in winter. • Rain negatively impacted ridership in all four seasons and snow was associated with lower ridership in autumn and winter.
Gkritza, et al. (2011) Estimating Multimodal Transit Ridership with a Varying Fare Structure	Monthly data from 1995 to 2006 Athens	Metro Bus Electric bus	Bus Riders Electric Bus Riders Metro Riders	(1) Ticket price and Travel card price (per mode) (2) Immigrants (3) Income per capita (4) GDP (5) Unemployment (6) Fuel price (7) Automobiles per capita (8) Seasonal dummies	SURE model under the assumption of higher autoregressive process for the error term	• Different transit modes have different elasticities • The effect of fare type on ridership varies by mode and by relative ticket to travel card prices • An increase in unemployment increases ridership • Seasonal fluctuations especially during the holiday period
Chiang et al. (2011) Forecasting ridership for a metropolitan transit authority	Monthly data from October 1998 to August 2008	Bus	Number of passengers	(1) Fare (2) Operating funds (3) participation data for the number of individuals receiving food stamps (4) Gas prices (5) Seasonal factors	✓ Multiple-regression model with autoregressive error correction ✓ Neutral networks, ✓ ARIMA models and ✓ Combination of these forecasting methodologies	• Operating funds was the most significant variable • Gas prices were not statistically significant • Bus fare had an expected negative impact on ridership. • A combination of the models yields greater forecast accuracy than the individual models separately.
Chen et al. (2011) What affects transit ridership? A Dynamic analysis involving multiple factors, lags and asymmetric behavior	Monthly data from January 1996 to February 2009. New York Non-stationary time series	Rail	Commuter rail trips	1)Fare (2)Service level (3)Employment (4)Fuel Price (5)Seasonal factors (6)Lagged variables	✓ARFIMA (auto regressive fractionally integrated moving average) ✓AR(1) model	• Short and Long run Elasticities of monthly PT ridership with respect to : Fare (SR:-0.40, LR:-0.80) Service level (SR:0.13, LR:0.27) Employment (SR:0.00, LR:0.59) Fuel Price(SR:0.11, LR:0.19) • Fare is found to exert the strongest impact both the short term and the long term. • Fuel price has a lag effect of 13 months • Transit demand is influenced by transit supply with zero and four month lag

Panel Data

Wang and Skinner (1984) The impact of fare and gasoline price changes on monthly transit ridership: empirical evidence from seven US transit authorities	Monthly data for 7 US cities	Surface transit NY city (surface, Rapid transit)	transit ridership	(1) Fare (2) Gasoline prices (3) oil embargo (4) seasonal variation (5) working day variation	Ordinary Least Squares methods ✓ linear and ✓ logarithmic function	• Elasticities of monthly transit ridership for the seven cities with respect to fare range from 0.042 to 0.62. gasoline price range from 0.08 to 0.80. • The monthly transit ridership for all seven cities exhibits strong seasonal and working-day variation.
De Rus (1990) Public Transport Demand Elasticities in Spain.	Monthly data from January1980 to May1988-eleven Spanish cities	Bus	Passenger trips	(1) Fare (ordinary and multiple ride ticket) (2) Vehicle kms (3) Trend (4) Seasonal factors (5) Disruption in services (6)lagged dependent variable	Ordinary least squares: ✓ Static and Dynamic specification ✓ Double log and semi log specification	• Passenger trips are explained by variations in fares, bus kms run and seasonal factors • The estimated elasticities of service level demand are higher than demand price elasticities for most of the cities.
Asensio (2000) The success story of Spanish suburban railways: determinants of demand and policy implications	Monthly data from 1991 to 1998 for 11 urban areas	Rail	Ridership in passenger kms	(1)Fare (2)Quality of Service (3)Suburbanization (4)Population (5)Petrol price (6)Seasonal factor (7) lagged values of quality and demand variables	Panel data models with fixed effects results (a two stage procedure)	• Short and long run elasticities of Railway demand with respect to rail quality and price were calculated • Petrol prices do not have a statistical significant effect on railway demand • Residential suburbanization and population have a significant positive effect on railway demand
Dargay and Hanly (2002a) The Demand for Local Bus Services in England	Combination of time series (9 years1987-1996) and cross section data for 46 English counties	Bus	Bus patronage per capita	(1)Bus fares (2)Service (bus vehicle kms) (3)Motoring costs (4)Income per capita (5)% pensioners in population (6) Lagged dependent variable	Dynamic Partial Adjustment Model ✓ fixed effects ✓ random effects	• Demand is less-elastic in metropolitan areas. • Long Run (LR) elasticities are higher than the short run (SR) ones. • SR and LR Elasticities of bus ridership in metropolitan areas with respect to : Fare (SR:-0.26, LR:-0.54) Service level (SR:0.36, LR:0.73) Income (SR:-1.26, LR:-2.58) Motoring costs (SR:0.34, LR:0.69)
Dargay and Hanly (2002b) Bus Patronage in Great Britain: Econometric Analysis	Annual data from 1986 to 1996, Great Britain	Bus	Bus patronage per capita Passenger Kms per capita	(1) Bus fares (2)Service (bus vehicle kms) (3) Income per capita (4) Motoring costs (5) Car ownership	Cointegration and Error Correction Model (ECM)	• Long-run elasticities are at least twice the short-run elasticities • Fare elasticity for all Great Britain is -0.4 in the short run and -0.9 in the long run.

Bresson et al. (2003) The main determinants of the demand for public transport: a comparative analysis of England and France using shrinkage estimators	England (46 counties 1988-1996) France (62 areas, 1975-1995)	England (Bus) France (Rail and Bus) public transport	Passenger trips per capita	(1) Mean fare (2) Vehicle km/per capita (3) Income per capita	Panel Dynamic Econometric Model ✓ fixed effect ✓ Random-effect models.	• Variation in the elasticities among areas. • Income elasticities are very different between the 2 countries l • PT demand is relatively sensitive to fare changes • Fare elasticity increases with the fare level.
Crotte et al. (2008) Demand Estimation of metro usage in Mexico City	Annual Time series and panel data in the Mexico city from 1980 to 2005. 11 metro lines	Metro	Metro partonage per capita	(1) Fares, (2) Income per capita (3) Quality of service (kms travelled) (4) Fuel prices	Time series and panel cointegration models	• Metro patronage, is cointegrated with income and quality of service. • The zero patronage response to fares suggests that the vast majority of metro riders are metro dependent • Income elasticities are negative and close to unity in the long run, while service elasticities show a positive but inelastic effect on demand.
Currie and Phung (2008) Understanding links Between Transit ridership and auto gas prices-us and Australian evidence	Monthly data from 2002 to 2006 for 3 cities	Public Transport Bus, Rail, BRT	Total PT ridership, mode and route transit ridership	(1) Gas prices (2) Interest rates (3) seasonal dummies	Regression Analysis	• High values of cross elasticity of demand to gas prices were found for high quality transit. • Longer distance travel was associated with higher gas price ridership effects
Graham et al. (2009) A dynamic panel analysis of urban metro demand	22 urban metros over 13 year period London	Metro	Metro partonage per capita	(1) Fares (2) Income (3) Quality of service (4) Lagged dependent variable	Autoregressive Distributed Lag (ADL) dynamic panel model (GMM estimator)	• Elasticities with respect to Fares SR:-0.047 LR:-0.331 Income SR:0.026 LR:0.183 Quality of service SR:0.072 LR:0.507
Abrate et al (2009) The impact of integrated tariff system on public transport Demand: Evidence from Italy	12 year panel of 69 public transit providers, Italy	Public Transport	Number of passengers	(1) Fare (2) Service (3) Income (4) Tariff integration (5) Lagged dependent variable	Dynamic Panel Analysis ✓ Difference GMM ✓ System GMM ✓ LSDV	• Income is not statistically significant • Route density and Service frequency are highly significant • Tariff integration can increase demand 2% in the short run and 12% in the long run
Lane (2012) A time series analysis of gasoline prices and public transportation in US metropolitan areas.	Monthly data from January 2001 to March 2009 for 33 metropolitan areas	Bus Rail	Unlinked passenger trips (UPTs)	(1) Gasoline price (2) Lags of gasoline prices (3) Service (vehicle revenue miles) (4) Trend variables (5) Seasonal dummies	Time Series Regression Analysis	• An increase in transit ridership of up to 4% per significant lag for bus and up to 8% for rail, for every 10% increase in gasoline prices. • It takes time (up to 13 months) to see the full impact of gasoline prices • Variability across cities

3. METHODOLOGY

The non-stationary time series analysis is a field in econometrics of active research and continuous progress. In this chapter a survey of the related contributions and techniques is presented including: stationary properties, unit root tests, autocorrelation, Autoregressive Conditional Heteroskedasticity, cointegration tests, cointegrating regressions and Error Correction Models. Finally, a methodology for analysing non-stationary time series, introduced by Engle and Granger (1987), is presented.

3.1. Stationarity

"Experience with real-world data, however, soon convinces one that both stationarity and Gaussianity are fairy tales invented for the amusement of undergraduates." (Thomson, 1994)

3.1.1. Stochastic Process

A random variable X_t is a variable which takes values with some probabilities. A collection of random variables indexed by time is called a stochastic process $\{X_t\}$. The word stochastic has a Greek origin and means pertaining to change. For many applications t is taken to be a discrete variable and although t belongs to an infinite set, under certain regularity conditions the process can be described by a finite dimensional distribution. The joint distribution F (X_{t1}, …, X_{tn}) completely specifies the probabilistic structure of the stochastic process $\{X_t\}$ for all values of n (a positive integer) and any subset (t_1,.., t_n) of T (Maddala and Kim, 1998). Since the joint distribution is hard to define, the stochastic process is usually characterized by the first moment (mean) and the second moments (variance and covariance) which are both functions of t. An observed realization of a stochastic process indexed by time is called a time series.

3.1.2. Stationary Time Series

3.1.2.1. Definition of Stationarity

The concept of stationarity appears mainly with two forms in econometrics: strict stationarity and weak or second order stationarity. A stochastic process is said to be strongly stationary if its distribution is constant through time. It is second order weakly or covariance stationary if it has a constant mean, constant variances and the covariances depend only upon the distance between two time periods and not upon the particular time period. In practice weak stationarity is the most commonly used form of stationarity. This is partly due to the fact that in the case of a normal stationary process weak stationarity is equivalent to strict stationarity, because the first two moments completely characterize the normal distribution. In the following the two main forms of stationarity are described in greater detail.

Definition: Strict stationarity. A time series process $\{X_t,\ t \in T\}$ is said to be strictly stationary if the joint distribution of $(X_{t1}, X_{t2}, \ldots, X_{tn})$ is the same as that of $(X_{t1+s}, X_{t2+s}, \ldots, X_{tn+s})$ for all $t_1,\ldots t_n$ and s. In other words, strict stationarity means that the joint distribution only depends on the lag s, not the time $(t_1, \ldots, t_n)$. This implies that the joint distribution $(X_{t1}, X_{t2}, \ldots, X_{tn})$ is time invariant.

Definition: weak or covariance stationarity. A time series process {Xt, t ∈ T} is said to be covariance stationary (or weakly stationary) if the following conditions are satisfied (Enders, 1995):

4. Constant mean (μ) for all t

$$E(X_t)=\mu\ \forall\ t \in T \tag{3.1}$$

5. Constant variance (σ^2) for all t

$$Var(X_t)=E[X_t-E(X_t)]^2=\sigma^2\quad \forall\ t \in T \tag{3.2}$$

6. Covariances depend only upon the lag s

$$Cov\ (X_t, X_{t+s}) = Cov\ (X_{t+k}, X_{t+k+s})=\gamma_s \leftrightarrow$$

$$\leftrightarrow E[(X_t-\mu)(X_{t+s}-\mu)]= E[(X_{t+k}-\mu)(X_{t+k+s}-\mu)]=\gamma_s\quad \forall\ t \in T \tag{3.3}$$

The first condition implies that the unconditional mean of the process $\{X_t\}$ is the same and it is constant for all t. The second condition implies that the variance of $\{X_t\}$ does also not depend on time, it is constant and equal to σ^2. The third condition implies that the covariances depend only upon the distance (lag s) between the two time periods, but not on the actual time at which the covariance is computed.

The covariance between X_t and X_{t+s} is called autocovariance γ_s and is given by

$$\gamma_s = \mathrm{cov}\,(X_t\ , X_{t+s}) = E[(X_t - \mu)(X_t - \mu)] \tag{3.4}$$

For the lag s=0

$$\gamma_0 = \mathrm{cov}\,(X_t, X_t) = \mathrm{var}(X_t). \tag{3.5}$$

The autocorrelation coefficient of a time series X_t for lag s is defined as:

$$\rho_s = \frac{\mathrm{cov}(X_t,\ X_{t+s})}{\sqrt{\mathrm{var}(X_t\ )}\sqrt{\mathrm{var}(X_{t+s}\ )}} \tag{3.6}$$

If the time series is stationary the variance is constant over time $\mathrm{var}(X_t)=\mathrm{var}(X_{t+s})$. Combining the Equations (3.4), (3.5), (3.6) the autocorrelation coefficient is simplified as

$$\rho_s = \frac{\mathrm{cov}(X_t,\ X_{t+s})}{\mathrm{var}(X_t\ )} = \frac{\gamma_s}{\gamma_0} \tag{3.7}$$

The sample autocorrelation coefficient is given by $\hat{\rho}_s = \frac{\hat{\gamma}_s}{\hat{\gamma}_0}$ (3.8)

Where

$$\hat{\gamma}_0 = \sum_{t=1}^{T} (X_t - \hat{x})^2 / T \tag{3.9}$$

$$\hat{\gamma}_s = \sum_{t=1}^{T+s} (x_t - \hat{x})(x_{t+s} - \hat{x}) / T \tag{3.10}$$

The plot of $\hat{\rho}_s$ against s is called the sample Autocorrelation Function (ACF) or sample correlogram. For a stationary process, the sample ACF declines sharply as the number s of lags increases. For non-stationary time series the sample ACF declines towards zero at a slow rate as s increases.

3.1.2.2. The White Noise Process

Among stationary processes there is a simple type of process, called white noise process, which is widely used in constructing more complicated processes. A stochastic process (e_t) is said to be a white noise process if:

1. $E(e_t) = 0$ for all t (3.11)
2. $Var(e_t) = \sigma^2$ for all t, $\sigma^2 < \infty$ (3.12)
3. $Cov(e_t, e_{t+s}) = 0$ if $s \neq 0$ (3.13)

The three conditions imply that a white noise is a serially uncorrelated, zero-mean, constant and finite variance process. Since all three requirements of weak stationarity are satisfied (Equations 3.1, 3.2 and 3.3), a white noise process is a second–order stationary process and has no memory. The white noise process (e_t) is Independently and Identically Distributed (iid) denoted as:

$$e_t \sim \text{iid } (0, \sigma^2)$$

If $e_t \sim$ iid $(0, \sigma^2)$ then the autocovariance function is

$$\gamma_e(s) = \begin{cases} \sigma_e^2 & \text{if } s = 0 \\ 0 & \text{if } s \neq 0 \end{cases}$$

and the autocorrelation function is

$$\rho_e(s) = \begin{cases} 1 & \text{if } s = 0 \\ 0 & \text{if } s \neq 0 \end{cases}$$

3.1.3. Non-stationary Time Series

3.1.3.1. Definition of Non-sationarity

Stationarity is a usual assumption in the analysis of standard econometric time series models. However, many observed time series in economics, as well as in transportation, have empirical features that are inconsistent with the assumptions of stationarity. A non-stationary process X_t is, by definition, one which violates the stationarity requirements (Hendry and Juselius, 1999). Non-stationarity means that a time series has no clear tendency to return to a constant value or to a linear trend and, therefore, a non-stationary time series will have a time-varying mean or a time-varying variance or both.

3.1.3.2. The Non-stationary Random Walk Process

The simplest example of a non-stationary process (or a process with a uint root) is a random walk process of the form:

$$X_t = X_{t-1} + e_t \qquad (3.14)$$

$$e_t \sim \text{iid}\ (0, \sigma^2)$$

In a random walk model the expected value of X_t will be constant over time but the variance and the autocovariances will increase with t.

1. $E(X_t) = \mu\ \forall\ t \in T$ (3.15)
2. $Var(X_t)=E[X_t-E(X_t)]^2 =t\sigma^2\ \ \forall\ t \in T$ (3.16)
3. $Cov\ (X_t, X_{t+s})=E[(X_t-\mu)(X_{t+s}-\mu)]= (t-s)\sigma^2\ \ \forall\ t \in T.$ (3.17)

Thus, a random walk model is a non-stationary process since the last two conditions of stationarity (Equations 3.2 and 3.3) are not satisfied.

3.1.4. Trend vs Difference Stationarity

The persistence of a trend in a stochastic process is a common violation of stationarity. The trend can be either deterministic (the trending variable changes by a constant amount each period) or stochastic (the trending variable changes by a random amount each period). Since classical econometric models are not valid for non-stationary time series, the series should be made stationary by removing the trend. The method used for detrending (removing the trend) depends on identifying the type of trend.

I. If the trend is deterministic the non-stationary time series can be made stationary by estimating the trend and removing it from the data. In this case the time series is a trend stationary process (TSP).

II. If the trend is stochastic the non-stationary time series can be made stationary by differencing the series D times. In this case the series is a difference stationary process (DSP).

3.1.5. Order of Integration

Time series that can be made stationary by differencing are called integrated processes. Specifically, when D differences are required to make a series stationary, that series is said to be integrated of order D, denoted I(D). The order of integration is the number of times a series needs to be differenced in order to be made stationary. A series X_t is said to be:

- Integrated of order zero, I(0), if X_t is stationary
- Integrated of order one, I(1), if the first difference $\Delta X_t = X_t - X_{t-1}$ is stationary
- Integrated of order two, I(2), if the second difference $\Delta^2 X_t = \Delta X_t - \Delta X_{t-1}$ is stationary

The most commonly observed time series are I(0) or I(1), each of them with the following features as described by Engle and Granger (1987) and Dolado et al. (1990).

For the case of an I(0) series:

(i) the variance is finite and time independent

(ii) the process has short memory (effects due to an innovation are temporary)

(iii) the process tends to fluctuate around a mean or a deterministic trend

(iv) the autocorrelations decline sharply as the lag increases

For the case of an I(1) series:

(i) the variance is time dependent and goes to infinity as time goes to infinity,

(ii) the process has long memory (effects due to an innovation are permanent)

(iii) the process has a stochastic trend

(iv) the autocorrelations tend to one in magnitude for all time separations

3.2. Unit Root Tests

3.2.1. Introduction

When analyzing time series models, it is important to identify the order of integration of each variable in a model to establish whether it is stationary or not. The order of integration of a series is ascertained by the application of a set of tests, commonly known as tests for unit roots. Several tests are used in the literature in order to test for the presence of a unit root. The most popular unit root tests are the Dickey-Fuller (DF) test (1976, 1979), the Augmented Dickey-Fuller (ADF) test (1979), the Phillips-Perron (PP) test (1988) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (1992). In this section, the emphasis will be on tests of the Dickey-Fuller type, which have been described in detail by Dickey et al. (1986).

3.2.2. The Dickey Fuller (DF) Test

3.2.2.1. The DF Test

Unit root tests were first implemented by Dickey (1976) and Dickey and Fuller (1979) in a simple AR(1) model of the form

$$Y_t = \rho Y_{t-1} + u_t \tag{3.18}$$

$$u_t \sim \text{iid}\ (0, \sigma^2)$$

where:

Y_t is the variable of interest

t is the time index

ρ is a coefficient

u_t is the error term

Equation 3.18 can be reparameterized as

$$\Delta Y_t = (\rho - 1)Y_{t-1} + u_t = \delta Y_{t-1} + u_t$$

where Δ is the first difference operator (i.e. $\Delta Y_t = Y_t - Y_{t-1}$) and δ is a coefficient ($\delta=\rho-1$). Testing whether a unit root exists ($\rho=1$ and $\delta=0$) is equivalent to testing that the variable Y_t is integrated of order one I(1). Using the above notation Dickey and Fuller (1979) consider the following three main regression equations that can be used to test for the presence of a unit root.

1. Test for a unit root:

$$\Delta Y_t = \delta Y_{t-1} + u_t \tag{3.19}$$

2. Test for a unit root with constant (a_0):

$$\Delta Y_t = a_0 + \delta Y_{t-1} + u_t \tag{3.20}$$

3. Test for a unit root with constant (a_0) and deterministic time trend (t):

$$\Delta Y_t = a_0 + a_1 t + \delta Y_{t-1} + u_t \tag{3.21}$$

The difference between the above three regression equations lies in the presence of three different combinations of the deterministic component. The first is a pure random walk model, the second includes a constant term and the third includes both a constant term and a linear time trend. The null hypothesis in the Dickey-Fuller test is that a series contains a unit root (i.e. it is non-stationary) against the alternative of stationarity.

H_0: $\delta=0$ Series contains a unit root $\leftrightarrow$ Y_t is I(1)

H_1: $\delta<0$ Series is stationary $\leftrightarrow$ Y_t is I(0)

To test for the presence of a unit root it is required to calculate the Dickey-Fuller τ statistic.

$$\mathrm{DF}_{\tau} = \frac{\hat{\delta}}{\mathrm{SE}(\hat{\delta})} \tag{3.22}$$

Once a value for the Dickey-Fuller τ statistic is computed it can be compared to the corresponding critical value at a particular level of significance to see if the null hypothesis is rejected. If the null hypothesis is rejected, it is concluded that a series Y_t doesn't contain a unit root and therefore is stationary. Non rejection of the null hypothesis means that we do not reject the presence of a unit root and hence the non-stationarity of a time series. If the variable is found to be non-stationary the next step is to apply a unit root test to the differenced variable and test its order of integration.

$$\Delta(\Delta Y_t) = \delta \Delta Y_{t-1} + \varepsilon_t \tag{3.23}$$

H_0: δ=0 Series is integrated of order 2 or higher

H_1: δ<0 Series is integrated of order one $\leftrightarrow$ Y_t is I(1)

If the null hypothesis is rejected, then the series is integrated of order 1, as most of the observed time series in transportation and in economics. Failure to reject the null hypothesis again means that the series is integrated of order two or higher.

3.2.2.2. Critical Values for the Dickey Fuller Test

In order to test the null hypothesis of a unit root, the standard approach would be to construct a t-test. However under non-stationarity, it is not possible to use standard t-distribution to obtain critical values. Therefore, in place of the classical t statistic the τ statistic is used, which has a specific distribution simply known as the Dickey–Fuller distribution. The critical values of the DF distribution depend on:

1. the sample size
2. the regression model which is consider in describing the data (3.19, 3.20 or 3.21).

Approximate critical values for specific sample sizes in all three cases represented by Equations 3.19, 3.20 and 3.21, have first been provided first by Fuller (1976) and then by Dickey and Fuller (1979, 1981) and were derived using simulations. MacKinnon (1991) provided finite sample critical values at various significance levels based on the DF distribution using Monte Carlo simulations. These critical values were obtained for models used to test the null hypothesis of a unit root containing i) no constant or trend, ii) only a constant, iii) both a constant and a trend. MacKinnon (1996) provided also a computer program to calculate numerically highly accurate critical values at any desired level and for any sample size.

3.2.3. The Augmented Dickey Fuller (ADF) Test

3.2.3.1. The ADF Test

The above testing procedures assume that the time series (or as it is alternatively said the data generating mechanism) is a random walk model. However, it is well-known that not all time-series variables can be well represented by the first-order autoregressive AR(1) process. In case an AR(1) model of the form 3.19, 3.20 or 3.21 is used to conduct the DF test when Y_t actually follows an AR(p) process, then, the misspecification of the dynamics from the regression tests will lead to autocorrelated errors (see section 3.3 for details). Since the DF distributions, are based on the assumption that u_t follows a white noise process, autocorrelated errors will make the use of the DF distributions invalid (Harris and Sollis, 2003). Thus, omission of the higher order dynamics from the regression tests may lead to small biases in the tests. To avoid these biases we must add dynamics to the model by supplementing lags of the first differences of the dependent variable. These tests are known as Augmented Dickey Fuller (ADF) tests. As with the simple DF model, the augmented model can be extended to take care the possibility that the time series contains deterministic components (constant and trend). In the case that the error term u_t is autocorrelated, the three versions of the ADF test take the following form.

1. Test for a unit root:

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{p} \beta_\iota \Delta Y_{t-i} + u_t \tag{3.24}$$

2. Test for a unit root with constant (a_0):

$$\Delta Y_t = \alpha_0 + \delta Y_{t-1} + \sum_{i=1}^{p} \beta_\iota \Delta Y_{t-i} + u_t \tag{3.25}$$

3. Test for a unit root with constant (a_0) and deterministic time trend (t):

$$\Delta Y_t = \alpha_0 + \alpha_1 t + \delta Y_{t-1} + \sum_{i=1}^{p} \beta_\iota \Delta Y_{t-i} + u_t \tag{3.26}$$

where p is the lag order of the first-differences autoregressive process.

The null hypothesis of non-stationarity is the same as in DF test. Besides this, the ADF test statistic has the same asymptotic distribution as the DF statistic, so the critical values are unchanged if the models used to test for the null of a unit root (Equations 3.19, 3.20 and 3.21) are extended to allow for higher order autoregressive processes.

3.2.3.2. Issues in the ADF Test

When using ADF tests to detect the stationarity of a time series two main issues usually arise:

- Which version of the ADF test should be used?
- How the optimal lag length of the dependent variable is decided?

Selecting the correct form for the ADF test: When testing for the presence of a unit root it is important to determine the appropriate form for the ADF test (3.24, 3.25or 3.26) before conducting the test, since the inclusion or exclusion of deterministic components lead to different critical values for the ADF test (Harris and Sollis, 2003). The applicability of each model (Equations 3.24, 3.25 and 3.26) depends on what is known about the properties of the time series. Verbeek (2004) reports that the appropriate form of the ADF test can be based on graphical inspection. From the plot it can be estimated if the time series has a mean around zero (Equation 3.24), if the time series has a mean different from zero (Equation 3.25) or if there is a clear upward or downward trend in the time series (Equation 3.26). For example, if the plot of a series indicates that the time series exhibits a deterministic trend (a clear upward or downward movement), it is most appropriate to use model 3.26 for the test. By applying 3.26 and rejecting the null of a unit root it is concluded that the time series is stationary around a deterministic trend.

Selection of the optimal lag length: By including lags of the order p the ADF formulation allows for higher-order autoregressive processes. The choice of the lag order p in ADF test is an important step of the unit root procedure. If p is too small then the remaining serial correlation will biased the test. If p is too large then the power of the test will suffer, since too many lags reduce the number of observations available. Using different lag lengths often results in different outcomes with respect to rejecting the null hypothesis of non-stationarity. However, the literature is not at all precise on the choice of the order of the approximating autoregression (Agiakloglou and Newbold, 1992). Schwert (1989), Agiakloglou and Newbold (1992) and Harris (1992) examine in detail the sensitivity of the ADF test to the number of lagged terms (p) used. Ng and Perron (1995) provide a formal analysis of the relevance of p in the ADF test and suggest several guidelines for the choice of the lag length p.

One possible approach is to start with a relatively long lag length and pare down by examining the t-values on coefficients. Repeat the process until all the lags are significantly different from zero (Enders, 1995). An alternative approach of the determination of the appropriate lag length can be also used based on the lower value of information criteria such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) or the Hannan-Quinn information criterion. The information criteria suggest choosing p to minimize an objective function (Equation 3.27) that trades off parsimony against reduction in sum of squared residuals (Ng and Perron, 1995). The Akaike Information Criterion (AIC) (Akaike, 1974) chooses C_T =2 and the Schwarz (1978) chooses C_T=logT.

$$I_p = \log\hat{\sigma}_p^2 + p\frac{C_T}{T} \qquad (3.27)$$

where p is the lag length , T is the sample size and C_T is a sequence that satisfies $C_T>0$, $C_T/T \rightarrow 0$.

3.2.4. The DF-GLS Test

The DF-GLS test is a second generation ADF unit root test proposed by Elliot, Rothenberg and Stock (1996). Elliott et al. (1996) as well as later studies have shown that this test has significantly greater power than the previous versions of the augmented Dickey–Fuller test. In essence, the test is an Augmented Dickey-Fuller test, except that the time series is transformed via a generalized least squares regression before performing the test. Thus, the DF-GLS test is accomplished in two steps. Let Y_t be the process we consider. The first step is GLS detrending of Y_t and the second step is to apply an ADF test to the locally detrented series Y_t^d. The local detrending depends on whether we consider a model with a drift only or a linear trend. DF-GLS and ADF test for the same hypotheses:

H_0: Y_t has a unit root

H_1: Y_t is stationary

The DF-GLS t test is performed by testing the hypothesis $a_0=0$ in the regression

$$\Delta Y_t^d = \alpha_0 Y_{t-1}^d + \sum_{i=1}^{p} \psi_i \Delta_{t-1}^d + u_t \tag{3.28}$$

Elliot, Rothenberg and Stock (1996) provide critical values for the DF-GLS test.

3.2.5. Seasonality and Unit Roots

When dealing with seasonality in the data, the Augmented Dickey Fuller test must be modified in order to test for seasonal unit roots. When seasonality is deterministic, a test to examine whether a non-stationary time series can be made stationary by removing the seasonality is performed following the next two steps.

Let D1, D2, D3……, D12 represent monthly dummy variables (D_i is unity in month i and zero otherwise).

I. Regress Y_t variable to all dummies and take the residuals

$$Y_t = a_1 D_1 + a_2 D_2 + \cdots + a_{12} D_{12} + e_t \tag{3.29}$$

II. Check whether the residuals e_t are stationary or not by applying an ADF test.

$$\Delta e_t = \gamma e_{t-1} + \sum_{i=1}^{p} b_i e_{t-i} + \varepsilon_t \tag{3.30}$$

H_0: e_t has a unit root

H_1: e_t is stationary

If the null hypothesis is rejected then the variable Yt can be made stationary by properly removing the seasonality.

3.3. Autocorrelation

3.3.1. Introduction -Definition

Ordinary regression analysis is based on several statistical assumptions. The assumption of no serial correlation in the linear regression model states that the covariances and the correlations between two different disturbances are all zero.

$$\mathrm{Cov}\left(\varepsilon_i, \varepsilon_j\right) = 0, \ \forall \ i \neq j \tag{3.31}$$

The violation of this assumption is most likely to occur in time series data. In this case disturbances from different time periods are correlated and the problem is called disturbance serial correlation or autocorrelation. Autocorrelation refers to the correlation of a time series with its own past and future values and results to a non zero covariance in the error term.

$$\mathrm{Cov}\left(\varepsilon_i, \varepsilon_j\right) \neq 0, \ \ i \neq j \tag{3.32}$$

Autocorrelation can be positive as well as negative. Economic and Transportation time series generally exhibit positive autocorrelation (consecutive errors usually have the same sign) as the series move in an upward or downward pattern. If the series move in a constant upward and downward movement, then autocorrelation is negative (consecutive errors typically have opposite signs).

Consider the model $$Y_t = a_0 + a_1X_{t1} + a_2X_{t2} + a_3X_{t3} + \cdots + a_kX_{tk} + \varepsilon_t \qquad (3.33)$$

First order autocorrelation occurs when the current observation of the error term ε_t is a function of the previous observation of the error term

$$\varepsilon_t = \rho_1\varepsilon_{t-1} + u_t \qquad u_t \sim \text{iid}\,(0, \sigma^2) \qquad (3.34)$$

Higher order autocorrelation occurs when the current observation of the error term ε_t is a function of the previous observations of the error term

$$\varepsilon_t = \rho_1\varepsilon_{t-1} + \rho_2\varepsilon_{t-2} + \cdots . + \rho_p\varepsilon_{p-1} + u_t \qquad u_t \sim \text{iid}\,(0, \sigma^2) \qquad (3.35)$$

The major causes of autocorrelation existence are (Washington et al., 2011):

- Systemic measurement errors in the explanatory variables
- Cyclical movements and shocks
- Omitting an important independent variable from the model
- Misspecified dynamics
- ARCH effects

A non-stationarity property in the time series data also gives rise to the phenomenon of autocorrelation. However if the series are cointegrated the autocorrelation is not a problem due to the superconsistency property of the OLS estimator (see section 2.5.2.2. for details).

In the presence of autocorrelation, the major consequences of using OLS are:

- Although OLS estimators are unbiased and consistent, they are inefficient.
- The estimated variances of the regression coefficient will be biased and inconsistent
- The hypothesis tests based on t and F distributions will give invalid results
- R^2 will be overestimated and the t-statistics will tend to be higher.

3.3.2. Breusch-Godfrey Test for Autocorrelation

Although, the Durbin-Watson is the most commonly used test for autocorrelation in time series analysis, it is important to know that it is not relevant in many cases, for instance when the error distribution is not normal. Durbin Watson test has the following limitations:

- It assumes that the regression model contains an intercept
- It assumes that the error term is normally distributed
- The test is inconclusive if the computed value falls in the indeterminate range.
- The statistic is biased (towards two, thus falsely showing that there is no autocorrelation) when lagged values of the dependent variable are used as independent variables.
- The statistic tests only for first-order serial correlation.

In the above cases, Durbin-Watson is not an appropriate test for autocorrelation. Breusch-Godfrey (BG) test (1979) or Lagrance Multipier test (LM) is useful in that it allows for lagged dependent variables and it can be generalized to higher order of autocorrelation. The null hypothesis is that there is no serial correlation of any order up to p.

Consider the model $$Y_t = a_0 + a_1X_{t1} + a_2X_{t2} + a_3X_{t3} + \cdots + a_kX_{tk} + \varepsilon_t \qquad (3.36)$$

where ε_t might follow an AR(p) autoregressive scheme, as follows:

$$\varepsilon_t = \rho_1\varepsilon_{t-1} + \rho_2\varepsilon_{t-2} + \cdots . +\rho_p\varepsilon_{t-p} + e_t \qquad (3.37)$$

The basic steps for conducting the test are:

1. Estimate the model (Equation 3.32) by OLS and save the residuals $\hat{\varepsilon}_t$.
2. Regress the residuals $\hat{\varepsilon}_t$ on all of the independent variables included in the original model and on the lagged values of the residuals $\hat{\varepsilon}_{t-1}$, $\hat{\varepsilon}_{t-2}$ .... $\hat{\varepsilon}_{t-p}$. This regression is called the auxiliary regression.

$$\hat{\varepsilon}_t = \gamma_0 + \gamma_1X_{t1} + \gamma_2X_{t2} + \gamma_3X_{t3} + \cdots + \gamma_kX_{tk} + \rho_1\hat{\varepsilon}_{t-1} + \rho_2\hat{\varepsilon}_{t-2} + \cdots + \rho_p\hat{\varepsilon}_{t-p} + v_t \qquad (3.38)$$

3. Compute the Breusch-Godfrey statistic:

$$LM_{BG} = (T - p) \times R^2 \tag{3.39}$$

where

T= number of observations

P=number of lagged residual terms

R^2 =the coefficient of determination

4. Compare the Breusch-Godfrey statistic with the relevant critical value and conclude. The null hypothesis in the Breusch-Godfrey test (BG) is that there is no autocorrelation up to order p against the alternative of autocorrelation in the residuals.

$$H_0: \rho_1 = \rho_2 = \rho_3 = \ldots\ldots = \rho_p = 0 \qquad \text{No autocorrelation}$$

$$H_1: \rho_1 \neq 0 \text{ or } \rho_2 \neq 0 \ldots\ldots \text{ or } \rho_3 \neq 0 \qquad \text{Autocorrelation}$$

If the sample size is large, Breusch and Godfrey proved that under the null hypothesis of no autocorrelation the statistic is distributed chi-squared with p degrees of freedom.

$$LM_{BG} = (T - p) \times R^2 \sim x^2_{(p)}$$

If LM_{BG} exceeds the critical value $x^2_{(p)}$ at the chosen level of significance, then the null hypothesis of no serial correlation is rejected.

3.3.3. Correction for Autocorrelation

In order to avoid the consequences of the violation of the uncorrelated errors assumption underlying least squares regression model, Beach and MacKinnon (1978) proposed the estimation of the ordinary regression under the assumption of higher order autoregressive process of the error term.

Instead of the usual regression model, the following autoregressive error model is used:

$$Y_t = a_0 + a_1 X_{t1} + a_2 X_{t2} + a_3 X_{t3} + \cdots + a_k X_{tk} + \varepsilon_t \tag{3.40}$$

$$\varepsilon_t = \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + \cdots . + \rho_p \varepsilon_{p-1} + u_t \tag{3.41}$$

$$u_t \sim \text{iid } (0, \sigma^2) \tag{3.42}$$

By simultaneously estimating the regression coefficients a_i and the autoregressive error model parameters ρ_i, the procedure corrects the regression estimates for autocorrelation. The regression analysis under the assumption of higher order autoregressive process of the error term is often called autoregressive error correction or serial correlation correction. The Maximum Likelihood (ML) method obtained by Beach and MacKinnon (1978 a, b) is usually used for the estimation of the autocorrelation coefficients ρ_i.

3.4. Autoregressive Conditional Heteroskedasticity

3.4.1. Introduction-Definition

One of the assumptions of ordinary least squares regression is that the error variance (σ^2) is constant across the sample. The violation of this assumption results to the existence of heteroskedasticity. Heteroskedasticity (unequal error variance across observations) usually occurs in cross sectional data. In time series analysis heteroskedasticity (time varying error variance) may be due to business cycles or monetary and fiscal changes. When heteroskedasticity is observed in time series data it is analyzed using Autoregressive Conditional Heteroskadastic (ARCH) models, introduced by Engle (1982). ARCH models assume that while the unconditional error variance is constant, the conditional error variance is non constant over time and is denoted as σ_t^2 (Nobel Prize Committee, 2003). The essential characteristic of these models is that they capture systematic features in the movements of variance over time (Washington et al., 2011).

3.4.2. The ARCH Model

An ARCH (p) Model (Engle, 1982) assumes that the conditional variance of the disturbance term at time t is related to the squared disturbance terms in the recent past. More formally, consider the following basic model

$$Y_t = \beta X_t + \varepsilon_t \tag{3.43}$$

Engle (1982) assumed that the error term can be decomposed as

$$\varepsilon_t = v_t\sqrt{\sigma_t^2} \quad v_t \sim \text{iid}\ (0, 1) \tag{3.44}$$

The conditional error variance (σ_t^2) is the variance of ε_t conditional on information available up to the end of a period t-1 and is given by

$$\sigma_t^2 = \text{var}(\varepsilon_t|F_t) = \delta_0 + \delta_1\varepsilon_{t-1}^2 + \delta_2\varepsilon_{t-2}^2 + \cdots + \delta_p\varepsilon_{t-p}^2 = \delta_0 + \sum_{i=1}^{p}\delta_i\,\varepsilon_{t-i}^2 \tag{3.45}$$

Where

σ_t^2= the conditional error variance

ε_t= the error term defined as ε_t= Y_t-E[Y_t| X_t]

F_t = the information set defined as $F_t = [\varepsilon_{t-i}: i \geq 1]$

ε^2 =ARCH terms

$\delta_0 > 0, \quad \delta_i \geq 0, \quad i = 1, \ldots\ldots, p$ and

p=the the number of lags of the error term

The ARCH (p) Model is usually estimated using feasible GLS or maximum likelihood methods.

The simplest model is an ARCH(1) model. The unconditional variance is $\sigma_t^2 = \delta_0 + \delta_1\varepsilon_{t-1}^2$

And hence the model is

$$Y_t = \beta X_t + v_t\sqrt{\delta_0 + \delta_1\varepsilon_{t-1}^2} \tag{3.46}$$

where $v_t \sim \text{iid}\ (0, 1)$, $\delta_0 > 0$ and $\delta_1 > 0$

The unconditional mean and variance of the error term are:

$$E(\varepsilon_t) = 0$$

$$\mathrm{var}(\varepsilon_t) = \frac{a_0}{(1 - a_1)}$$

The conditional mean and variance of the error term are:

$$E(\varepsilon_t | F_{t-1}) = 0$$

$$\mathrm{var}(\varepsilon_t | F_{t-1}) = E(\varepsilon_t^2 | F_{t-1}) = \delta_0 + \delta_1 \varepsilon_{t-1}^2$$

The ARCH(1) model has a short-run (conditional) variance (volatility) which is a function of the squared error term from the last period ε_{t-1}^2. This means that the effect of each new shock depends, in part, on the size of the shock in the previous period.

The concept of ARCH can be extended to multiple regression models. The ARCH (p) multiple regression model can be written as (Harris and Sollis, 2003):

$$Y_t = \beta_0 + \sum_{i=1}^{k} \beta i\, X_{it} + \varepsilon_t \tag{3.47}$$

$$\varepsilon_t = v_t \sqrt{\sigma_t^2}$$

$$v_t \sim \mathrm{iid}\ (0, 1)$$

$$\sigma_t^2 = \delta_0 + \sum_{i=1}^{p} \delta_i\, \varepsilon_{t-i}^2$$

where X_{it} are exogenous explanatory variables or lagged values of the dependent variable.

In case of seasonal monthly data dummy variables may also be included in the model for the conditional mean to capture seasonal features. In this case the Equation 3.41 is replaced by the following equation:

$$Y_t = \beta_0 + \sum_{i=1}^{k} \beta i\, X_{it} + \sum_{j=1}^{12} a_j D_{jt} + \varepsilon_t \tag{3.48}$$

3.4.3. Engle's LM test for ARCH

Engle (1982) proposed a Lagrange Multiplier test for ARCH disturbances. There is a clear intuition behind this test. In the case that the data are homoskedastic, the variance cannot be predicted and variations in ε_t^2 will be purely random. However, in the presence of ARCH, large values of the present squared residuals (ε_t^2) will be predicted by large values of the past squared residuals (Bollerslev et al., 1994). Engle's Lagrange multiplier test for the pth order ARCH process has the following steps:

1. Estimate the model (Equation 3.43) by OLS and save the residuals $\hat{\varepsilon}_t$.
2. Generate the squared residuals.
3. Regress the squared residuals on the lagged squared residuals. This regression is called the auxiliary regression.

$$\hat{\varepsilon}_t^2 = \delta_0 + \delta_1\hat{\varepsilon}_{t-1}^2 + \delta_2\hat{\varepsilon}_{t-2}^2 + \cdots + \delta_p\hat{\varepsilon}_{t-p}^2 + v_t \qquad (3.49)$$

4. Compute the LM statistic:

$$LM_{ARCH} = (T - p) \times R^2 \qquad (3.50)$$

where

T= number of observations

p=number of lagged residual terms

R^2 =the coefficient of determination

5. Compare the LM statistic with the critical value and conclude .The null hypothesis in the LM test for ARCH is that the error term is a normal white noise process. The alternative hypothesis is that the error term is driven by an ARCH (p) model.

$$H_0: \delta_1 = \delta_2 = \delta_3 = \dots\dots = \delta_p = 0 \qquad \text{No ARCH}$$

$$H_1: \delta_1 \neq 0 \text{ or } \delta_2 \neq 0 \dots\text{. or } \delta_3 \neq 0 \quad \text{ARCH}$$

Under the null hypothesis of no ARCH errors, the test statistic converges asymptotically to a Chi-squared (p, α) distribution, where p is the number of lags of the squared residuals included in the auxiliary regression and α is the level of significance.

$$LM_{ARCH} = (T - p) \times R^2 \sim x^2_{(p)}$$

If LM_{ARCH} exceeds the critical value $x^2_{(p)}$ at the chosen level of significance, then the null hypothesis of no ARCH is rejected and the regression presents time varying variance.

3.5. Cointegration

3.5.1. Unit root, Spurious Regression and Cointegration

The results of classical econometric theory are derived under the assumption that variables of concern are stationary. However, many time series do not conform to the assumptions of classical econometric theory. Using standard regressions techniques with non-stationary data can lead to the problem of spurious regressions. This problem originated from Yule (1926). In a spurious regression, the results suggest the presence of significant relationships among time series variables, when, in fact, there is no true relationship between the dependent variable and the regressors. Consider two uncorrelated random walk processes

$$Y_t = Y_{t-1} + v_t \quad v_t \sim \text{iid}\ (0, \sigma^2) \tag{3.51}$$

$$X_t = X_{t-1} + u_t \quad u_t \sim \text{iid}\ (0, \sigma^2) \tag{3.52}$$

where u_t and v_t are assumed to be serially uncorrelated as well as mutually uncorrelated. In their simulation study Granger and Newbold (1974) regressed two independently generated random walks on each other.

$$Y_t = \alpha_0 + \beta X_t + \varepsilon_t \tag{3.53}$$

Since both Y_t and X_t are uncorrelated non-stationary variables it would be expected that the R^2 corresponding to the regression (3.53) would tend to zero. Granger and Newbold (1974) observed that the least squares regression parameters did not converge towards zero, but towards random variables with a non generated distribution. Testing these parameters by employing the critical values of the t distribution, the null hypothesis of a zero coefficient was rejected too frequently (Kirchgassner and Wolters, 2007). The regression gave a high R^2 but a low Durbin Watson statistic. When the regression was run in first differences, the R^2 was close to zero and the Durbin Watson statistic close to 2, thus demonstrating that there was no relationship between Y and X and that the R^2 obtained was spurious (Maddala and Kim, 1998).

Granger and Newbold (1974) called this phenomenon a spurious regression. In a spurious regression as $T \to \infty$ the OLS estimate of the regression coefficient β and its t ratio will not go to zero, as they should, but to non zero random variables. Indeed, Phillips (1986) showed that in a spurious regression the corresponding t statistic will reject H_0; $\beta=0$ with probability one as $T \to \infty$. Moreover, the R^2 of the regression will go to unity and the Durbin Watson statistic to zero.

If X_t, Y_t are non-stationary and the residual series ε_t from the regression is also non-stationary, then the equation is spurious and necessarily meaningless. In that case the correlation between the two time series, which is reflected in the regression model, is due to the fact that the two series are growing together, although each one may be growing for different reasons. Thus, non-stationary time series may show a correlation just because they share a common trend, without thus necessarily implying the causal relationship that might be inferred in the case of stationary series (Harris and Sollis, 2003).

However, in some cases, there may exist a linear combination of two series that yields a stationary series. If such a combination does exist, then the variables are known to be cointegrated and their long run relationship is a valid one (Granger and Weiss, 1983). Cointegration states that there is a long run relationship between non-stationary variables towards which they always come back. The absence of cointegration leads back to the problem of spurious regression (Harris and Sollis, 2003).

3.5.2. Cointegration

3.5.2.1. Cointegrating Regressions

In the previous section the need to test for the presence of unit roots in order to avoid spurious regressions was stressed. In order to overcome the problem of spurious regressions statisticians suggested analyzing the relationships between the differences of the series, which are usually stationary. However, this approach is not suitable since it throws away useful information about the long run. A model that includes only differenced variables assumes the effects of the X variables on Y never last longer than one time period. The development of the concept of cointegration helped to avoid this problem.

Granger (1981) and Granger and Weiss (1983) observe that two non-stationary variables, which become stationary after differencing, may have a linear combination which achieves stationarity without differencing. If such a combination does exist, then the variables are said to be cointegrated (Granger and Weiss, 1983). Cointegrated series share a stochastic component and a long term equilibrium relationship. Engle and Granger (1987) formalize the idea of cointegration and provide an estimation procedure for analyzing long run as well as short run relations among non-stationary variables. More formally consider a regression model

$$Y_t = \alpha_0 + \beta X_t + \varepsilon_t \tag{3.54}$$

where Y_t is the dependent variable and X_t is a single exogenous regressor. If both Y_t and X_t are I(1), then, in general, it is expected that $\varepsilon_t = Y_t - \alpha_0 - \beta X_t$ will be also I(1). However if there exists a linear combination of X_t and Yt, which is stationary I(0), then the variables are cointegrated. In that case, the Equation (3.54) is the cointegrating regression and (1-β) is the cointegrating vector. Since there exists only one such combination, the coefficient β is unique. If X_t and Y_t are I(1) and the residuals from the regression (Equation 3.54) are also I(1) then the variables are not cointegrated and the regresion is spurious. The above definition of cointegration can be extended to a vector of more than two time series.

Engle and Granger (1987) generalized the concept of cointegration to time series that are integrated of a higher order. Assume that Y_t and X_t are integrated of order d. Then, in general, any linear combination of these valiables will be also I(d). However, there may exist a linear combination of I(d) variables such that the error term ε_t of the regression ($\varepsilon_t = Y_t - a_0 - \beta X_t$) will be of a lower order of integration I(d-b) where b>0 and d>b. If such a combination does exist then the variables are cointegrated of order (d, b). In practice, however, variables are usually integrated of order one and their combination is stationary I(0).

3.5.2.2. Superconsistency Property of the OLS estimator

Stock (1987) found that if the variables Y_t and X_t are non-stationary I(1) and the estimated residuals from the cointegrating regression are stationary I(0) (the variables are cointegrated), then OLS estimates of β will be consistent. Indeed, Stock went further and suggested that estimated coefficients from the cointegrating regression are super consistent, they converge towards their true value at a much faster rate than normal as sample sizes increases

$$(\hat{\beta}_{OLS} - \beta) = 0 \text{ as } T \to \infty$$

The superconsistency property of the OLS estimator implies that the parameters estimated from the cointegrating regression converge with a rate of T (T is the number of observations) towards their true value. Therefore, their convergence is faster than the convergence of the OLS estimators in a regression with stationary variables, which converge with a rate of $\sqrt{T}$ to their true values (consistency property of the OLS estimator).

Due to the superconsistency property of the OLS estimator when the series are cointegrated:

I. The rate T of convergence is very quick and thus the bias of βols $\left[E\left(\hat{\beta}_{OLS} - \beta\right)\right]$ is expected to be very small.

II. The dynamic misspecification and the consequent serial correlation in the residuals ε_t of the cointegrating regression is not a problem (Harris and Sollis, 2003)

3.5.3. Cointegration Tests

3.5.3.1. Residual Based Tests

The earlier tests for the presence of cointegration were introduced by Engle and Granger (1987). The basic idea behind these tests for cointegration is to test whether the estimated residuals from the regression (Equation 3.54) ε_t are I(0) against the alternative that ε_t are I(1). Since these tests are performed by applying a unit root to the residuals, they are called residual based tests. There are several unit root tests that can be applied to the residuals to test whether they are stationary or not, for example the Dickey -Fuller (DF) test, the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test. Engle and Granger (1987) used the DF test to test if the estimated residuals from the regression (Equation 3.54) contain a unit root.

The Engle Granger cointegration test is carried out in two steps.

I. Run the OLS regression (3.54) and obtain the residuals $\hat{\varepsilon}_t = Y_t - \hat{a}_0 - \hat{\beta} X_t$

II. Apply a unit root to $\hat{\varepsilon}_t$ and test the null hypothesis of non-stationarity. Since serial correlation is often a problem in time series data, an augmented version of DF test is usually used. The version of the ADF test without deterministic terms should be used (3.24), since the estimated residuals from the cointegrating regression using OLS have a zero mean by construction (Kirchgassner and Wolters, 2007).

$$\Delta\hat{\varepsilon}_t = \delta\,\hat{\varepsilon}_{t-1} + \sum_{i-1}^{p} \mathrm{bi}\,\Delta\hat{\varepsilon}_{t-i} + w_t \tag{3.55}$$

$$w_{t\sim}\text{iid}\,(0, \sigma^2)$$

The null hypothesis is that the residuals contain a unit root against the alternative of stationarity.

H_0: $\delta=0$ Residuals contain a unit root-No cointegration

H_0: $\delta<0$ Residuals are stationary- Cointegration

If the residuals are stationary, then there is a cointegrating relationship between the variables. If the residuals have a unit root, there is no cointegrating relationship between the variables and the results are spurious. Thus, a test for a unit root in the residuals is a test for non-cointegration.

3.5.3.2. Critical Values for Residual Based Tests

Critical values for cointegration tests are not the same as in ordinary unit root tests. Two reasons explain why the asymptotic distribution is not the same. First, the test is applied on the estimated residuals and not on the true disturbances. Since the OLS estimator is used to estimate the cointegrating regression, the estimated residuals are chosen so as to have the smallest sample variance, resulting to over rejecting the null hypothesis of non-stationarity (Harris and Sollis, 2003). Second, the asymptotic distribution, under the null hypothesis of non-stationarity, is affected by the number of regressors included in the cointegrating regression (3.54). The asymptotic distributions will also differ according to the number of deterministic components of the equilibrium relation. The cointegrating regression may contain a constant and a deterministic trend taking one of the following forms.

(a) $$Y_t = \beta X_t + \varepsilon_t \tag{3.56}$$

(b) $$Y_t = a_0 + \beta X_t + \varepsilon_t \tag{3.57}$$

(c) $$Y_t = a_0 + a_1 t + \beta X_t + \varepsilon_t \tag{3.58}$$

Thus, the critical values for cointegration tests will depend on:

I. the sample size (number of observations T)

II. the number of regressors included on the Cointegrating regression

III. whether a constant or a deterministic trend is included in the Cointegrating regression

In order to derive critical values for cointegration tests, MacKinnon (1991) estimated response surface regressions by feasible GLS with an approximation formula

$$C_k(p, T_k) = \beta_\infty + \beta_1 T_\kappa^{-1} + \beta_2 T_\kappa^{-2} + e_k \qquad (3.59)$$

Where

K: the number of variables included in the cointegrating regression

T_k = the sample size

$C_k(p, T_k)$ =the per cent critical values for the sample size T_k

p= the level of one-tail test of the unit root null against the alternative of stationarity

β_∞= an estimate of the asymptotic critical for the test at level p

β_∞, β_1, β_2 = response surface estimates derived from MacKinnon's table

The GLS estimates of all βs parameters for the three cases (a), (b) and (c) are presented in a Table entitled Response surface Estimates of Critical Values of cointegration tests (MacKinnon, 1991). Critical values for finite sample sizes T can be computed using the estimates for the three parameters (derived from MacKinnon's table) and the following relation:

$$C_k(p, T_k) = \beta_\infty + \beta_1 T_\kappa^{-1} + \beta_2 T_\kappa^{-2} \qquad (3.60)$$

3.5.4. Valid Regressions with Stationary and Non-stationary Variables

When dealing with stationary and non-stationary time series there are four cases to consider regarding whether the regression models are valid or not:

1. X_t and Y_t are stationary →Classical regression model can be applied.
2. X_t and Y_t are integrated of different orders →Regressions are meaningless. However, if some of the variables are I(1) and some I(2), they may be multicointegrated (Granger and Lee, 1990).
3. X_t and Y_t are integrated of the same order and the residual time series is non-stationary (contains a stochastic trend) →The regression is spurious.
4. X_t and Y_t are integrated of the same order and the residual time series is stationary→X_t and Y_t are cointegrated.

3.6. Error Correction Models

3.6.1. Granger Representation Theorem

The Granger Representation Theorem (GRT) states that if a set of variables are cointegrated the short run dynamic relationship between them can be represented by an Error correction Mechanism (ECM). According to Granger Representation Theorem cointegration is a necessary condition for the Error Correction and vice versa. If there is an Error Correction Mechanism, the variables are cointegrated. The principle behind the Granger Representation Theorem is that cointegrated time series share a long run equilibrium relation to which the system converges in the long run. Short run deviations from this equilibrium will be corrected over time by an ECM.

3.6.2. The Error Correction Model

The ECM brings together the static long run equilibrium relationship of cointegrated time series with its dynamic short run disequilibrium. The error correction model is a representaion of the short run dynamic relationship between X_t and Y_t , in which the error correction term incorporates the long run information about X_t and Y_t in the Model. This has a nice economic interpretation: Y_t can wander away from its long-run (equilibrium) path in the short run, but will be pulled back to it by the ECM over the longer term. The ECM contains information on both the short and the long run properties of the model and it can be used to estimate:

I. Short run effects of X_t on Y_t

II. Accelaration speed of the short run deviation to the long run equilibrium

An Error Correction Model is applied by using the estimated residuals from the cointegrating Equation (3.54) as a regressor in Equation (3.61) and takes the following general form.

$$\Delta Y_t = \sum_{i=1}^{q} a_{yi} \ \Delta Y_{t-i} + \sum_{i=0}^{p} a_{xi} \ \Delta X_{t-i} + a_{resid} \ \varepsilon_{t-1} + e_t \qquad (3.61)$$

Where

Δ denotes the first time differences

p, q the lag lengths chosen so as the e_t ~iid $(0, \sigma^2)$

ε_{t-1} the lagged residuals namely the lagged Error Correction Term (ECT)

a_{resid} the coefficient of the lagged residuals or speed of adjustment coefficient

e_t the error term

Equation (3.61) implies that the current changes in ΔY_t are a linear function of the past cointegration residuals ε_{t-1} , the lags of the first differenced dependent variables and the lags of the first differenced independent variables. All the variables in the ECM are stationary and therefore the estimates of the parameters of the ECM do not exhibit spurious regression effects. If there are other stationary variables that affect the short-run behavior of Y_t (ex. seasonal dummy variables), they can be included in the ECM. The lagged residuals derived from the cointegrating regression, namely the lagged Error Correction Term (ECT), represent the speed of adjustment towards the long run equilibrium. The coefficients a_{xi} of the first differenced independent variable (ΔX_t) represent the short run effects of X_t on Y_t.

3.6.2.1. Speed of adjustment coefficient:

The coefficient of the lagged ECT (a_{resid}) tells us the speed with which the model returns to equilibrium following an exogenous shock. It should be negatively signed, indicating a move back towards equilibrium. A positive sign indicates movement away from equilibrium. The interpretation given to this negative reaction of ΔY_t on u_{t-1} is that changes in ΔY_t are due to an error correction to Y_t due to its past deviations from equilibrium captured by $\hat{\varepsilon}_t = Y_t - \hat{a}_0 - \hat{\beta} X_t$. This is the reason that ε_{t-1} is usually called disequilibrium error. The coefficient of the disequilibrium error should lie between zero and one, zero suggesting no adjustment one time period later, one suggesting full adjustment one time period later.

3.7. Single Equation Esimation with I(1) variables - The Engle Granger two-step Procedure.

Engle Granger procedure is an appropriate technique when there is one dependent variable (endogenous variable) that is explained by other variables which are assumed to be weakly exogenous. Engle Granger two step procedure (1987) is implemented in the following four steps (shown also in the flow chart of figure 3.1):

1. Identify the statistical properties of the variables. The first step in the analysis is to implement a unit root test for each of the variables and test their order of integration. By definition, cointegration necessitates that the variables are integrated of the same order. If the variables are integrated of order zero (they are stationary) it is not necessary to proceed, since standard time series methods can be applied. If the variables are integrated of different orders, it is possible to conclude that they are not cointegrated. However, if some of the variables are I(1) and some I(2), they may be multicointegrated (Granger and Lee, 1990). If the variables are integrated of the same order we proceed to the next step.

2. Demonstrate that the series are cointegrated. Estimate the long run relationship including all variables that (a) are expected to be cointegrated (b) have sustained shocks on the equilibrium. The variables that have sustained shocks on the equilibrium are usually regarded as exogenous shocks and often take the form of dummy variables. Apply a cointegrating regression (Equation 3.54) and test whether the residuals are stationary. This is determined by a unit root test to the residuals with MacKinnon's Critical values, since critical values for cointegration tests are not the same as in ordinary unit root tests. If the residuals $\hat{\varepsilon}_t$ are stationary, then there is a cointegration

relationship between the variables and the long run parameters are estimated through the cointegrating regression.

3. Estimate the Error Corrrection Model. Once the long run equilibrium relationship is established, the residuals from the equilibrium regression can be used to estimate the error Correction Model. Thus, the short run elasticities and the rate of adjustment from the short to the long run are estimated through the Error Correction Model (ECM, Equation 3.61).

4. Determine whether the ECM estimated is appropriate. Performe diagnostic checks to determine whether the residuals of the error correction equations are approximately white noise (Gerrard and Godfrey, 1998). Apply Engle's LM test to check the existence of autocorrelation (first order or higher) and Breusch-Godfrey test to check the existence of or autoregressive conditional heteroskadasticity (first order or higher) in the residuals. In case that exist serial correlation and/or ARCH effects on the ECM, correct it by running the appropriate model. Moreover, cointegrating regressions imply that the speed of adjustment coefficient (α_{resid}) should be significantly different from zero. If it zero the variables are not cointegrated and they do not converge to the long run equilibrium.

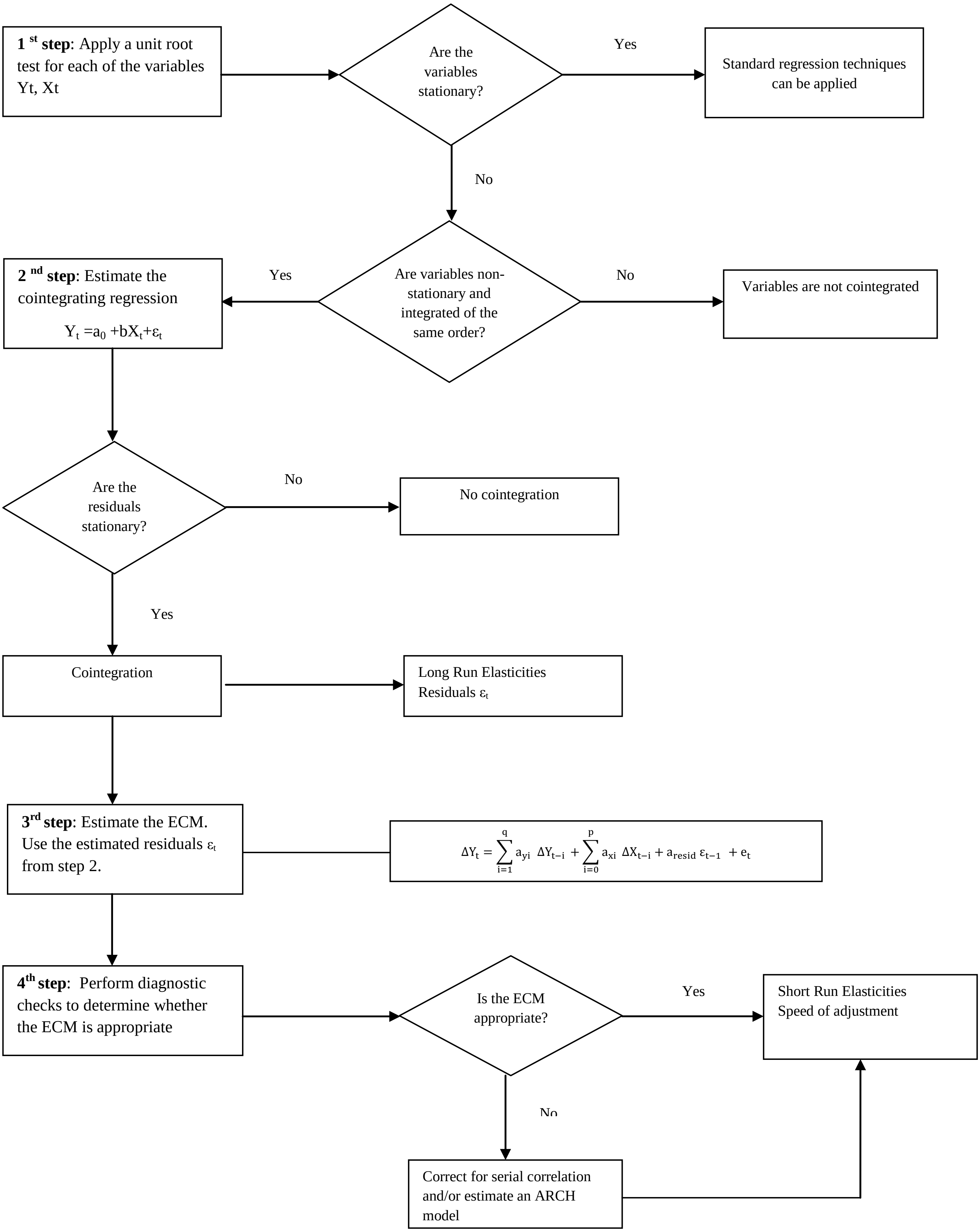

Figure 3.1. Flow chart of methodology

4. MULTIMODAL PUBLIC TRANSPORT DEMAND: A COINTEGRATION TIME-SERIES APPROACH

4.1. Introduction

Public transportation offers low cost, equitable and environmentally friendly services to societies and as such is an important player in sustainable transportation and mobility in urban areas. Public transportation (PT) frequently operates in a highly competitive and complex environment and its demand is affected by various socioeconomic and operational characteristics. For instance, higher incomes and lower fuel prices encourage the use of private vehicles, while suboptimal scheduling and increased fares could have a negative impact on public transport usage.

In this chapter we explore demand characteristics of a multimodal public transportation system using a non-stationary time-series modeling approach. Demand data for the Athens public transportation system are exploited, and the aims of the analysis are: First, to quantify the effects of various factors (i.e. fares, fuel prices, income, motorcycle sales) that affect the demand for different PT modes. Second, to estimate the elasticities of different modes of public transport with respect to the above factors (both in the short and in the long run), and thus analyze the trends of demand in these modes. This study provides useful information for the design of policy measures concerning pricing policies regarding fares and fuel prices and, also, policies for strengthening the public transport network. The analysis is performed using cointegration techniques in a time series analysis framework since this allows for treating non-stationary data and for determining short and long term elasticities. At the same time it allows for estimating the speed of convergence towards long term equilibrium. The modeling approach addopted is presented in section 4.3 following a brief literature review in section 4.2. Data and system description are given in section 4.4. Finally, the results and the conclusions of the chapter are presented in sections 4.5 and 4.6 respectively.

4.2. Background

The effect of different factors on the demand for public transport has been investigated in several publications, with many of them summarizing relevant findings (Goodwin, 1992; Litman, 2004; Oum et al., 1992; Paulley et al., 2006; Taylor and Fink, 2004; TRACE, 1999).

Fare has been an important parameter affecting demand and has thus been widely examined in the literature (for example, Dargay and Hanly, 1999; de Rus, 1990; Gillen, 1994; Litman, 2004). In general, when fares increase, ridership decreases (Balcombe et al., 2004). Fare elastisities are dynamic, varying over time and following fare changes. However, fare elasticities depend not only on the time period examined, but also on a number of other factors such as the type of the public transportation mode analyzed, user characteristics, and so on. This explains the differences in the values of fare elastisities among different studies (Paulley et al., 2006). The quality of service is another important factor that affects demand for public transportation. Some studies have found that quality of service factors are more important in attracting riders than changes in fares (Iseki and Taylor, 2010; Litman, 2004). Moreover, many studies have estimated the degree to which variablitiy in transit ridership is related to fuel price (Agthe and Billings, 1978; Chiang et al., 2011; Currie and Phung, 2007; Lane 2010; Doi and Allen, 1986; Rose, 1986; Storchman, 2001; Wang and Skinner, 1984). Most of these studies found that transit demand elasticities with respect to fuel prices are positive and lower than unity. Concerning the effect of income on public transport demand, some studies have found that it has a positive effect because it creates additional activities that require more transport services (Romilly, 2001), while others have found that it has a negative effect because it creates a shift to private cars (Crotte et al., 2008; Dargay and Hanly 2002a). The effect of car ownership and the effect of employment level have been studied by Gomez Ibanez (1996), Hendrikscon (1986) and Kain and Liu (1999). More recently, researchers examined the impact of the number of immigrants on transit ridership (Blumenberg and Evans, 2007; Gritza et al., 2011), as well as the impact of weather on transit (Guo et al., 2007; Stover and McCormark, 2012).

However, research using cointegration techniques for estimating demand elasticities in transportation is limited, with papers by Crotte et al. (2008), Dargay and Hanly (2002b) and Romilly (2001) being the exceptions. The Cointegration/Error Correction Model Approach is likely to offer much more reliable information, particularly when the stationarity assumption underlying least squares regression is violated (Kulendran and Stephen, 2001; Gil-Alana et al., 2012). Further, it allows for the specification of the long run equilibrium properties and the short run dynamics (via the cointegration relationships and the Error Correction Models respectively). The paper by Dargay and Hanly (2002b) is based on a dynamic econometric model relating per capita bus partonage to fares, income and service level. The results indicate that bus partonage is relatively fare-sensitive and that long run elasticities are at least twice those of short-run elasticities. Romilly's study (2001) used both system and single equation cointegration methods to determine long and short run bus demand elasticities and identify the influence of subsidy reduction on bus fares. The fact that there are some important differences between these studies with respect to the short and long run bus fare elasticities reflects the sensitivity of Error Correction Models to data and model spesifications (Balcombe et al., 2004). Crotte et al. (2008) estimated time series and panel cointegration models to determine the effect that fares, income, quality of service, and fuel prices have on the demand for the Mexico City metro ridership. They found that the metro ridership is cointegrated with income and quality of service.

All the above studies were based on annual time series data and their analyses using cointegration did not model seasonality of public transport demand. This suggests that these studies may have missed important dynamics connecting the explanatory factors with demand on a monthly time frame. On the contrary, Chen et al. (2011) used monthly data to investigate the impacts of various factors in rail ridership. In order to deal with the seasonality and non-stationarity issues, they estimated a dynamic model and they quantified short and long run effects.

There are few papers investigating the factors affecting multimodal public transportation system ridership (Garcia-Ferrer et al., 2006; Gkritza et al., 2004; 2011). Gkritza et al. (2004, 2011) investigated the factors that affect public transport ridership by mode for the multi-modal public transport system of Athens through seemingly unrelated regression equations. Although these papers estimate elasticities for multi modal transport demand, they do not consider the non-stationary nature of the demand time series. Garcia-Ferrer et al. (2006) investigated user response to changes in prices and to the characteristics of the service for Madrid's multimodal public transport system using two different approaches capable of dealing with the nonstationarity and strong seasonality of the data.

Our contribution to the literature includes the use of cointegration and error correction approaches for investigating demand in a multimodal public transportation system by considering a number of operational and macroeconomic factors and estimating short and long run demand elasticities for the different modes of the system.

4.3. Methodology

In the third chapter a detailed description of the methodology followed in order to estimate short and long run elasticities for the multimodal public transprotation system of Athens was given. Here we include a brief description in order to make the chapter self contained.

In economics, long run is the equilibrium state where no changes occur, while short run is the period of time during which adjustment to the long run equilibrium is occuring. In the case of non-stationary data, the existence of a long run equilibrium state is synonymous with the concept of cointegration (Harris and Sollis, 2003).

The use of standard regression techniques with independent, non-stationary variables can lead to spurious regressions since the statistical significance of the parameters is overstated (Granger and Newbold, 1974). In a spurious regression, the estimated parameters are statistically significant while there is no true relationship between the dependent variable and the regressors. Thus, correlation between non-stationary series may not imply the kind of causal relationship that might be inferred from stationary series. Granger and Newbold (1974) showed this phenomenon using Monte Carlo Simulation.

However, in some cases, there may exist a linear combination of two series that yields a stationary series. If such a combination does exist, then the variables are known to be cointegrated and their long run relationship in is a valid one (Granger and Weiss, 1983). More formally, if ψ_t and x_t are both I(1), but there exists a linear combination of

$$\psi_t - \alpha - \beta x_t = u_t \tag{4.1}$$

which is I(0), then ψ_t and x_t are cointegrated, equation (4.1) is the cointegrating regression, and β is the cointegrating parameter. *The estimated parameters will be superconsistent*. The superconsistency property implies that if all the variables (dependent and independent) are non-stationary and the residuals are stationary, the OLS estimators in Equation (4.1) converge to their true value at a much faster rate than the usual OLS estimators with stationary variables (Stock, 1987).

This idea can be extended to a vector of more than two time series. Engle and Granger (1987) proved that the cointegrated series have an Error Correction Mechanism (ECM) representation which permits the derivation of short run parameters. The ECM is defined as

$$\Delta\psi_t = \sum_{i=1}^{q} a_{\psi i}\ \Delta\psi_{t-i} + \sum_{i=0}^{p} a_{xi}\ \Delta x_{t-i} + a_{resid}\, u_{t-1} + e_t \tag{4.2}$$

where Δ defines the difference variable, p, q the number of the lags needed to make e_t white noise, and u_{t-1} the lagged residuals derived from equation (4.1).

All the variables in the ECM are stationary and therefore the estimates of the parameters of the ECM do not exhibit spurious regression effects. The ECM equation implies that $\Delta\psi_t$ can be explained by the lagged u_{t-1}, the lagged $\Delta\psi_t$ and Δx_t. Notice that u_{t-1} can be thought of as an equilibrium error (or disequilibrium term) occurred in the previous period. If it is nonzero, the model is not at equilibrium state and vice verca. Most cointegration econometric models that have been examined in the literature follow the Engle-Granger two step procedure (1987) to estimate short and long run elasticities. A general strategy for examining and modeling cointegrated series according to the Engle-Granger procedure includes the following:

1. Pre-testing the variables for their order of integration. The first step in the analysis is to implement a unit root test for each of the variables. By definition, cointegration necessitates that the variables are integrated of the same order. If the variables are stationary it is not necessary to proceed, since standard time series methods can be applied. If the variables are integrated of different orders, it is possible to conclude that they are not cointegrated. However, if some of the variables are I(1) and some I(2), they may be multicointegrated (Granger and Lee, 1990).
2. Applying a cointegrating regression and testing the residuals for stationarity. If the residuals are stationary, then there is a cointegration relationship between the variables and the long run parameters are estimated through the cointegrating regression. Thus, a test for a unit root in the residuals is a test for non-cointegration. In practice, any of the unit root tests can be applied. However, the critical values are not the same because we are applying the tests to the residuals and not to the true disturbances (Maddala and Kim, 1998). The critical values will depend on the number of regressors and whether a constant or/and a time trend is included in the cointegrating regression.
3. Once the long run equilibrium relationship is established, the residuals from the equilibrium regression can be used to estimate the error correction model. Thus, the short run elasticities and the rate of adjustment from the short to the long run are estimated through the Error Correction Model (ECM, Equation 4.2).
4. Determining whether the ECM estimated is appropriate. Performing diagnostic checks to determine whether the residuals of the error correction equations are approximately white noise. Moreover, cointegrating regressions imply that the speed of adjustment coefficient (α_{resid}) should be significantly different from zero.

4.4. Public Ttransport System and Data Description

4.4.1. The Athens Multimodal Public Transport System

The Athens multimodal public transport system includes five modes: metro, urban rail, bus, electric bus and tram. The network has an average daily passenger demand of 2.5 million passengers and is spread over an area of about 650 km^2. The underground metro system in Athens has 2 metro lines with a total length of 32 km and 36 stations. The frequency of the trips is 3 minutes during peak-hour periods and 5 to 10 minutes during non peak periods. Urban rail is the 'oldest' Public Transport Mode in the city of Athens with a length 25.6 km. The two metro lines and the urban rail line are connected in four central stations.

The bus network includes approximately 330 bus lines covering the entire greater Athens Metropolitan Area, with a fleet of almost 2,500 buses. The electric bus network consists of 22 lines that primarily serve the Athens city centre with 366 trolley (electric) buses. There are dedicated bus lanes (total length 50.53 km) for the bus and the electric bus mode in the most congested parts of the network, in hopes that this will increase speed and reduce traveler times. The bus and electric bus networks are connected to the metro and the urban rail through bus/electric bus stops that are close to the metro stations. The Tram has 3 lines mainly linking the south suburbs of Athens to the city center with a limited network of approximately 26 km and 48 stops. We do not analyze the tram because sufficient data were not available and its modal share of daily public transport trips is below 3%.

The modes discussed are interconnected. The integrated ticket, which was applied during the last two years of the study, encourages the use of different modes in a single journey. However, for large parts of the network there are parallel lines of different public transport modes that serve the proximate OD pairs (particularly for bus and metro). To this extent, there is competition between PT modes because fares, although centrally regulated, differ among modes.

4.4.2. The Data

The dataset used originates from the Athens Public transportation System described in the previous section. In order to investigate short and long run elasticities for the Athens multimodal transit system, monthly data from January 2002 to December 2010 (a total of 108 observations) were used. The variables used in this study were grouped in two general categories: public transport variables (internal factors) and macroeconomic and demographic variables (external factors). Table 4.1 shows the mean and the standard deviation of each variable.

Table 4.1: Summary statistics per mode (monthly)

Variable	Mean	Standard Deviation
Public Transport variables		
Metro Riders	14,295,245	2,544,766
Bus Riders	30,338,756	3,127,397
Electric bus Riders	6,573,172	7,852,62
Urban Rail Riders	9,661,460	1,526,618
Metro ticket price (in €)	0.922	0.074
Bus/electric bus ticket price (in €)	0.695	0.205
Urban rail ticket price (in €)	0.879	0.095
Macroeconomic and Demographic Variables		
Unemployment Rate (percent)	9.076	1.752
Gasoline price (in €)	0.799	0.143
Gross Domestic Product (in millions €)	19.768	1.657
Gross Domestic Product per capita (in €)	1,772	138
Population of Athens	4,014,567	71,742
Population of Greece	11,149,942	112,053
Number of motorcycle sales	2,763.57	1,043.26
Number of cars sales	10.755,55	3.471,38

Public transport data (monthly ridership and single ticket price per mode) were obtained from the Athens Urban Transport Organization. It should be noted that in the absence of reliable and consistent monthly data on factors such as comfort and service, these variables were not included in our analysis.[1] Figure 4.1 depicts monthly ridership for each of the four transit modes (metro, bus electric bus, train). As shown in Figure 4.1, the summer months particularly August have a clear negative effect on transit demand.

[1] Data such as comfort and service are potentially important for obtaining demand estimates at least at the "line" level. However, these data are usually collected by questionnaires (del Castillo and Benistez, 2012) and it is this impossible to obtain them on a monthly basis.

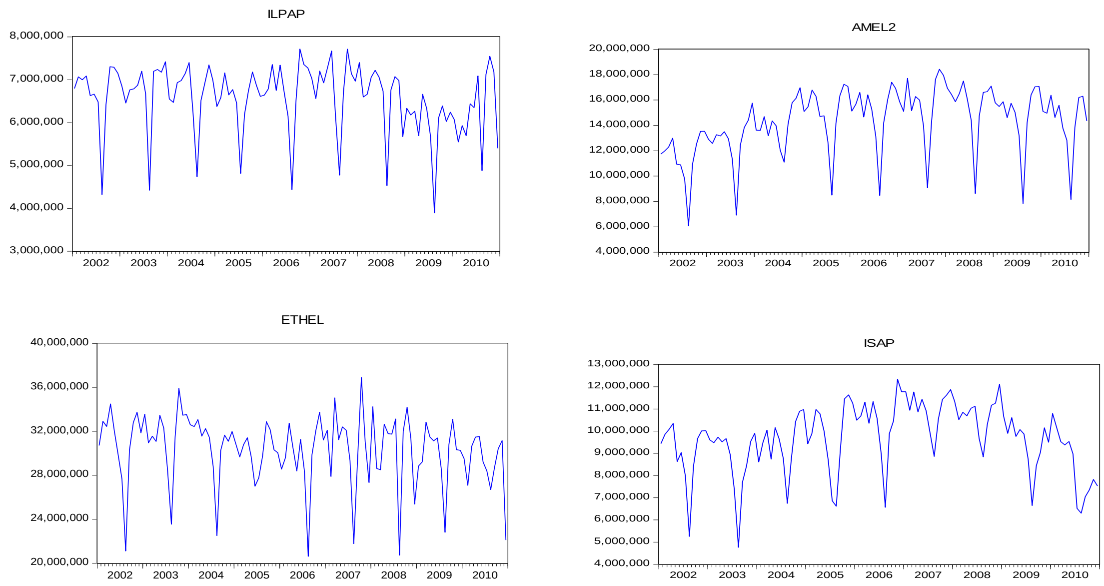

Figure 4.1. Monthly transit ridership (2002-2010)

Population of Greece, population of Athens, Unemployment rate and Gross Domestic Product (GDP) were obtained from the Hellenic Statistical Authority. Population estimation at monthly intervals was not available, so a monthly estimation of the labor force was incorporated here as a proxy, while daily gasoline price data provided by the Greek Ministry of Development were used in this analysis. The monthly range of gasoline prices is calculated and tested for significance in explaining transit ridership. Finally, monthly motorcycle and car sales in Attika per month were obtained from the Association of Motor Vehicle Importers Representatives. Ticket prices, fuel prices and gross domestic product were normalized at year 2010 € using the consumer price index for Greece.

4.5. Results

4.5.1. Unit Root Tests

The first step in the analysis is to implement a unit root test for each of the variables in order to test their sationarity. To determine whether the logarithmic form of each of the variables examined in this study contains a unit root or not, we employ the Dickey-Fuller –GLS test.

Then, if the variables are non-stationary, we proceed to determine the order of integration of the variables by applying a unit root test to each differenced variable (Table 4.2).

The modified Dickey–Fuller t test (known as the DF-GLS test) proposed by Elliott et al. (1996), is an augmented Dickey–Fuller test, except that the time series are transformed via a generalized least squares (GLS) regression before performing the test. Elliott et al. (1996) as well as later studies (Maddala and Kim, 1998) have shown that this test has significantly greater power than the previous versions of the augmented Dickey–Fuller test. It should be mentioned that the Dickey-Fuller GLS test is sensitive to the choice of the lag length so, in order to choose the optimum lag length, we apply Akaike Information criteria, Schwarz Information criteria, and Modified Akaike Information criteria. We choose the lag length supported by the majority of these criteria.

Table 4.2. DF-GLS test for the presence of Unit Root

	level		First differences			
Variable[a]	**Number of lags**	**DF-GLS test**	**Number of lags**	**DF-GLS test**	**5% DF-GLS critical values**	**Order of integration**
Public Transport variables						
Metro Riders	12	-0.324	11	-3.453	-1.944	I(1)
Bus Riders	11	-1.290	1	-10.068	-1.944	I(1)
Electric bus Riders	11	-0.569	11	-2.404	-1.944	I(1)
Urban rail Riders	12	-0.562	10	-3.583	-1.944	I(1)
Metro ticket price	0	-1.641	0	-9.2112	-1.944	I(1)
Bus/electric bus ticket price	0	-0.296	0	-10.226	-1.944	I(1)
Urban rail ticket price	0	-1.110	0	-9.383	-1.944	I(1)
Macroeconomic and Demographic Variables						
Unemployment Rate	3	-0.604	2	-5.439	-1.944	I(1)
Gasoline price	1	-0.805	0	-7.081	-1.944	I(1)
Gross Domestic Product	12	-1.409	6	-7.930	-1.944	I(1)
Gross Domestic Product per capita	12	-1.421	6	-7.917	-1.944	I(1)
Population of Athens	1	-1.412	0	-0.845	-1.944	I(2)
Population of Greece	1	-0.271	0	-1.615	-1.944	I(2)
Number of motorcycle sales	12	-0.981	2	-2.77	-1.944	I(1)

[a] variables are in logarithms

Based on MacKinnon’s (1996) critical values, the null hypothesis that each of the variables contains a unit root was not rejected at the 5% critical level. That is, all the variables are characterized by integration of degree one or higher. The DF-GLS t-statistics for the first difference of the variables are statistically significant (except for the population of Greece and the population of Athens), leading to the rejection of the null hypothesis that the first differences are non-stationary and indicating that almost all the variables are integrated of order one.

In general, seasonality is a component that is known to influence public transportation ridership. In Athens, in particular, seasonality takes on a significant value during the summer period. So, in order to treat seasonality, we create dummy variables for all months. Especially for the dependent variables (metro, bus, electric bus and urban rail ridership), we checked whether they may be transformed from non-stationary to stationary, by properly treating seasonality. We regressed each dependent variable to all dummies, we took the residuals and then we checked whether the residuals of these equations were stationary or not. The results from the DF-GLS test indicated that the variables metro and urban rail riders were still non-stationary at the 5% significance level, whereas bus and electric bus riders were stationary. We decided to treat all the dependent variables as non-stationary and to treat seasonality by including dummy variables in the cointegrating regression and in the error correction model.

4.5.2. Long Run Analysis

According to the previous discussion, the reason for using cointegration techniques is that non-stationary time series result to spurious regressions and, hence, do not allow statistical interpretation of the estimated model. Since it is necessary to examine whether there is a long run co-movement of the variables, we apply Engle-Granger's two step procedure (Engle and Granger, 1987). The first step is to estimate the cointegrating regressions and check the residuals for stationarity. If the residuals (u_t) have a unit root, there is no cointegrating relationship among the variables. All variables are expressed in logarithms. The cointegrating regression for every transit mode is estimated using the following general form:

$$Ridership = a_0 + a_1 ticket\ price + a_2\ gasoline\ price + a_3\ GDP\ per\ capita\ + a_4 motorcycle\ sales + u_t \tag{4.3}$$

In all cointegrating equations we included a constant, but we did not include a time trend. Although some transportation studies using cointegration techniques include a time trend, Liddle (2009) suggests that GDP per capita is a more accurate measure to account for technical change than a simple linear trend.

Several variables were included in the initial models (GDP per capita, fares, gasoline price, unemployment rate, car sales, motorcycle sales). Only the variables that were found to significantly affect the ridership of each mode and to be cointegrated, were included in the final cointegrating regressions. The results of the cointegrating regressions and the residuals unit root tests for each of the transit modes (metro, bus, electric bus, urban rail) are reported in Table 4.3. Based on MacKinnon's critical values for cointegration tests (1991), the residuals of the four equations have been found to be stationary I(0) indicating the existence of a cointegrating relationship among the variables for each of the transit modes. Therefore, the estimated coefficients represent the long run elasticities of each transit mode's ridership.

Estimating the above cointegrating regressions using ordinary least squares (OLS) achieves a consistent estimate of the long run relationship between the variables in the four models due to the superconsistency property of the OLS estimator, when the variables are cointegrated (Harris and Sollis, 2003). However, the omitted dynamic terms in Equation (4.3) will lead to serial correlation on the residuals of each cointegrating regression; but, this is not a problem due to the superconsistency property (Harris and Sollis, 2003). So, there is no need to check the residuals for serial correlation.

Table 4.3. Cointegrating Regressions
(t-statistic in parenthesis)

	Dependent variable			
Explanatory variables	**Metro**	**Bus**	**Electric Bus**	**Urban rail**
Constant	9.21 (9.29)	17.23 (1250.95)	15.68 (1049.59)	10.33 (9.34)
Ticket price_metro	-0.23 (-1.92)			
Ticket price_bus/electric bus		-0.05 (-1.83)	-0.16 (-5.18)	
Ticket price_urban rail				-0.33(-3.18)
GDP per capita	1.03 (7.57)			0.76 (5.20)
Motorcycle sales	-0.04 (-1.92)			
Gasoline Price	0.13 (2.12)		0.08 (1.53)	
July	-0.23 (-6.99)	-0.07 (-2.71)	-0.09 (-3.51)	-0.25 (-6.13)
August	-0.69 (-20.55)	-0.29 (-11.14)	-0.37 (-14.34)	-0.47 (-11.53)
Test diagnostics				
Adjusted R^2	0.809	0.547	0.690	0.599
Durbin-Watson stat	1.57	1.71	1.83	1.02
DF-GLS test for Residual unit root	-8.27	-7.88	-9.34	-5.41
MacKinnon's Critical Values (at the 5% level)	-4.20	-2.88	-3.39	-3.39
Number of observations	108	108	108	108

Fare level is one of the internal factors most frequently analyzed in relevant studies of transit use. Table 4.3 shows that ridership for each mode is determined by its ticket price [2]. Moreover, according to a-priori expectations, there is a decrease in the transit ridership of all modes during the summer period and particularly during August.

For the case of metro, it is evident that all coefficients are statistically significant and have the expected signs. More specifically, the effect of GDP per capita on metro ridership is positive and very high, as indicated by a long run elasticity above unity (1.03). This can be explained since GDP per capita is a measure of development both in economic and technical terms. GDP's increase is usually related to additional economic activities that require more transport services. Metro ticket price was found to be among the most significant factors affecting ridership. An increase in the price of the metro ticket would result in a decrease in metro riders and vice versa. Further, an increase in the price of gasoline leads to an increase in transit ridership. This conclusion is based on the assumption that high gasoline prices will encourage people to use transit (Maghelal, 2011; Mc Leod et al., 1991). However, we found

[2] Fares of different PT modes were not included in the same model, since there was high collinearity among them.

that gasoline price has a small influence on transit ridership. The estimated elasticity is equal to 0.13. This is in agreement with other studies which argue that fuel prices represent only a small part of automobile operating costs (Small and van Vender, 2006). Finally, the number of motorcycle sales in Attica has a statistically significant, though small negative effect, on metro ridership.

Looking at the specific results for bus riders, the only variable that seems to affect bus ridership is bus/electric bus ticket price. However, the ticket price elasticity is very low (-0.05) indicating that bus ridership is inelastic. Ridership for the electric bus system is also significantly affected by bus/electric bus fare price with an long run elasticity of -0.16. Electric bus ridership is also affected by the gasoline price (0.08). This elasticity is smaller than the gasoline price elasticity of the metro system. It is possible that people who switch from car to metro transit system are more than those who switch from car to electric bus system and hence, an increase in gasoline price affects them.

The urban rail system has the highest fare price elasticity (-0.33) among all modes in the multimodal transit system. This can be attributed to the limited network of the urban rail, which results in an inferior quality of service compared to the bus system and to lower speeds compared to the metro system. Additionally, as with the metro system, there is a positive effect of the gross domestic product per capita on the urban rail ridership (the elasticity is equal to 0.76).

4.5.2.1. Seemingly Unrelated Regression Estimation (SURE)

In the previous step we examined the demand for the four transit modes by estimating four separate models, with the demand for each mode as the dependent variable. However, the four dependent variables are from the same process and they may be considered as a group. In this case the four equations are likely to share unobserved characteristics. They are seemingly unrelated but include a contemporaneous correlation of error terms (Washington et al., 2011). Estimating the four equations separately gives consistent, but not efficient estimates of the parameters. To obtain efficient estimates the Seemingly Unrelated Regression Estimation (SURE) methodology, as developed by Zellner (1962) must be implemented. Seemingly unrelated regression (SUR), also called joint generalized least squares (JGLS) or Zellner estimation, is a generalization of OLS for multi-equation systems. Gkritza et al (2004; 2011) used this methodology to estimate public transport demand for the multimodal transit system of Athens, but they assumed that the variables (both dependent and independent) are stationary.

Since we are interested in investigating the factors that affect transit ridership by mode in a multimodal operating environment, we estimate seemingly unrelated regression equation models, we check the variables for cointegration and we compare the results with those of single equation estimation, which were discussed earlier.

Table 4.4. Seemingly unrelated equations

	Dependent variable			
Explanatory variables	**Metro**	**Bus**	**Electric Bus**	**Urban rail**
Constant	9.55 (10.04)	17.23 (1253.00)	15.68 (1087.79)	10.31 (9.38)
Ticket price_metro	-0.27 (-2.34)			
Ticket price_bus/electric bus		-0.05 (-1.83)	-0.17 (-5.91)	
Ticket price_urban rail				-0.33 (-3.24)
GDP per capita	0.99 (7.67)			0.77 (5.24)
Number of motorcycle sales	-0.06 (-2.73)			
Gasoline price	0.18 (3.48)		0.11 (2.97)	
August	-0.70 (-20.73)	-0.29 (-11.14)	-0.37 (-14.50)	-0.46 (-11.54)
July	-0.23 (-6.97)	-0.07 (-2.71)	-0.09 (-3.64)	-0.24 (-6.13)
Test diagnostics				
Adjusted R^2	0.8184	0.56	0.70	0.61
Durbin-Watson stat	1.56	1.707	1.83	1.02
DF-GLS test for Residual unit root	-8.17	-7.87	-9.43	-5.40
Critical Values for cointegration test	-4.20	-2.88	-3.39	-3.39
Number of observations	108	108	108	108

*t statistic in parenthesis

The results are similar and the DF-GLS test on the residuals reveals again that there is a cointegrating relationship between the variables. The long run elasticities are almost equal to those of the single equation estimation. The gasoline price elasticity of the metro and the electric bus system changes slightly (from 0.13 to 0.18 and from 0.07 to 0.11 respectively). Also there is a small difference in the ticket price elasticity of the metro system (from -0.23 to -0.27).

4.5.3. Short Run Analysis

4.5.3.1. Error Correction Models

An efficient time series modeling effort should describe both the short run dynamics and the long-run equilibrium simultaneously (Enders, 1995). The Granger Representation Theorem developed by Engle and Granger (1987) suggests that, if a set of variables are I(1) and cointegrated, then there exists a valid error correction representation of the time series. So, once the cointegrating relationship for every public transport mode is found and the long run elasticities are calculated, the next step is to estimate the Error Correction Model in order to obtain the short run responses. The Error Correction Model for every transit mode is estimated using the following general Equation.

$$\Delta ridership_t = \sum_{i=1}^{q} a_{ri}\, \Delta ridership_{t-i} + \sum_{i=0}^{p} a_{pi}\, \Delta ticket\ price_{t-i} + \sum_{i=0}^{g} a_{gi}\, \Delta gasoline\ price_{t-i} + \\ + \sum_{i=0}^{d} a_{di}\, \Delta GDP_{t-i} + \sum_{i=0}^{m} a_{mi}\, \Delta motorcycle\ sales_{t-i} + a_{resid}\, u_{t-1} + e_t \quad (4.4)$$

In addition, monthly dummies were included in each model to account for seasonal fluctuations in public transportation ridership. Table 4.5 shows the results from the estimation of the four Error Correction Models for the transit ridership of each mode. The coefficient of the residuals, namely the Error correction term, represents the speed of adjustment towards the long run equilibrium. A cointegrating relationship implies that the coefficient of the residuals be negative and statistically significant. As presented in Table 4.5, the estimated coefficient of the ECT (a_{resid}) is statistically significantly different from zero at the 5% level for the equations of the metro, the bus and the urban rail ridership, indicating that there is a cointegrating relationship among the variables. Moreover, the coefficients of the unlagged differenced variables are the short run elasticities. As expected, short run elasticities are lower than their long run counterparts satisfying the Le Chatelier principle (Le Chatelier and Boudouard, 1898).

Table 4.5. Error Correction Models

	Dependent variable (t-statistic in parenthesis)			
Explanatory variables	**Metro**	**Bus**	**Electric Bus**	**Urban rail**
Δ_metro_lag1	-0.12 (-1.50)			
Δ_bus_lag1				
Δ_electric bus_lag1			-0.75 (-8.66)	
Δ_urban_rail_lag1				-0.21 (-2.16)
Δ_ticket price_metro	-0.04 (-0.13)			
Δ_ticket price_bus/electric bus		-0.041 (-0.31)		
Δ_ticket price_urban rail				-0.18 (-0.59)
Δ_GDP per capita	0.28 (1.45)			0.06 (0.27)
Δ_motorcycle sales	-0.05 (-2.21)			
Δ_gasoline price_lag1	0.03 (0.24)		0.06 (0.32)	
February		-0.45 (-1.92)	-0.06 (-1.72)	
March	0.08 (3.67)			
August	-0.46 (-16.99)	-0.22 (-9.52)	-0.36 (-10.72)	-0.25 (-8.27)
July	-0.17 (-6.83)	-0.07 (-2.99)	-0.10 (-3.32)	0.19 (-6.17)
September	0.47 (11.36)	0.28 (11.90)		
October	0.12 (2.31)	0.06 (2.86)	0.35 (7.52)	
November				0.07 (2.52)
u_{t-1}	-0.55 (-5.76)	-0.88 (-8.70)	-0.25 (-1.60)	-0.32 (-3.60)
Adjusted R^2	0.91	0.76	0.69	0.73
Number of observations	108	108	108	108
		Residuals tests		
Breusch-Godfrey LM test for autocorrelation				
Lag1	1.63 (p=0.201)	0.53 (p=0.467)	0.05 (p=0.816)	0.57 (p=0.450)
Lag2	2.28 (p=0.320)	1.49 (p=0.474)	6.78 (p=0.034)	0.59 (p=0.745)
Lag3	4.10 (p=0.251)	2.45 (p=0.485)	7.60 (p=0.055)	1.01 (p=0.798)
Lag4	4.13 (p=0.388)	3.14 (p=0.534)	15.25 (p=0.004)	2.23 (p=0.693)
Lag5	5.04 (p=0.410)	5.37 (p=0.372)	17.76 (p=0.003)	3.26 (p=0.660)
Lag6	6.80 (p=0.339)	5.46 (p=0.486)	17.80 (p=0.007)	3.37 (p=0.761)
Lag7	6.92 (p=0.437)	5.60 (p=0.587)	17.93 (p=0.012)	4.60 (p=0.708)
Lag8	12.47 (p=0.131)	6.34 (p=0.609)	17.94 (p=0.021)	4.77 (p=0.782)
Lag9	12.76 (p=0.174)	6.35 (p=0.704)	18.44 (p=0.030)	4.96 (p=0.838)
Lag10	12.82 (p=0.234)	6.56 (p=0.766)	18.44 (p=0.048)	5.01 (p=0.891)
Lag11	13.44 (p=0.265)	6.69 (p=0.823)	18.54 (p=0.070)	5.89 (p=0.881)
Lag12	13.46 (p=0.336)	6.98 (p=0.859)	23.30 (p=0.025)	9.62 (p=0.649)
Engle' s LM test for ARCH				
Lag1	0.01 (p=0.911)	0.81 (p=0.369)	36.88 (p=0.000)	0.34 (p=0.558)
Lag2	0.13 (p=0.936)	1.95 (p=0.377)	39.81 (p=0.000)	0.35 (p=0.841)
Lag3	0.15 (p=0.985)	2.03 (p=0.566)	40.88 (p=0.000)	0.39 (p=0.943)
Lag4	0.16 (p=0.997)	3.35 (p=0.500)	41.73 (p=0.000)	0.81 (p=0.937)
Lag5	0.45 (p=0.994)	3.36 (p=0.645).	42.94 (p=0.000)	0.92 (p=0.968)
Lag6	0.54 (p=0.997)	4.04 (p=0.672)	44.99 (p=0.000)	2.22 (p=0.898)
Lag7	0.55 (p=0.999)	4.08 (p=0.769)	45.03 (p=0.000)	3.19 (p=0.867)
Lag8	0.56 (p=0.999)	4.11 (p=0.847)	45.14 (p=0.000)	3.59 (p=0.892)
Lag9	0.58 (p=0.999)	4.22 (p=0.896)	45.15 (p=0.000)	3.85 (p=0.921)
Lag10	0.83 (p=0.999)	4.26 (p=0.935)	45.24 (p=0.000)	5.10 (p=0.884)
Lag11	1.25 (p=0.999)	4.82 (p=0.939)	45.24 (p=0.000)	5.22 (p=0.917)
Lag12	1.26 (p=0.999)	5.17 (p=0.952)	45.34 (p=0.000)	8.51 (p=0.744)

Generally speaking, the above dynamic models for ridership of all modes appear to fit well into the data showing a high R^2. We performed diagnostic checks to determine whether the residuals or the error correction equations are approximately white noise (Enders, 1995), by checking the residuals of the ECM for persistence of serial correlation (first or higher order) and autoregressive conditional heteroskedasticity (first or higher order). We used the Breusch-Godfrey test (Breusch, 1979; Godfrey, 1978*)* that can be generalized to higher order of autocorrelation. Since the data were monthly observations we implement the Breusch-Godfrey test and the autoregressive conditional heteroskedasticity test for up to 12^{th} order.

The statistical tests for the dynamic equations of metro, bus, and urban rail ridership lead to the rejection for the presence of autocorrelation of first or higher order and for the presence of heteroskedasticity. However, the same tests reveal the existence of higher order serial correlation and autoregressive conditional heteroskedasticity in the Error Correction Model of electric bus ridership.

4.5.3.2. Autoregressive Conditional Heteroskedasticity

Serial correlation mainly occurs as a result of error term correlation over time, but may be also the result of an autoregressive error variance (ARCH Effects). ARCH effects observed in transportation (time series) data should not be ignored (Karlaftis, 2010). The ARCH LM test (Table 4.5) shows that Autoregressive Conditional Heteroskedasticity (ARCH) is a problem in the Error Correction Model for the electric bus ridership. To model such data, Engle (1982) introduced the ARCH model, which captures changes in the variability of a time series (Washington et al., 2011). The Lagrange Multiplier (LM) tests shown in Table 4.5 are significant ($p<0.001$) through order 12, which indicates that an ARCH model is needed to model heteroskedasticity.

The simplest ARCH(p) model is a short memory process in that only the most recent p squared residuals are used to estimate the changing variance and is given as (Shumway and Stoffer, 2000)

$$h_t^2 = var\,(\varepsilon_t \;\; |\psi_t) = a_0 + \sum_{i=1}^{p} a_i\; \varepsilon_{t-i}^2 \tag{4.5}$$

where $\varepsilon_t = Y_t - E[Y_t\,|X_t]$, the information set $\psi_t = [\varepsilon_{t-i} : j \geq 1]$, $a_0 > 0$, $a_j \geq 0, j = 1, \ldots p$, and where p is the number of lags of the number of the error term to be included in estimating volatility. Here, we consider p equal to one. The results for the ARCH model are presented in Table 4.6. It should be noted that, after the inclusion of the moving average terms in the ECM of the electric bus, there is no longer evidence of ARCH effects. Engle's LM test for ARCH accepts the null hypothesis of no autoregressive conditional heteroskedasticity.

Table 4.6. Arch model

	Dependent variable t statistic in parenthesis
Explanatory variables	**Electric Bus**
Δ_electric bus_lag1	-0.87 (-13.11)
Δ_electric bus_lag2	-0.12 (-2.62)
Δ_gasoline price_lag1	0.03 (0.26)
February	-0.07 (-2.02)
August	-0.42(-7.53)
July	-0.10(-4.52)
October	0.35 (8.50)
u_{t-1}	-0.24 (-1.78)
ARCH0	0.004 (2.97)
ARCH1	0.58 (1.69)
Adjusted R^2	0.691
Number of observations	108
Engle' s LM test for ARCH	
Lag1	0.23 (p=0.627)
Lag2	0.14 (p=0.861)
Lag3	1.11 (p=0.347)
Lag4	0.84 (p=0.491)
Lag5	0.99 (p=0.423)
Lag6	0.81 (p=0.568)
Lag7	0.68 (p=0.685)
Lag8	0.66 (p=0.725)
Lag9	0.61 (p=0.778)
Lag10	0.60 (p=0.808)
Lag11	0.57 (p=0.843)
Lag12	0.58 (p=0.850)

Finally, it should be noted that due to the ARCH effects found in the Error correction model of the electric bus ridership, we could not run seemingly unrelated regression equations in the short run.

4.5.3.3. Speed of Adjustment Coefficient

The speed of adjustment coefficient of the metro Error Correction Model indicates that the Athens metro demand adjusted relatively quickly to the long run equilibrium relationship since the estimated coefficient of the u_{t-1} removed 55% of the disequilibrium in the first month. Short run GDP elasticity is below unity and is estimated to be 0.28, implying that 1% increase in per capita GDP will increase metro demand at a much slower rate (0.28%). The short run elasticities of metro demand with respect to ticket price and gasoline price are all very low and smaller than the long run ones (-0.04 and -0.03 in the short run to -0.23 and 0.13 in the long run respectively).

Bus ridership ECM shows the speed of adjustment to be very high (-0.88) and is also statistically significant. This implies that bus ridership adjusts towards its long run equilibrium at a very fast rate, with about 88% of the adjustment occurring within the first month. This finding agrees with the fact that the long run price elasticity on bus demand is almost equal to the short run one. No other variables (except of the dummy variables of the months of February, August, July, September, October) were found to significantly affect bus ridership, possibly a result of the captive nature of its riders.

The estimated coefficient of the error correction term is -0.32 for the urban rail ridership model and -0.25 for the electric bus ridership model (Tables 4.5 and 4.6 respectively). This suggests that ridership for the two modes adjusts towards their long run equilibrium level at a moderate speed, with about 32% and 24% respectively of the adjustment towards their equilibrium taking place within the first month. Moreover, the metro demand a month before the current demand (the lagged dependent variable of the model, Δ_metro_lag1) has a statistically significant negative effect in the transit ridership of metro. The same appears to also happen in the electric bus and urban rail demand equations.

4.6. Discussion and Conclusions

In this chapter we estimated long and short run demand elasticities for a multimodal public transportation system. Long run equilibrium properties were estimated via the cointegration relationships and short run dynamics through the speed of adjustment from the short to the long run. The results from the cointegrating regressions indicate that metro ridership is cointegrated with metro ticket price, gasoline price, GDP per capita and number of motorcycle sales; bus partonage is cointegrated with bus/electric bus ticket price; urban rail ridership is cointegrated with GDP per capita and urban rail ticket price; electric bus ridership is cointegrated with fuel price and bus/electric bus ticket price. An ARCH model was developed to model volatility in the ECM of electric bus ridership.

The estimates of demand elasticities, both in the short and in the long run, for the four main modes of public transport are summarized in Table 4.7. Generally, the short run elasticities are lower than the long run because in the short run changes are smaller and, because, to some extent, the short run behavior is governed by resistance to change. Therefore, the full extent of a change is realized in the long run (Harris and Sollis, 2003). Indeed, comparing the short and long run elasticities from Table 4.7 we observe that the impact of fare changes and GDP per capita take time to reach maturity.

Table 4.7. Summary of elasticity estimates of cointegration models

	Long run	Short run
Metro		
GDP per capita	1.03	0.28
Motorcycle sales	-0.05	-0.05
Metro ticket price	-0.23	-0.04
Fuel price	0.13	0.03
Bus		
Bus/electric bus ticket price	-0.05	-0.04
Urban Rail		
GDP per capita	0.76	0.06
Urban rail ticket price	-0.33	-0.18
Electric Bus		
Bus/electric bus ticket price	-0.16	-
Fuel price	0.08	0.03

Metro and urban rail are the most expensive transport modes and in most cases there are bus lanes, with a cheaper fare, that run in parallel with the metro and the urban rail line. This probably explains the relatively high elasticities of metro and urban rail demand with respect to fares (-0.23 and -0.33 respectively). Demand for bus appears to be quite inelastic. Of the factors examined, only fare was found to significantly affect demand and this with a very low elasticity (-0.05). This is because bus is the cheapest mode and, in many parts of the PT network, the only mode available.

The short run ticket price elasticity of all transit modes is either lower than the long run elasticity or equal to zero, indicating that transit ridership in Athens is rather insensitive to price changes, at least in the short run. The highest short run elasticity of the urban rail ticket price elasticity (-0.18), compared to the ticket price elasticities of the other modes, reveals that urban rail users have a higher response to fare changes in the short run.

The high long run demand elasticity with respect to GDP both for the metro mode (1.03) and the urban rail mode (0.76) is probably explained by the fact that an increase in GDP will, generally, induce more trips, which are mainly diverted to metro and urban rail. Since the consequential changes on travel behavior take time to be realized the corresponding short run GDP elasticities appear to be much lower (0.28 for the metro and 0.06 for the urban rail).

It should be mentioned that the elasticities of public transport demand estimated in our study using cointegration techniques are lower than those estimated by most other studies (Gkritza et al., 2004; 2011). But, this is common in most cointegration studies (Wadud, 2007).

Current economic conditions in Greece are expected to affect the PT demand in conflicting ways. First, GDP has already shown significant negative rates resulting to reduced trips, while public debt limits the possibility of funding the high deficit of PT. Second, a shift from private car to public transport may be expected. In this work the shift was partly reflected by the fuel prices which constitute only a small part of total cost of private car usage (elasticities of 0.13 for the metro and 0.08 for the electric bus in the long run) and by motorcycle sales (elasticity of 0.05 for the metro mode). Third, the need for restricting subsidies to PT will lead to a fare increase. The relatively low elasticities of demand with respect to fares for all modes suggest that fare increase will not have a significant impact on demand and therefore this policy will succeed in making up for some of PT's deficit.

5. ESTIMATING MULTIMODAL PUBLIC TRANSPORT MODE SHARES

5.1. Introduction

The limited availability of resources and the need to reduce operating subsidies as current economic conditions dictate, increase the complexity of efficient management of public transportation systems. Demand analysis is a necessary condition for efficient decision making in a public transport system; network expansion, pricing policies, subsidy and operational decisions are based on demand analysis. The analysis of the share of each transport mode in a multimodal urban public transport system is a key factor that explains the relative position of each mode in the system. It may also be a useful index for making investment decisions concerning the public transport infrastructure and for allocating subsidies.

Many researchers have studied the policies and the factors that influence public transport demand (Dargay and Hanly, 2002; Lane, 2010; 2012; Taylor et al., 2009; Wang and Skinner, 1984), while others have summarized relevant findings (Goodwin, 1992; Litman, 2004; Oum et al., 1992; Paulley et al., 2006; Taylor and Fink., 2004; TRACE 1999). Some of these studies have analyzed both short and long run demand elasticities, as this distinction has important policy implications. Rose (1986) examined the short and the long run effects of fares, service and gasoline prices on rail ridership using time series analysis. In a similar context, combining cross sectional and time series data, Lane (2012) estimated lagged effects of gasoline price and service on transit patronage.

There are also papers that investigate the factors influencing ridership in a multimodal public transportation system (Garcia-Ferrer et al., 2006; Gkritza et al., 2004; 2011). In a multimodal public transportation context, methodologically acknowledging the coexistence of modes allows for explicitly considering the substitution effects that competition implies. Competition between modes is measured through the use of cross elasticities, which are highly dependent on the relative market share of each mode (Balcombe et al., 2004). Gilbert and Jalilian (1991) and Glaister (2001) have developed multimodal models for estimating cross elasticities.

Mode share of public transport is also an indicator of public transport demand (Buehler and Pucher, 2012), and it is usually related to funding for public transportation (Polzin and Chu, 2005). Numerous studies worldwide have been performed to investigate the determinants of mode choice between public transport and private car using aggregate descriptive analysis as well as disaggregated mode choice models (for example, Beirão and Cabral, 2007; Buehler, 2011; Clark and McKimm, 2005; Moniruzzaman and Páez, 2012; Vovsha, 1997). Although public transport demand studies differ on the type of data collected, the estimation methods used, the country and the number of modes included in the study, it is clear that fares, income, gasoline price and service level are among the most important factors affecting ridership.

We investigate the factors that determine the share of each transport mode in total public transport ridership for the urban public transport system of the city of Athens, both in the short and in the long run. The analysis uses cointegration and error correction techniques in a time series analysis framework, since this methodology allows for treating non-stationary data and for determining short term and long term elasticities. In the public transport sector the long run responses are mainly associated with investment decisions, while the short run responses are associated with operational decisions. The main goal is to distinguish and quantify short and long term effects of various factors on public transport mode shares since they provide useful information in the assessment of transport policies.

5.2. Data Description

The monthly time series data used in the analysis concern the period from January 2002 to December 2010 (a total of 108 observations). The percent share of each public transport mode is measured by dividing the monthly ridership of each of the four public transport modes (metro, bus, electric bus, urban rail) by the total public transport trips of the same month.

Table 5.1: Summary statistics (monthly)

Variable	Mean	Standard Deviation
Public Transport variables		
Metro Riders	14,295,245	2,544,766
Bus Riders	30,338,756	3,127,397
Electric bus Riders	6,573,172	7,852,62
Urban Rail Riders	9,661,460	1,526,618
Metro share	0.233	0.025
Bus share	0.500	0.030
Electric bus share	0.109	0.007
Urban rail share	0.158	0.015
Metro ticket price (in €)	0.922	0.074
Bus/electric bus ticket price (in €)	0.695	0.205
Urban rail ticket price (in €)	0.879	0.095
Integrated ticket (1 if yes; 0 if no)	0.220	0.410
Macroeconomic and Demographic Variables		
Unemployment Rate (percent)	9.076	1.752
Gasoline price (in €)	0.799	0.143
Gross Domestic Product (in millions €)	19.768	1.657
Population of Athens	4,014,567	71,742

Fares of the different public transport modes, dummy variables, as well as macroeconomic and demographic factors were used in our models. Table 5.1 shows the mean and the deviation for each of the variables included in the study over the period examined.

5.3. Methodology

In economics, the Almost Ideal Demand System (AIDS) model of Deaton and Muellbauer (1980 a, b), based on the theory of consumer demand, has been widely used for analyzing expenditure shares in empirical demand analysis (e.g. De Melo et al., 2002; O' Hagan and Harrison, 1984; Syriopoulos and Sinclair, 1993; Chen and Veeman, 1991; Mergos and Donatos, 1989; Romero-Jordan et al., 2010).

In our analysis, share equations of public transport modes are not based on the consumer demand theory and thus the AIDS model, in its strict form, is not suitable for analyzing the market shares of a multimodal public transport system of Athens. Instead, we estimate the shares of different modes of the public transport system using cointegration and error correction techniques. This methodology allows for treating non-stationary time series data and for evaluating both short and long run responses.

The concept of cointegration and error correction models was first proposed by Engle and Granger (1987) and has been widely used, particularly in modeling and forecasting macroeconomic activities. The Cointegration/Error correction Model Approach is likely to offer much more reliable information because, in cases where the stationarity assumption underlying least squares regression models is violated, standard regression techniques can lead to spurious results (Granger and Newbold, 1974). According to the Engle-Granger two step procerdure (1987), first we estimate the cointegrating regressions to derive the long run elasticities and second we estimate the Error Correction Models to derive the short run elasticities of the share of every mode.

5.3.1. Cointegrating Regressions

We start our estimation procedure by considering the following general equation for every public transport mode share[3]

$$\text{Mode share}_t = a_0 + a_1 ln\ ticket\ price + a_2\ lntotal\ \ ridership + a_3\ lnGDP\ + a_4 lngasoline\ price + u_t \quad (5.1)$$

The first step in the analysis is to check the order of integration of each of the variables included in Equation (5.1). The order of integration of each variable is found by applying a unit root test. If the variables are stationary i.e. I(0), standard time series methods can be applied. If the variables are integrated of different orders, it is possible to conclude that they

[3] The model developed in this study is a 'network level' model. Therefore, to use an aggregate estimation for variables such as travel speed, stop frequency, etc would possibly lead to erroneous or spurious results. These variables should be used for 'line' demand models.

are not cointegrated. However, if some of the variables are I(1) and some I(2), they may be multicointegrated (Granger and Lee, 1990). In order to proceed further, we assume that all the variables in Equation (5.1) are generally non-stationary and integrated of order one (that is they become stationary after first differencing). Having established that the variables display all the characteristics of I(1) variables, the next step is to test the share equations for cointegration by estimating the cointegrating regression (Equation 5.1) for every mode share and testing the residuals for stationarity. If the residuals of Equation (5.1) are stationary, then there is a cointegrating relationship between the variables and the long run parameters are estimated through the cointegrating regression.

In order to check whether the residuals are stationary and, thus, the variables are cointegrated, a unit root test (ex. Augmented Dickey Fuller) is applied to the estimated residuals (u_t). As OLS residuals have a zero mean by construction, the version of the Augmented Dickey Fuller test without deterministic terms is used. However, the critical values are different because the test is applied to a "generated" and not to an observed time series (Kirchgassner and Wolters, 2007). They depend on the number of observations, on the number of I(1) variables but also on the deterministic components of the equilibrium relationship (MacKinnon, 1991).

Estimating the above cointegrating regressions using ordinary least squares (OLS) achieves a consistent estimate of the long run relationship between the variables in the four models. Stock (1987) found that if the variables are cointegrated, the estimated coefficients from the cointegrating regressions will be superconsistent. The superconsistency property of the OLS estimators implies that the parameters estimated from the cointegrating regression converge with a rate of T (T is the number of observations) towards their true value. Therefore, their convergence is faster than the convergence of the OLS estimators in a regression with stationary variables, which converge with a rate of $\sqrt{\mathrm{T}}$ to their true values (consistency property of the OLS estimator). Due to the superconsistency property all dynamics and endogeneity issues can be ignored asymptotically. Of course, the omitted dynamic terms are captured in the residuals of each cointegrating regression which will be serially correlated. But this is not a problem due to superconsistency (Harris and Sollis, 2003)**.**

5.3.2. Error Correction Models

Once the long run relationship is established, Engle and Granger (1987) proved that there is an Error Correction Mechanism (ECM), which allows to derive short run parameters and the speed of adjustment from the short to the long run. The ECM is simply defined as

$$\Delta_{mode\ share} = \sum_{i=1}^{q} a_{ri}\ \Delta mode\ share_{t-i} + \sum_{i=0}^{p} a_{pi}\ \Delta lnticket\ price_{t-i} + \sum_{i=0}^{g} a_{gi}\ \Delta lngasoline\ price_{t-i} + \sum_{i=0}^{d} a_{di}\ \Delta lnGDP_{t-i} + \sum_{i=0}^{m} a_{mi}\ \Delta lntotal\ ridership_{t-i} + a_{resid}\ u_{t-1} + e_t \tag{5.2}$$

where Δ defines the first differenced variable, p, q, g, d, m the number of the lags needed so as to make e_t white noise and u_{t-1} the lagged residuals derived from the Equation (5.1). Thus, an Error Correction Model is applied by using the estimated residuals from the cointegrating Equation (5.1) as a regressor in Equation (5.2). The lagged residuals, namely the lagged Error Correction Term (ECT), represent the speed of adjustment towards the long run equilibrium. The coefficient of the lagged residuals (α_{resid}) should be negative and statistically significant, lying between 0 and -1 (0 suggesting no adjustment one time period later, -1 suggesting full adjustment one time period later). For example, a speed of adjustment coefficient with a value of -0.25 suggests that 25% of the adjustment occurs within the first period and the full adjustment occurs after four time periods. Therefore, the long run elasticities refer to the time period after the full adjustment (in this case after four time periods), while the short run elasticities refer to the time period in which the adjustment has occurred.

The last step in the Engle-Granger two step procerdure is to determine whether the Error Correction Model estimated is well specified by performing diagnostic tests to check whether the residuals of the error correction equations approximate white noise (Enders, 1995).

5.4. Results

5.4.1. Unit Root

The first step in the empirical analysis is to investigate the time series properties of the data. In order to determine whether each of the variables examined in this study contains a unit root or not (i.e. to examine whether they are stationary or non-stationary), we employ the Augmented Dickey–Fuller test (1979, 1981). Then, if the variables are non-stationary, we proceed to determine the order of integration of the variables by applying a unit root test to the differenced variable.

Generally speaking, most economic data series are found to be non-stationary and several demand studies have shown that it is reasonable to treat economic data series used in demand analysis (prices, GDP) as non-stationary data series (e.g. Carone, 1996). Non-stationarity has also been observed in transportation demand studies including the works of Chen et al. (2011), Dargay and Hanly, (1999) and Romilly (2001). Share variables, in some cases, are taken to be stationary and in some other cases are taken to be non-stationary. Asche and Wessells (2002) suggest that there are strong arguments for treating expenditure shares as stationary. Of course, by construction, share variables are bound between zero and one and thus they are expected, in the very long run, to be stationary (Attfield, 1997). However, the mean and the variance of the shares need not be stable. Attfield (1997), Karagiannis and Mergos (2002), Karagiannis et al. (2000) and Ng (1995) find that shares in their demand models are non-stationary. Similarly, in our analysis, public transport mode shares display all the characteristics of I(1) variables and so we treat them as non-stationary.

Table 5.2. ADF test for the presence of Unit Root

Variable[a]	level Number of lags	level ADF test	First differences Number of lags	First differences ADF test	5% ADF critical values	Order of integration
Public Transport variables						
Metro share	10	-2.547	0	-13.303	-2.89	I(1)
Bus share	11	-1.734	0	-12.807	-2.89	I(1)
Electric bus share	2	-2.763	0	-18.732	-2.89	I(1)
Urban rail share	11	-0.627	10	-13.855	-2.89	I(1)
Total Ridership	11	-0.979	10	16.963	-2.89	I(1)
Metro ticket price	0	-1.621	0	-9.651	-2.89	I(1)
Bus/electric bus ticket price	0	-0.460	0	-10.224	-2.89	I(1)
Urban rail ticket price	0	-1.075	0	-9.736	-2.89	I(1)
Macroeconomic and Demographic Variables						
Unemployment Rate	3	-0.110	2	-5.433	-2.89	I(1)
Gasoline price	1	-1.590	0	-7.539	-2.89	I(1)
Gross Domestic Product	12	-1.011	10	-7.278	-2.89	I(1)

[a] all variables besides shares are in logarithms

Table 5.2 reports Augmented Dickey Fuller test statistics for the null hypothesis that the processes generating the variables contain unit roots. As unit root tests are sensitive to the choice of the lag length (Maddala and Kim, 1998), we apply Akaike Information Criteria, Schwarz Information Criteria, and Modified Akaike Information Criteria to choose the optimal lag length and we choose the lag length supported by the majority of these criteria. Based on MacKinnon's critical values (1996), all the variables were found to be non-stationary in levels and stationary in first differences, implying that they are I(1).

5.4.2. Long Run

Having established that the variables display all the characteristics of I(1) variables, we next turn to testing the share equations for cointegration using the Engle and Granger methodology (1987). Cointegration ensures that there is a valid long run stable relationship among non-stationary variables that are involved in the same regression equation (Granger, 1981; Maddala and Kim, 1998).

We start our cointegration analysis by examining for the collinearity among the independent variables. Since collinearity was observed among fares of different transport modes, they were not included in the same share equation. The cointegrating regression for every public transport mode is estimated using the general form of Equation (5.1). From the description of the multimodal public transportation system of Athens (section 4.3.1), it is clear that different modes have differing characteristics and may operate in competition or cooperation depending on a variety of circumstances. To this end, we expect that different modes are affected by different factors and even by the same factors in different ways.

First, the significance of the parameters included in each share equation was checked. Only the variables that were found to be statistically significant were included in the final cointegrating regression[4]. Then, we tested for cointegration each of the share equations by obtaining the OLS residuals and testing them for stationarity using Augmented Dickey-Fuller test. Table 5.3 presents the cointegrating equation of each public transport mode share as well as the results of the unit root test to the residuals of each equation. Based on MacKinnon's critical values for cointegration tests (1991), the residuals of the four equations have been found to be stationary I(0) indicating the existence of a cointegrating relationship among the variables of each share equation. It should be noted that serial correlation of the residuals, confirmed by the Durbin Watson test, is not a problem due to the superconsistency property of the OLS estimator when the series are cointegrated (Harris and Sollis, 2003).

[4] In our initial models we included dummy variables to capture expansion of the metro system. The metro network started its operation in early 2000 and there has been limited expansion of its network during the period of our study (in 2004, 2007 and 2009 a total of 8.1 additional network kilometers were added). Interestingly, however, when both the GDP and the dummy variables were included in the model the latter were statistically not-significant and thus removed from the model. We decided to use GDP as a basic explanatory variable in our models both because it is reliably collected and because of its economic implications. For all other PT modes included in our analysis, the network has remained almost constant during the entire period of the analysis; to this end, we did not include supply variables in the model as it would add only limited explanatory power and cause some (possibly important) statistical problems.

Table 5.3. Cointegrating Regressions (t-statistics in parentheses**)**

	Dependent variable			
Explanatory variables[a]	**Metro Share**	**Bus Share**	**Electric Bus Share**	**Urban rail Share**
Constant	-2.524 (-7.67)	1.939 (6.06)	0.548(4.54)	-0.711 (-2.58)
Ticket price_metro	-0.186 (-3.83)	0.166 (4.84)		
Ticket price_bus/electric bus			-0.009 (-3.51)	
Ticket price_urban rail				-0.027 (-1.85)
Total Ridership	0.103 (7.53)	-0.076 (-4.22)	-0.012 (-2.54)	0.021 (1.83)
GDP	0.090 (4.44)		-0.022(-2.83)	0.049 (2.84)
Gasoline Price		0.054 (2.50)		
Integrated Ticket	0.047 (5.15)			
Trend		-0.001(-6.62)		
Test diagnostics				
Adjusted R^2	0.539	0.503	0.234	0.115
Durbin-Watson stat	1.164	1.359	1.494	1.075
ADF test for Residual unit root	-6.23	-7.25	-4.84	-6.29
MacKinnon's Critical Values	-3.82	-3.51	-3.82	-3.82
Number of observations	108	108	108	108

[a] *explanatory variables are in logarithms*

According to the results reported in Table 5.3, mode shares of metro, electric bus and urban rail are cointegrated with ticket price, GDP and total ridership at 10% significance level, while bus share is cointegrated with gasoline price, metro fare and total ridership. Cointegration implies that there is a long run steady relationship between shares and theirs determinants, showing that these non-stationary variables are moving together in the long run.

5.4.3. Short Run

Once the long run relationship is established, the next step is to estimate the Error Correction Model for every mode share of the multimodal public transport system of Athens to derive the short run elasticities as well as the time required for the total response (from the short to the long run) to be complete. The Error Correction Model for every mode share is estimated using the general Equation (5.2). The results from the estimation of the four Error Correction Models for the share of each public transport mode are presented in Table 5.4. For the same mode (the same share equation), cointegrating regressions (Table 5.3) and Error Correction Models (Tables 5.4 and 5.5) include the same independent variables. The cointegrating regressions (Equation 5.1) include the variables in levels. The Error Correction Models (Equation 5.2) include the first differences of the same, as in Equation 5.1, independent variables, lagged first differences of the dependent variable and the lagged residuals from Equation (5.1).

In order to test the reliability of the four Error Correction Models, the diagnostic tests for autocorrelation and heteroskedasticity of the error term were applied. We implement the Breusch-Godfrey test (Breusch, 1979; Godfrey, 1978) (obtained by regressing the residuals from the original model on all the regressors of that model and the lagged residuals) to check the residuals for the persistence of serial correlation and ARCH LM test (obtained by regressing the squared residuals from the model to their lags and a constant) to check the residuals for the persistence of autoregressive conditional heteroskedasticity. Because the data are monthly observations, serial correlation and autoregressive conditional heteroskedasticity from 1^{st} to 12^{th} order was investigated.

Table 5.4. Error Correction Models

	Dependent variable (t-Statistic in parenthesis)			
Explanatory variables[a]	**Metro Share**	**Bus Share**	**Electric Bus Share**	**Urban rail Share**
Δ_metro share_lag1	-0.124 (-1.69)			
Δ_bus share_lag1		-0.187 (-1.94)		
Δ_electric bus share_lag1			-0.472 (-3.57)	
Δ_urban_rail share_lag1				-0.080 (-0.85)
Δ_metro share_lag2				
Δ_bus share_lag2		-0.172 (-1.87)		
Δ_electric bus share_lag2			-0.181 (-1.72)	
Δ_urban_rail share_lag2				
Δ_ticket price_metro	-0.066 (-1.27)			
Δ_ticket price_bus/electric bus		0.049 (0.67)	-0.001 (-0.11)	
Δ_ticket price_urban rail				-0.017 (-0.41)
Δ_GDP	-0.023 (-0.67)		-0.016 (-1.04)	0.008 (0.26)
Δ_gasoline price		0.028 (0.73)		
Δ_total ridership	0.051 (-6.64)	-0.042 (-3.11)	0.002 (0.43)	-0.023 (-2.86)
February	0.010 (2.00)			
March			-0.003 (-1.58)	
June			0.005 (2.72)	
August	-0.021 (-3.87)			
July		0.011 (1.66)	0.004 (2.01)	-0.013 (-3.17)
November		-0.017 (-2.26)		
December	0.017 (3.82)	-0.026 (-3.88)	-0.003 (-1.58)	0.007(1.72)
u_{t-1}	-0.574 (-6.64)	-0.557 (-4.90)	-0.443 (-3.52)	-0.430 (-5.03)
Adjusted R^2	0.595	0.495	0.450	0.393
Number of observations	108	108	108	108

[a] *all explanatory variables besides months are in logarithms*

Residuals tests				
Breusch-Godfrey LM test for autocorrelation (probability)				
Lag1	4.37 (p=0.037)	0.11 (p=0.736)	0.07 (p=0.795)	2.02 (p=0.155)
Lag2	9.39 (p=0.009)	0.38 (p=0.826)	1.81 (p=0.404)	2.16 (p=0.339)
Lag3	9.53 (p=0.023)	1.32 (p=0.725)	2.51 (p=0.474)	2.23 (p=0.526)
Lag4	10.20 (p=0.037)	2.05 (p=0.726)	2.52 (p=0.641)	4.59 (p=0.332)
Lag5	10.20 (p=0.069)	2.18 (p=0.824)	2.87 (p=0.719)	4.86 (p=0.433)
Lag6	10.31 (p=0.112)	2.25 (p=0.895)	3.05 (p=0.802)	5.54 (p=0.477)
Lag7	10.55 (p=0.159)	2.84 (p=0.899)	3.34 (p=0.852)	7.58 (p=0.371)
Lag8	10.96 (p=0.204)	3.21(p=0.921)	3.34 (p=0.911)	8.13 (p=0.421)
Lag9	11.85 (p=0.222)	3.25 (p=0.953)	4.41(p=0.882)	8.83 (p=0.453)
Lag10	13.02 (p=0.222)	3.92 (p=0.951)	5.96 (p=0.818)	10.03 (p=0.438)
Lag11	13.04 (p=0.291)	3.98 (p=0.971)	6.44 (p=0.842)	10.36 (p=0.498)
Lag12	13.89 (p=0.307)	4.00(p=0.984)	6.54 (p=0.886)	15.52 (p=0.214)
Engle' s LM test for ARCH (probability)				
Lag1	0.308 (p=0.579)	0.181 (p=0.670)	0.247 (p=0.619)	0.280 (p=0.597)
Lag2	0.352 (p=0.839)	0.182 (p=0.913)	0.354 (p=0.838)	0.549 (p=0.760)
Lag3	0.488 (p=0.922)	0.585 (p=0.900)	1.365 (p=0.714)	1.406 (p=0.704)
Lag4	0.524 (p=0.971)	0.616 (p=0.961)	1.411 (p=0.842)	2.008 (p=0.734)
Lag5	0.815 (p=0.976)	0.921 (p=0.969)	1.724 (p=0.886)	2.734 (p=0.741)
Lag6	0.905 (p=0.989)	1.082 (p=0.982)	1.741 (p=0.942)	3.861 (p=0.695)
Lag7	1.057 (p=0.994)	1.468 (p=0.983)	2.090 (p=0.955)	4.396 (p=0.733)
Lag8	1.220 (p=0.996)	1.554 (p=0.992)	2.131 (p=0.978)	5.658 (p=0.685)
Lag9	1.232(p=0.999)	4.759 (p=0.859)	2.378 (p=0.984)	6.307 (p=0.709)
Lag10	1.239 (p=0.999)	4.832 (p=0.902)	2.519 (p=0.991)	7. 199 (p=0.707)
Lag11	1.357(p=0.999)	5.670 (p=0.894)	5.251 (p=0.918)	7.277 (p=0.776)
Lag12	19.958(p=0.068)	6.937 (p=0.962)	5.400 (p=0.943)	12.381(p=0.416)

The results of the above statistical tests lead to the rejection of the presence of autocorrelation and heteroskedasticity of first and higher order in the dynamic equations of the bus share, the electric bus share and the urban rail share. However, the same tests reveal the existence of higher order serial correlation in the Error Correction Model of the metro share. This result indicates that the ECM has to be re-estimated in order to remove autocorrelation from the residuals.

5.4.4. Correction for Autocorrelation

Autocorrelation occurs in time series studies when the errors associated with observations in one time period are a function of past errors. Higher-order autocorrelation is prevalent in transportation time series and should not be ignored (Washington et al, 2011). In the Error Correction Models, if the residuals are serially correlated, lag lengths may be too short (Enders, 1995). We include different lags of the dependent variable in the ECM for the bus share and the electric bus share, to remove autocorrelation (Table 5.4). However, adding more lags does not resolve the issue of serial correlation on residuals in the ECM of the metro share. Therefore, in order to correct serial correlation, we estimate the ECM of the metro share under the assumption of higher-order scalar autoregressive process for the error term, i.e.

$$e_{it} = \rho_1 * e_{i,t-1} + \rho_2 * e_{i,t-2} + \cdots + \rho_n * e_{i,t-n} + u_{it} \quad (5.3)$$

Table 5.5 ECM with Correction for autocorrelation

	Dependent variable (t -Statistic in parenthesis)
Explanatory variables[a]	**Metro share**
Δ_metro share_lag1	-0.280(-3.37)
Δ_ticket price_metro	-0.052 (-1.08)
Δ_GDP	-0.056 (-1.64)
Δ_total ridership	0.037 (-2.77)
February	0.007 (1.42)
August	-0.026(-4.55)
December	0.019 (4.51)
u_{t-1}	-0.637 (-5.68)
1st order autoregressive parameter ε_{t-1}	0.324 (2.23)
2nd order autoregressive parameter ε_{t-2}	-0.276 (-2.20)
Adjusted R^2	0.614
Number of observations	108
Residuals tests	
Breusch-Godfrey LM test for autocorrelation	(probability)
Lag1	0.71 (p=0.399)
Lag2	3.56 (p=0.169)
Lag3	3.63 (p=0.305)
Lag4	3.66 (p=0.454)
Lag5	4.52 (p=0.478)
Lag6	6.10 (p=0.413)
Lag7	6.26 (p=0.509)
Lag8	7.72 (p=0.461)
Lag9	7.78 (p=0.556)
Lag10	7.89 (p=0.640)
Lag11	12.28 (p=0.343)
Lag12	12.29 (p=0.423)

[a] all explanatory variables besides months are in logarithms

Table 5.5 presents the results for the ECM of the metro share, using estimation with a correction for serial correlation. Since the data were monthly observations, serial correlation from 1st to 12th order was investigated. The augmented Error Correction Model with the moving average effects has been estimated based on the maximum likelihood method (Beach and MacKinnon, 1978). On the basis of the t-statistics for the autocorrelation parameter estimates, it appears that first and second order serial correlation parameters are statistically significant in the share equation of metro and conceptually important. This conjecture is verified by the Breusch-Godfrey LM test, where the null hypothesis of no serial correlation, after the correction for serial correlation, is accepted.

5.4.5. Long and Short Run Elasticities and the Speed of Adjustment Coefficient

As presented in Table 5.4, the estimated coefficient of the lagged residuals (u_{t-1}) is negative and statistically significant different from zero at 5% level in all the Error Correction Models, indicating that there is a cointegrating relationship between the variables. The coefficient of the lagged residuals (u_{t-1}) or the speed of adjustment coefficient, measures the rate at which the system adjusts to the equilibrium state after any shock(s) to the determinants. In other words, it measures how long it takes to reach the long run equilibrium state.

As the metro share ECM shows (Table 5.5), the speed of adjustment is quite high (-0.64) and it is also statistically significant. This implies that the metro share adjusts towards its long run equilibrium at a quite fast rate, with about 64% of the adjustment occurring within the first month. The full adjustment occurs after 1.6 months. Thus, in the case of metro share, long run elasticities refer to the time period after 1.6 months, while short run elasticities refer to the time period in which the adjustment occurs. The speed of adjustment is almost equal in the Error Correction Model of the electric bus share and the urban rail share, taking values -0.44 and -0.43 respectively (Table 5.4). In the case of bus share the speed of adjustment is also negative and statistically significant with a value of -0.56.

Table 5.6 presents the short and long run mode share elasticities in the Athen's multimodal public transport system. Long run elasticities were derived from the models presented in Table 5.3, while short run elasticities were derived from the models presented in Tables 5.4 and 5.5. Share elasticities show variations in the competitive position of each public transport mode in relation to the other public transport modes, rather than variations in the demand in the particular transport mode. As expected the short run elasticities are lower than the long run ones for all modes.

Table 5.6. Short and long run Elasticities

	Long run	Short run
Metro		
GDP	0.39	-0.10
Metro ticket price	-0.80	-0.28
Total Ridership	0.44	0.22
Bus		
Metro ticket price	0.33	0.10
Gasoline price	0.10	0.06
Total Ridership	-0.15	-0.08
Urban Rail		
GDP	0.32	0.05
Uban rail ticket price	-0.17	-0.11
Total Ridership	0.13	-0.14
Electric Bus		
Bus/electric bus ticket price	-0.08	-0.01
GDP	-0.20	-0.15
Total Ridership	-0.11	0.02

As with the ridership models presented in the previous chapter, share models are significantly affected by fare and GDP. In the ridership model GDP is the factor that shows the highest elasticities, while in the share models fare is the factor that shows the highest elasticity. For example in the case of the metro mode GDP long run elasticity is 1.03 in the ridership model and 0.39 in the share model, while fare long run elasticity is -0.23 and -0.80 respectively.

The results show that the share elasticities of the metro take higher values compared to the elasticities of urban rail, electric bus and bus. Fare elasticity of the metro mode share takes the highest value compared to the other public transport mode shares, both in the long and in the short run taking the values of -0.80 and -0.28 respectively. This is probably explained since the metro is the most expensive public transport mode and in many parts of the network there exist parallel lines of alternative modes which become more attractive, particularly for short trips.

The integrated ticket, which allows people to use several public transport modes by buying one ticket only, has favored the metro mode in the long run (Table 5.3) since, in case of joint routes, it encourages the use of metro lines at no extra cost. The non-significance of the integrated ticket in the short run implies that passengers take time to react to changes in ticket price structures.

The positive long run elasticity of the metro mode share with respect to GDP (0.39) is attributed to the consideration that the metro is more expensive and thus favored in periods of increased GDP. The cointegrating relationship between metro share and total ridership shows that as total demand grows the metro mode tends to attract a relatively higher share of total demand. A 10% increase in total ridership results to a 4.4% increase in the metro mode share in the long run and to a 2.3% increase in the short run. This is explained by the fact that the metro is the most convenient mode in terms of frequency and speed.

The positive cointegrating relationship that was found between the urban rail share and the GDP reflects the fact that metro and urban rail operate in a complementary way through interconnection of their networks and therefore metro demand positively affects urban rail demand. This also explains the positive relationship between urban rail and total ridership. The electric bus share is negatively affected by an increase in GDP both in the short and in the long run (elasticity of -0.20 and -0.15 respectively). This negative relationship is explained by considering bus and electric bus to be inferior "good" (service) on the basis of convenience and price (Bresson et al., 2004; Dargay and Hanly, 2002a), particularly in comparison to the metro system. Electric bus share is negatively affected by total ridership in the long run, implying that electric bus tends to attract fewer riders compared to the other PT modes. However, Table 5.6 shows that the response of urban rail and electric bus shares to an increase in total ridership are different in the short run.

The bus share shows a positive elasticity to the metro fare explained by the fact that the metro fare is more expensive than the bus fare and an increase in the metro ticket will divert passengers to bus routes that run in parallel, particularly for short trips. This cross price elasticity (0.33 in the long run and 0.10 in the short run) suggests that the metro and the bus systems act as competitors in the larger part of their network (Gkritza et al., 2011). Gasoline price appears to have a small positive elasticity with regards to bus share both in the short and in the long run.

Finally, seasonal variables included in the Error Correction Models were found to significantly affect the public transport mode shares. Generally, the winter months positively affect the mode shares of metro and urban rail and negatively affect the mode shares of bus and electric bus. This is logical since cold temperatures and rain make waiting for bus and electric bus outside more uncomfortable. The results are in line with other studies that investigate the effects of weather on public transport usage (Kuby et al., 2004; Guo et al., 2007; Stover and McCormack, 2012). Stover and McCormack (2012) examined the effects of weather on bus ridership and found that cold temperatures led to decreases in bus ridership during winter months. Guo et al. (2007) found that bus ridership is more sensitive to weather than is rail ridership.

5.5. Conclusions

We investigated the factors that determine the share of each mode in the multimodal public transportation system of Athens. In order to deal with non-stationarity and seasonality in the data, cointegration techniques were applied to investigate the long run equilibrium relationships. The Error Correction Models were implemented to estimate the short run dynamics as well as the speed of adjustment from the short to the long run. The results from the cointegrating regressions indicate that the metro mode share is cointegrated with metro fare, GDP and total ridership; the bus mode share is cointegrated with metro fare, gasoline price and total ridership; the urban rail mode share is cointegrated with urban rail fare, GDP and total ridership; the electric bus mode share is cointegrated with electric bus fare, GDP and total ridership.

The relation of short run elasticities to their long run ones reflects the transition from the short run disequilibrium to the long run equilibrium state. It was found that the public transport mode shares, do not immediately adjust to their long run equilibrium, after a change in their determinants. Specifically, the coefficient of the lagged Error Correction Term (ranging from -0.43 to -0.64 in the four Error Correction Models) suggests that convergence to equilibrium after a shock to public transport mode shares takes approximately two months (ranging from 1.6 to 2.3 months). Moreover, the long run elasticities are consistently found to be statistically more significant and higher than the short run ones. Specifically, fare elasticities in the short run appear to be on average three times lower compared to the long run ones for all mode shares (except for the urban rail mode share). There is statistical evidence that public transport mode shares are more price sensitive at higher fare levels. The fare elasticity ranges from -0.80 in the long run and -0.28 in the short run for the metro mode share (metro is the public transport mode with the highest fares), to -0.08 in the long run and -0.01 in the short run for the electric bus mode share (electric bus and bus are the public transport modes with the lowest fares). The results obtained show that a policy of metro fare increase would result to a decrease in the metro share and to an increase in the bus share.

The analysis also shows that GDP is one of the most important determinants of public transport mode shares. Metro and urban rail mode shares elasticities with respect to the GDP are positive in the long run, but negative or very small in the short run, while electric bus mode share elasticity with respect to GDP is negative both in the short and in the long run.

Our findings also indicate the role of total ridership fluctuations in explaining variations in public transport mode shares. The metro and urban rail mode shares increase as total ridership increases, while the bus and electric bus mode shares decrease as total ridership increases in the long run. However, the results reveal that the response of urban rail and electric bus shares to an increase in total ridership is different in sign between the short and the long run. The relatively high negative short run elasticity of urban rail with respect to total ridership is probably explained by the reconstruction of some parts of the urban rail system and thus the related reduced level of service in the short run. Economic recession is expected to create a further shift from private car to public transport. As total ridership grows, it is useful to know how the increased demand will be distributed to the multimodal public transport system.

6. CONCLUSIONS

6.1. Introduction

In this thesis we have applied a methodology for analysing transport demand data when both demand and causal factors explaining demand are described by non-stationary time series data, which is the case for most factors such as transit ridership, GDP, fares, and fuel prices. The procedure for demand analysis proposed is applied to the Athens public transport system, where different modes may operate in competition or cooperation. Two different but complementary aspects of public transport demand were explored; first, the ridership of each mode; second, the share of each mode in total ridership. The second chapter reviewed past studies on public transport demand in order to identify areas that the present thesis may contribute. In Chapter three a methodological framework based on dynamic econometric modeling for analyzing non-stationary time series was presented.

Based on this methodological framework, demand for the multimodal public transportation system of Athens was investigated in Chapter four. Monthly data for the period 2002-2010 were used to account for seasonal effects. The analysis treats each mode of the public transport system separately (metro, bus, electric bus and urban rail) in order to account for substitution effects. Demand is expressed as a function of operational and macroeconomic factors and is analyzed using a time-series cointegration and error correction approach in order to treat the non-stationarity of the data. An ARCH model was developed to account for volatility in the error correction model of the electric bus ridership. Short and long term elasticities as well as the speed of convergence from the short to the long run were estimated.

Market shares for each public transport mode in total transport ridership were analyzed in Chapter five. This analysis provides useful information for making investment decisions concerning the public transport infrastructure and for allocating subsidies. Due to the non-stationary properties of the data, cointegration techniques were applied to investigate the long run equilibrium relationships and the Error Correction Models were implemented to estimate the short run dynamics as well as the speed of adjustment from the short to the long run. For the metro mode two models were developed in the short run, one with and one without correction for autocorrelation.

6.2. Methodology

In the present thesis a methodological framework for analyzing non-stationary transport demand data based on cointegration and error correction techniques was presented. This approach (Engle and Granger, 1987) allows for treating non stationary data, for determining short and long term elasticities and at the same time estimating the speed of convergence from the short to the long run.

Briefly, the method consists of the following modules: First, a unit root test is applied to test non-stationarity. Second, a cointegration test is performed to evaluate long run caused relation. Third, an error correction method is used to evaluate short run responses. Finally, in the cases that exists autocorrelation and/or autoregressive conditional heteroskedasticity on the residuals, new error correction models are developed to account for these effects. A model with correction for autocorrelation is used to correct serial correlation on the residuals and an ARCH model is used to capture changes in variability of the time series.

6.3. Findings and Discussion

The elasticities computed for the Athens transport system are within the range of elasticities computed in related international studies (Balcombe et al., 2004) and in other studies made for the Athens urban transport system (Gkritza et al., 2011). However, when comparing elasticities derived from different studies, it should be taken into account that each transport system has its own separate characteristics that affect elasticities and that elasticities computed by the cointegration methodology, according to experience reported in the literature, are lower than the elasticities computed by other methods (Wadud, 2007); this is a finding with far reaching policy implications.

6.3.1. Short Run and Long Run Elasticities

Most changes described in a complex PT system have a dynamic nature; i.e. following a fare change, or -more generally- a variation on an independent variable affecting demand, demand variation does not remain constant but usually increases as time elapses until the long run equilibrium state is reached. As expected, short run elasticities appear to be lower than the long run ones both in the models explaining ridership and in the models explaining the share of each mode. Demand tends to be more elastic in the long run rather than in the short run, because short run elasticities are governed by resistance to change, while long run elasticities are affected by consequential changes on behavior that take time to be realized (Mankiw, 2004). For example it was found that demand for public transport is more price inelastic in the short run as public transport users often need more time to respond and change their habits. In the long run passengers have enough time to respond to price changes switching to other modes of transport.

6.3.2. Speed of Adjustment

Regarding the policy measures, however, it is useful to know not only the long and short run effects of fares and other relevant factors on ridership but also the time required to adjust to the long run equilibrium state (Dargay and Hanly, 2002). The speed of adjustment coefficient computed for every PT mode in this study gives an accurate measurement of how long the short run period lasts. According to the results, convergence to equilibrium is very high for the bus ridership (bus adjusts to the long run equilibrium approximately in one month). For the metro mode the short run period lasts two months, while for the other modes (urban rail and electric bus) adjustment to the long run takes four months. For the four public transport mode shares adjustment to the long run equilibrium state takes approximately two months (ranging from 1.6 to 2.3 months).

6.3.3. Fare and GDP

In both the ridership and the shares model GDP and fares appear to be the factors with the higher elasticities both in the short and in the long run. Of the different modes, metro and urban rail show the highest elasticities with respect to the factors examined. Both the bus and the electric bus modes show a picture of demand stability as the factors affecting demand are fewer than in the metro and urban rail modes and with lower value elasticities.

Fare elasticities of all transit modes examined are negative and lower than unity in absolute values indicating that transit ridership in Athens is rather insensitive to price changes both in the short and in the long run. The relatively low elasticities of demand with respect to fares, suggest that the fare increase will not have a significant impact on demand and therefore this policy will succeed in bringing more revenues and making up for some of PT's deficit.

GDP is not a controllable factor. As such it provides a directive on how the transport system should adapt to changes in the economy. On the whole GDP contributes positively both to car sales, thus inducing a shift from public transport to private cars, but also to increased economic activities which in turn create new trips. The findings in this study show that the final result of the above influences has a distinct positive effect on public ridership. The demand elasticities of the metro and the urban rail with respect to GDP are high, showing that most of the increase in ridership as GDP increases will be absorbed by the metro and the urban rail modes. This finding is also verified by the share models.

In the ridership model GDP is the factor that shows the highest elasticities, while in the shares model fare is the factor that shows the highest elasticity. This is because the substitution effects between different PT modes resulting from an increase in fares are more clearly recorded in the share models. On the other hand an increase in GDP results to an increase in ridership in all modes, the greatest increase occurring in the metro and the urban rail modes.

6.3.4. Other Factors

Gasoline price appears also to have a small and positive impact on transit ridership, increasing PT demand for the metro and the electric bus modes. However, the very low elasticities with respect to fuel price, lead to the conclusion that a reasonable increase in fuel cost will not affect ridership. This happens because fuel cost is only a small part of total cost of car use.

Finally, results indicate the role of total ridership fluctuations in explaining variations in public transport mode shares. An increase in ridership favors the metro and the urban rail shares, especially in the long run.

6.4. Directions for Feature Research

The present thesis analyzed public transport demand and public transport mode shares using a time series analysis framework. In order to correctly analyze such data, it is imperative that they are stationary; if not, the estimated equation parameters will be biased. However, in practice, most time series data are non-stationary which affects the estimated models; this issue, despite its implications for policy recommendations, has not be fully addressed in the past. The issues of non-stationarity, autocorrelation and autoregressive conditional heteroskedasticity have to be accounted when analyzing transportation time series data.

There is a need to incorporate additional factors into the model the most important being quality of service. However, the fact that public transport demand is a function of service supply and, vice versa, service supply is a function of service demand usually leads to the issue of endogeneity. Single equation estimation used in this study is not an appropriate method in this case.

Another methodological development could be to estimate system equation models using Johansen Maximum Likelihood (GML) or Dynamic Seemingly Unrelated Regressions (DSURE) methods. In the present thesis, since we are interested in investigating the factors that affect transit ridership by mode in a multimodal operating environment, we try to estimate seemingly unrelated regression equation models. We check the variables for cointegration and we compare the results with those of single equation estimation. However, we could not run seemingly unrelated regression equations in the short run, due to the ARCH effects found in the Error correction model of the electric bus ridership.

Market share models are an additional strand in the transit literature that needs to be investigated further. In the present study we investigate the share of each PT mode in an aggregate level exploring the effect of some macroeconomic factors on PT mode shares. However, additional variables concerning the special characteristic of these models could be included in the case of line demand models, exploring in greater detail the competition or collaboration among the public transport modes of Athens.

Finally the models used in this study could be used to investigate the impact of economic recession on the PT sector. The present study used monthly data from 2002 to 2010. Economic recession in Greece, started from the beginning of 2010, makes demand analysis more complicated since it affects demand in a number of conflicting ways. The shrinking of economic activities, the resulting income reduction and, the increase in fares that a policy of reduced subsidies implies, affect ridership negatively. On the other hand the reduced use of private cars creates a shift on PT ridership. In addition, the economic recession destroys smooth variation of data. The above complicated interactions ask for a sophisticated method for analyzing demand. It would be interesting to investigate how the models described in this thesis will behave under such data variation, especially if the period investigated includes a period of development followed by a period of recession. Data for a complete assessment of the impact that the economic recession in Greece will have on the transport sector are not yet available. We hope that current results will provide a reference point for a future evaluation of the changes that the new economic era will bring to public transport.

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