EMPIRICAL ESSAYS ON RENEWABLE ENERGY ADOPTION

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ABSTRACT

Emmanouil V. Vergis: EMPIRICAL ESSAYS ON RENEWABLE ENERGY ADOPTION

(Under the direction of Associate Prof. Margarita Genius)

This Ph.D. thesis empirically analyzes the factors that act as facilitators or impediments of Renewable Energy adoption by economic agents. Within three interrelated chapters, this thesis focuses on the adoption process of micro and large-scale Renewable Energy Technologies (RETs).

The first chapter improves the understanding of the on-grid renewable energy micro-generation technology innovation borrowing elements from the Diffusion of Innovations Theory and empirically analyzes its adoption process by using data from households in Crete, Greece. The results shed light on preference heterogeneity for micro-generation technologies and lead to useful implications for policy-making and market development. The second chapter provides a comparative analysis of the performance of parametric and nonparametric methodologies for predicting the choice of micro-generation technologies based on renewable energy from stated preference data. Chapters 1 and 2 use a novel dataset from survey data of Cretan homeowners.

The third chapter explores the main factors affecting the propagation of large-scale RETs investments focusing on supporting policy mechanisms and on the institutional factor of government corruption. The data used in the third chapter are panel data for 48 countries, and they come from environmental statistics and accounts and self-gathered data on country-based policy mechanisms. Their analysis provides useful implications for large-scale RETs policy-making and further explains their adoption process.

Keywords: Renewable Energy, Stated preference, Choice Modelling, Structural Equation Model, Willingness-to-pay, Machine Learning, Nonparametric, Panel Data, Endogeneity

ΠΕΡΙΛΗΨΗ

Εμμανουήλ Β. Βέργης: ΕΜΠΕΙΡΙΚΕΣ ΕΚΘΕΣΕΙΣ ΓΙΑ ΤΗΝ ΥΙΟΘΕΤΗΣΗ ΑΝΑΝΕΩΣΙΜΩΝ ΠΗΓΩΝ ΕΝΕΡΓΕΙΑΣ

(Υπό την καθοδήγηση της Αναπλ. Καθ. Margarita Genius)

Η παρούσα διδακτορική διατριβή έχει ως αντικείμενο την μελέτη των παραγόντων που μπορούν να διευκολύνουν ή να αποτρέψουν την υιοθέτηση των Ανανεώσιμων Πηγών Ενέργειας (ΑΠΕ). Συγκεκριμένα, μέσω τριών αλληλεξαρτώμενων κεφαλαίων, μελετάει εμπειρικά την διαδικασία υιοθέτησης τεχνολογιών ΑΠΕ σε επίπεδο μικρής αλλά και ευρείας κλίμακας εγκατάστασης.

Το πρώτο κεφάλαιο βελτιώνει την κατανόηση των διασυνδεδεμένων τεχνολογιών παραγωγής ηλεκτρικής ενέργειας μικρής κλίμακας (μικρό-παραγωγής) με ΑΠΕ χρησιμοποιώντας στοιχεία από την θεωρία της Διάχυσης της Καινοτομίας (Diffusion of Innovation Theory - DIT), ενώ παράλληλα αναλύει εμπειρικά την διαδικασία διάχυσης τους, χρησιμοποιώντας δεδομένα δεδηλωμένων προτιμήσεων (Stated Preference) νοικοκυριών της Κρήτης. Τα αποτελέσματα αναδεικνύουν σημαντικά στοιχεία που αφορούν την ετερογένεια των προτιμήσεων για τις εν λόγω τεχνολογίες και οδηγούν σε χρήσιμα συμπεράσματα για την μελλοντική χάραξη πολιτικής και την ανάπτυξη της αγοράς. Στο δεύτερο κεφάλαιο διενεργείτε μια συγκριτική μελέτη της απόδοσης παραμετρικών αλλά και μη παραμετρικών μεθόδων προς την κατεύθυνση πρόβλεψης και ερμηνείας της απόφασης των νοικοκυριών για την υιοθέτηση τεχνολογιών μικρό-παραγωγής ΑΠΕ, χρησιμοποιώντας τα δεδομένα που συλλέχθηκαν στο πλαίσιο της έρευνας του κεφαλαίου 1.

Το τρίτο κεφάλαιο μελετά τους παράγοντες εκείνους που επηρεάζουν την διάχυση των τεχνολογιών μεγάλης κλίμακας που παράγουν ηλεκτρική ενέργεια μέσω ΑΠΕ, δίνοντας ιδιαίτερη βαρύτητα στα άμεσα μέτρα πολιτικής υποστήριξης των, καθώς και στον θεσμικό παράγοντα της διαφθοράς που ορίζει το πλαίσιο δραστηριοποίησης και αλληλεπίδρασης των οικονομικών φορέων. Με την χρήση διαστρωματικών δεδομένων

(panel data) για 48 χώρες για τα έτη 2005-2012, πραγματοποιείται ανάλυση των βασικών παραγόντων που επηρεάζουν τις επενδύσεις σε νέες εγκαταστάσεις ανεμογεννητριών. Η ανάλυση των στοιχείων αυτών, οδηγεί σε χρήσιμα συμπεράσματα για την χάραξη πολιτικής και επιπλέον εξηγεί την διαδικασία υιοθέτησης τους.

Λέξεις Κλειδιά: Ανανεώσιμες Πηγές Ενέργειας, Δεδηλωμένες Προτιμήσεις, Υπόδειγμα Επιλογής Καταναλωτή, Μοντέλα Δομικών Εξισώσεων, Προθυμία Πληρωμής, Νοημοσύνη των Μηχανών, Μη Παραμετρικές Μέθοδοι, Διαστρωματικά Δεδομένα, Ενδογένεια

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TABLE OF CONTENTS

LIST OF TABLES

Chapter 1

Chapter 2

Chapter 3

LIST OF FIGURES

Chapter 1

Chapter 2

Chapter 3

LIST OF ABBREVIATIONS

COP21: 21st Conference of the United Nations Parties

FE: Fixed Effects

FIT: Feed-in-Tariffs

KCDMD: Kernel Conditional Density Mixed data

ML: Machine Learning

MNL: Multinomial Logit

MXL: Mixed Logit

NECP: National Energy Climate Plans

NN: Neural Networks

RET: Renewable Energy Technology

RE: Renewable Energy

RF: Random Forest

RP: Revealed Preference

RUT: Random Utility Theory

SCOGEN: Solar Cogeneration

SP: Stated Preference

SPV: Solar Photovoltaic

SQ: Status Quo

TGC: Tradable Green Certificate

ΕΚΤΕΤΑΜΕΝΗ ΠΕΡΙΛΗΨΗ

Η παρούσα διδακτορική διατριβή έχει ως αντικείμενο την μελέτη των παραγόντων που μπορούν να διευκολύνουν ή να αποτρέψουν την υιοθέτηση των Ανανεώσιμων Πηγών Ενέργειας (ΑΠΕ). Συγκεκριμένα, μέσω τριών αλληλεξαρτώμενων κεφαλαίων, μελετάει εμπειρικά την διαδικασία υιοθέτησης τεχνολογιών ΑΠΕ σε επίπεδο μικρής αλλά και ευρείας κλίμακας εγκατάστασης.

Κεφάλαιο 1: Μελέτη της ετερογένειας των προτιμήσεων των νοικοκυριών της Κρήτης για την υιοθέτηση τεχνολογιών μικρό-παραγωγής από Ανανεώσιμες Πηγές Ενέργειας

Το πρώτο κεφάλαιο πραγματεύεται την μελέτη των προτιμήσεων νοικοκυριών για την υιοθέτηση τεχνολογιών παραγωγής ηλεκτρικής ενέργειας μικρής κλίμακας (μικρό-παραγωγής) με ΑΠΕ. Τα δεδομένα που χρησιμοποιήθηκαν στην παρούσα έρευνα συγκεντρώθηκαν από την διενέργεια έρευνας με την χρήση της μεθοδολογίας των δεδηλωμένων προτιμήσεων (Stated Preference Choice Experiment, SP) σε 187 νοικοκυριά στο νησί της Κρήτης. Οι τεχνολογίες μικρό-παραγωγής ΑΠΕ εξετάζονται ως μια τεχνολογική καινοτομία και η διάχυση τους αναλύεται μέσω των βασικών στοιχείων της όπως αναφέρονται από την θεωρία της Διάχυσης της Καινοτομίας (Diffusion of Innovation Theory - DIT) (Rogers 2003). Ειδικότερα, μελετώνται τα χαρακτηριστικά της τα οποία και επηρεάζουν την υιοθέτηση της, ενώ επιπλέον γίνεται χρήση κάποιων στοιχείων της θεωρίας αυτής στην εμπειρική μελέτη της ετερογένειας των προτιμήσεων των νοικοκυριών. Το χαρακτηριστικό της συμβατότητας της καινοτομίας με τις αξίες ή τις εμπειρίες των νοικοκυριών που δυνητικά θα την υιοθετήσουν, είναι μια λανθάνουσα μεταβλητή (latent variable), και εισάγεται στην μεθοδολογία εκτίμησης Integrated Choice Latent Variable. Τα αποτελέσματα της εμπειρικής εκτίμησης δείχνουν ότι ο βαθμός συμβατότητας της καινοτομίας των τεχνολογιών μικρό-παραγωγής ΑΠΕ με τις περιβαλλοντολογικές αξίες των νοικοκυριών είναι παράγοντας που επηρεάζει την ετερογένεια των προτιμήσεων τους. Συνεπώς, ο σχεδιασμός και η παραγωγή πολιτικών μέτρων που θα υποστηρίζουν τις διασυνδεδεμένες τεχνολογίες μικρό-παραγωγής ΑΠΕ θα πρέπει να κατευθυνθεί επίσης και στην ενίσχυση των περιβαλλοντολογικών αξίων των νοικοκυριών, προκειμένου να ενισχύσει της αποδοτικότητα τους αλλά παράλληλα να μειώσει και το κόστος εφαρμογής τους.

Η βασική συνεισφορά του παρόντος κεφαλαίου στην βιβλιογραφία έγκειται σε τρία βασικά σημεία. Αρχικά, η συγκεκριμένη μελέτη αναδεικνύει σημαντικές πληροφορίες σχετικά με την υιοθέτηση των διασυνδεδεμένων τεχνολογιών μικρό-παραγωγής ΑΠΕ από τα νοικοκυριά, αναλύοντας την εν λόγω καινοτομία χρησιμοποιώντας την θεωρία DIT. Ειδικότερα, αναλύονται τα χαρακτηριστικά της καινοτομίας και παράλληλα αναγνωρίζεται ο σημαντικός ρόλος της πολιτείας, που αποτελεί το τρίτο μέλος του κοινωνικού συστήματος (social system) της καινοτομίας των διασυνδεδεμένων τεχνολογιών μικρό-παραγωγής ΑΠΕ, η οποία είναι και υπεύθυνη για την εκκίνηση, την διευκόλυνση ή την αποτροπή υιοθέτησης της. Σε αντίθεση με την υπάρχουσα εμπειρική βιβλιογραφία η οποία μελετά τις προτιμήσεις των νοικοκυριών για τεχνολογίες μικρό-παραγωγής ΑΠΕ μέσω της DIT (Claudy et al. 2011; Simpson and Clifton, 2017), η παρούσα μελέτη είναι η πρώτη η οποία χρησιμοποιεί το χαρακτηριστικό της συμβατότητας, ως λανθάνουσα μεταβλητή, και την εισάγει στην εμπειρική μεθοδολογίας εκτίμησης Integrated Choice Latent Variable (Ben-Akiva et al. 2002b). Τέλος, μέσα από την παρούσα μελέτη δημιουργείται μια νέα SP βάση δεδομένων η οποία θα μπορεί να χρησιμοποιηθεί μεταγενέστερα για περαιτέρω ανάλυση της αγοράς ενέργειας στο νησί της Κρήτης.

Για τις ανάγκες της παρούσας έρευνας δημιουργήθηκε ένα SP ερωτηματολόγιο στο οποίο κλήθηκαν να απαντήσουν νοικοκυριά της Κρήτης σχετικά με διαφορετικές επιλογές και χαρακτηριστικά τεχνολογιών μικρό-παραγωγής ΑΠΕ τα οποία και εμφανίζονταν σε διαφορετικές κάρτες επιλογής. Οι διαφορετικές επιλογές των τεχνολογιών μικρό-παραγωγής ΑΠΕ, τα χαρακτηριστικά αυτών και τα επίπεδα των χαρακτηριστικών επιλέχθηκαν μέσω της διαδικασίας συνεντεύξεων με φορείς της αγοράς και μέσω της δημιουργίας ομάδων εστίασης σε νοικοκυριά της Κρήτης, αντίστοιχα. Οι διαφορετικές τεχνολογίες που επιλέχθηκαν για την διεξαγωγή της έρευνας ήταν, τα φωτοβολταϊκά (SPV), οι ανεμογεννήτριες (Windmils), τεχνολογίες ηλιακής συμπαραγωγής (SCOGEN) στις οποίες παράγεται ρεύμα αλλά και θερμότητα, και τέλος, όπως συνηθίζεται στην βιβλιογραφία η επιλογή του «παραμένω ως έχω». Τα χαρακτηριστικά που επιλέχθηκαν να διαφοροποιούνται για κάθε μια από τις τρεις διαφορετικές επιλογές, είναι το κόστος εγκατάστασης, τα έσοδα από την διάθεση ηλεκτρικής ενέργειας στο δίκτυο, τα έτη εγγύησης, το κόστος συντήρησης, τα έσοδα από της θερμική ενέργεια, η καλαισθησία της εγκατάστασης και τέλος ο χρόνος που απαιτείται για την έκδοση της άδειας παραγωγής. Η επιλογή των χαρακτηριστικών που εμφανίστηκαν στις καρτέλες επιλογής καθώς και ο αριθμός των καρτελών που τελικά απάντησαν οι ερωτώμενοι, έγινε με την χρήση D_p-efficient design (Rose and Bliemer, 2009), στην οποία γίνεται χρήση των αρχικών τιμών των εκτιμήσεων των παραπάνω χαρακτηριστικών. Οι τιμές αυτές (priors) αποκτήθηκαν με δύο διαφορετικές πιλοτικές εφαρμογές της εν λόγω έρευνας πριν την τελική διεξαγωγή της. Το σύνολο των καρτών που κλήθηκαν να απαντήσουν οι ερωτώμενοι, ήταν 6. Η δειγματοληψία διενεργήθηκε τυχαία και με στρωματοποίηση ανάλογα με τον πληθυσμό των διαφορετικών δήμων της Κρήτης καταλήγοντας σε 187 πλήρεις απαντήσεις. Παράλληλα, επιπλέον των δεδηλωμένων προτιμήσεων των νοικοκυριών, συγκεντρώθηκαν δεδομένα που αφορούν χαρακτηριστικά της οικία τους, τα κοινωνικό-οικονομικά γνωρίσματα τους αλλά και πληροφορίες σχετικά με την θεωρία DIT.

Με τα δεδομένα που συγκεντρώθηκαν και αφορούν τα γνωρίσματα των ερωτώμενων σχετικά με την DIT, διαμορφώθηκαν δύο διαφορετικές λανθάνουσες μεταβλητές, η συμβατότητα των τεχνολογιών παραγωγής ηλεκτρικής ενέργειας με τις περιβαλλοντολογικές αξίες και με την συμπεριφορά εξοικονόμησης των νοικοκυριών. Και οι δυο λανθάνουσες μεταβλητές εισήχθησαν στο υπόδειγμα και εκτιμήθηκαν με την μέθοδο Integrated Choice Latent Variable, η οποία συνδυάζει την ταυτόχρονη εκτίμηση των μοντέλων επιλογής (choice) και μοντέλα δομικών εξισώσεων (structural equation models, SEM). Η συνάρτηση χρησιμότητας για κάθε επιλογή τεχνολογίας μικρό-παραγωγής διαμορφώθηκε σύμφωνα με τα χαρακτηριστικά όπως αναφέρονται παραπάνω. Η συμβατότητα με τις περιβαλλοντολογικές αξίες των νοικοκυριών εισήχθη στο υπόδειγμα ως στοιχείο που επηρεάζει την εκτίμηση της παραμέτρου του κόστους εγκατάστασης ενώ η συμβατότητα με τις εμπειρίες εξοικονόμησης εισήχθη στο υπόδειγμα ως μεταβλητή που επηρεάζει την χρησιμότητα της εναλλακτικής του «παραμένω ως έχω». Για την επιλογή «παραμένω ως έχω», χρησιμοποιήθηκαν ως ερμηνευτικές μεταβλητές κοινωνικό-οικονομικά στοιχεία των νοικοκυριών και άλλα στοιχεία σχετικά με την παρατηρησιμότητα της τεχνολογίας αλλά και η προηγούμενη εμπειρία των ερωτώμενων σχετικά με την αναζήτηση πληροφοριών για την καινοτομία. Τα εμπειρικά αποτελέσματα της μεθόδου Integrated Choice Latent Variable συγκρίθηκαν με αυτά της μεθοδολογίας Multinomial Logit (McFadden, 1973), και Mixed Logit (McFadden & Train, 2000), μεθοδολογίες που βασίζονται στην θεωρία της τυχαίας επιλογής των καταναλωτών (Random Utility Theory) (Marschak, 1960; Manski, 1977). Τα εμπειρικά αποτελέσματα της παρούσας έρευνας δείχνουν ότι η μεθοδολογίας Integrated Choice Latent Variable, αναδεικνύει ότι βασικό στοιχείο της ετερογένειας των προτιμήσεων του κόστους εγκατάστασης των νοικοκυριών επηρεάζεται από τον βαθμό συμβατότητας των περιβαλλοντολογικών αξιών τους με την τεχνολογία. Αντίστοιχα, η μεθοδολογία του Mixed Logit αναγνωρίζει ότι υπάρχει ετερογένεια στις προτιμήσεις για το κόστος εγκατάστασης, όμως δεν δίνει απαντήσεις σχετικά με το ποια είναι η πηγή της.

Τα αποτελέσματα της παρούσας έρευνας μπορούν να έχουν μεγάλη χρησιμότητα τόσο στην χάραξη πολιτικής για την υποστήριξη των τεχνολογιών μικρό-παραγωγής ΑΠΕ, αλλά παράλληλα μπορούν να έχουν εφαρμογή στην στρατηγική marketing των εταιριών που δραστηριοποιούνται στην συγκεκριμένη αγορά. Ειδικότερα, τα εμπειρικά αποτελέσματα δείχνουν ότι ο βαθμός συμβατότητας της τεχνολογίας με τις περιβαλλοντολογικές αξίες των ερωτώμενων αυξάνει την προθυμία υιοθέτησης τους, καθώς είναι διατεθειμένοι να πληρώσουν περισσότερο για να προχωρήσουν στην εγκατάσταση τους. Επιπλέον, όσο αυξάνει η συμβατότητα με συμπεριφορές εξοικονόμησης αυξάνεται και η πιθανότητα υιοθέτησης των εν λόγω τεχνολογιών. Επιπρόσθετα, τα εμπειρικά αποτελέσματα της παρούσας έρευνας, δείχνουν ότι για την αγορά της Κρήτης μια αύξηση στην τιμή αποζημίωσης των νοικοκυριών από την διάθεση της ηλεκτρικής ενέργειας στο δίκτυο, με συνολικό ετήσιο κέρδος 100 ευρώ για το νοικοκυριό, μπορεί να αποζημιώσει μια δυνητική εγκατάσταση έως και 500 ευρώ από το αρχικό κόστος εγκατάστασης. Τέλος, η καλαισθησία, σε αντίθεση με ένα επιπλέον έτος εγγύησης, είναι ένα χαρακτηριστικό της τεχνολογίας για το οποίο υπάρχει μεγαλύτερη προθυμία πληρωμής από τα νοικοκυριά της Κρήτης.

Κεφάλαιο 2: Συγκριτική μελέτη εφαρμογής παραμετρικών και μη παραμετρικών μεθοδολογιών για την ερμηνεία και πρόβλεψη των επιλογών για τεχνολογίες μικρό-παραγωγής Ανανεώσιμων Πηγών Ενέργειας

Στο δεύτερο κεφάλαιο διενεργείται μια συγκριτική μελέτη της απόδοσης παραμετρικών αλλά και μη παραμετρικών μεθόδων προς την κατεύθυνση πρόβλεψης και ερμηνείας της απόφασης των νοικοκυριών για την υιοθέτηση τεχνολογιών μικρό-παραγωγής ΑΠΕ, χρησιμοποιώντας τα δεδομένα που συλλέχθηκαν στο πλαίσιο της έρευνας του κεφαλαίου 1. Ειδικότερα, μέσω της συγκριτικής αυτής ανάλυσης, το παρόν κεφάλαιο προσπαθεί να απαντήσει σε δύο ερευνητικά ερωτήματα τα οποία είναι, α) ποια μεθοδολογία θα πρέπει ένας ερευνητής να επιλέξει για την μελέτη αλλά και πρόβλεψη των προτιμήσεων των νοικοκυριών και β) αν αναδυόμενες μεθοδολογικές τεχνικές που βασίζονται σε τεχνολογίες προηγμένης εξαγωγής δεδομένων, μηχανικής μάθησης (Machine Learning, ML), μπορούν να χρησιμοποιηθούν προς αυτή την κατεύθυνση. Ειδικότερα, σε αυτό το κεφάλαιο εξετάζονται δύο βασικές παραμετρικές μέθοδοι, Multinomial Logit (McFadden, 1973), και Mixed Logit (McFadden & Train, 2000) και συγκρίνονται με την προηγμένη ML μέθοδο των Random Forest (RF) (Breiman 2001a) και την μη παραμετρική μέθοδο kernel conditional density mixed data (KCDMD) (Racine, 2019; Hall et al. 2014). Η σύγκριση των μοντέλων γίνεται τόσο σε επίπεδο πρόβλεψης των επιλογών των νοικοκυριών αλλά ταυτόχρονα και στην δυνατότητα που δίδουν στον ερευνητή να ερμηνευθούν τα αποτελέσματα τους. Η συγκριτική ανάλυση γίνεται με δεδομένα που είναι μικρού αριθμού παρατηρήσεων και αφορούν SP προτιμήσεις νοικοκυριών του νησιού της Κρήτης όσον αφορά την υιοθέτηση τεχνολογιών μικρό-παραγωγής ΑΠΕ.

Τα αποτελέσματα του παρόντος κεφαλαίου αποδεικνύουν ότι όταν σημαντικές πληροφορίες λείπουν από το δείγμα, οι μη παραμετρικές μέθοδοι δεν αποτελούν καλύτερη λύση από τις παραμετρικές μεθόδους για την πρόβλεψη των επιλογών των νοικοκυριών. Ιδιαίτερα, υποστηρίζεται ότι όταν χρησιμοποιούνται δεδομένα μικρού μεγέθους, και σημαντικές πληροφορίες λείπουν από το δείγμα, τότε κανένα μη παραμετρικό ή παραμετρικό μοντέλο δεν έχει την δυνατότητα μεταφοράς της πρόβλεψης του σε νέα άτομα του δείγματος. Ειδοποιός διαφορά μεταξύ των παραμετρικών και των μη παραμετρικών μεθόδων είναι ότι τα τελευταία, σε ότι αφορά την ερμηνεία των αποτελεσμάτων, καταλήγουν σε μη γραμμικές επιδράσεις των ερμηνευτικών μεταβλητών, αποτελέσματα τα οποία όμως δεν μπορούν να εξαχθούν με την χρήση παραμετρικών μεθόδων.

Η βασική συνεισφορά του παρόντος κεφαλαίου στην βιβλιογραφία έγκειται στα παρακάτω στοιχεία. Η συγκριτική ανάλυση περιλαμβάνει και την KCDMD μη παραμετρική μεθοδολογία, η οποία σπάνια έχει χρησιμοποιηθεί, και καθίσταται ως μια αποτελεσματική επιλογή για την μελέτη SP δεδομένων διακριτής επιλογής (discrete choice data), ισάξια της RF. Αντίθετα με τα όσα υποστηρίζει η αναδυόμενη βιβλιογραφία η οποία συγκρίνει τις παραμετρικές μεθόδους με την μέθοδο RF αλλά και η αντίστοιχη βιβλιογραφία που μελετά την μεθοδολογία KCDMD, οι μη παραμετρικές μέθοδοι δεν είναι επικρατέστερες των συμβατικών όταν σημαντικές πληροφορίες απουσιάζουν από τον πληθυσμό που εξετάζεται. Σε ότι αφορά την σύγκριση των σημαντικότερων μεταβλητών κάθε μεθοδολογίας, οι μέθοδοι των RF και KCDMD φαίνεται ότι δεν δίνουν μεγάλη βαρύτητα σε μεταβλητές που έχουν κατασκευαστεί από τον ερευνητή, όπως αυτό συμβαίνει σε SP choice experiment δεδομένα που αναλύονται στην παρούσα έρευνα.

Η επιλογή της χρήσης της RF μεθοδολογίας έγινε με γνώμονα την σχετική βιβλιογραφία (Tribby et al. 2017; Sekhar et al. 2016; Hagenauer, and Helbich, 2017) καθώς φαίνεται να συμπεριφέρεται αποδοτικότερα όσον αφορά την προβλεψιμότητα, ακόμα και σε δεδομένα μικρού μεγέθους αντίθετα με άλλες μεθοδολογίες, όπως για παράδειγμα των Νευρωνικών Δικτύων (NN Neural Networks). Παράλληλα, λήφθηκε υπόψη και το γεγονός ότι στην βιβλιογραφία που μελετά τον τρόπο επιλογής μεταφοράς (mode choice) (Chen et al. 2019; Lhéritier et al. 2018; Alwosheel et al. 2018; Brathwaite et al. 2017; Hagenauer and Helbich, 2017; Tribby et al. 2017; Sekhar et al. 2016; Wang et al. 2016; Vafeiadis et al. 2015; and Mohammadian and Miller, 2002), η μεθοδολογία των RF φαίνεται σε επίπεδο πρόβλεψης να συμπεριφέρεται καλύτερα από άλλες μεθοδολογίες. Στην συγκριτική ανάλυση επιλέχθηκε επιπλέον και ο KCDMD εκτιμητής, ο οποίος βασίζεται στην μη παραμετρική οικογένεια εκτιμητών Kernel και αποτελεί μια μη παραμετρική μεθοδολογία η οποία σπάνια έχει χρησιμοποιηθεί στην βιβλιογραφία.

Η συγκριτική ανάλυση όπως προαναφέραμε, πραγματοποιήθηκε σε επίπεδο πρόβλεψης αλλά και ερμηνείας των εκτιμητών. Σε ότι αφορά την ικανότητα πρόβλεψης των διαφορετικών μεθοδολογιών που χρησιμοποιούνται στην παρούσα έρευνα, αρχικά μέσω cross-validation το δείγμα χωρίστηκε σε 10 ίσα μέρη, και κάθε φορά ένα μέρος επιλέγεται να βγει εκτός από το δείγμα προκειμένου να χρησιμοποιηθεί για την διαδικασία της πρόβλεψης. Για το διαχωρισμό του δείγματος ακολουθήθηκαν δύο βασικές διαδικασίες, η πρώτη αφορά μέσω τυχαίας κατανομής όλου του δείγματος και η δεύτερη μέσω τυχαίας κατανομής ερωτώμενων. Κατά την διαδικασία τυχαίας κατανομής του δείγματος, διαδικασία που χρησιμοποιείται ευρέως στην βιβλιογραφία, επιβεβαιώνοντας τα ευρήματα άλλων ερευνών, τα αποτελέσματα μας δείχνουν ότι οι προβλέψεις των μη παραμετρικών μεθόδων έχουν μεγαλύτερο ποσοστό επιτυχίας πρόβλεψης. Στην περίπτωση όμως όπου τυχαία αφαιρούνται ερωτώμενοι από το δείγμα, τότε το ποσοστό πρόβλεψης των μη παραμετρικών μεθοδολογιών είναι το ίδιο χαμηλό, με τις παραμετρικές μεθόδους. Αποτέλεσμα που μας οδηγεί στο συμπέρασμα ότι οι μη παραμετρικές μεθοδολογίες αδυνατούν να μεταφέρουν την εμπειρία τους για την πρόβλεψη των προτιμήσεων ερωτώμενων για τους οποίους δεν έχουν εκπαιδευτεί να το κάνουν. Αντίστοιχα όμως είναι τα αποτελέσματα και για τις παραμετρικές μεθόδους.

Κατόπιν, πραγματοποιήθηκε η συγκριτική ανάλυση της ερμηνείας των αποτελεσμάτων τους χρησιμοποιώντας όλα τα δεδομένα. Για την διεξαγωγή της ανάλυσης αυτής αρχικά έγινε η σύγκριση των σημαντικότερων μεταβλητών για κάθε μεθοδολογία . Ενώ ακολούθησε η χρήση διαγραμμάτων μερικής εξάρτησης (partial-dependence plots) (Friedman et al. 2001) για την σύγκριση της μέσης οριακής επίδρασης κάθε μεταβλητής για κάθε επιλογή, δεδομένων των άλλων μεταβλητών του υποδείγματος. Σε επίπεδο σύγκρισης των σημαντικότερων μεταβλητών που καταδεικνύει κάθε μεθοδολογία, παρατηρούμε ότι οι μη-παραμετρικές μέθοδοι δίνουν μεγαλύτερη βαρύτητα σε κοινωνικό-οικονομικές μεταβλητές, παρά στις μεταβλητές που αφορούν χαρακτηριστικά της πληροφορίας και που ο ίδιος ο ερευνητής έχει ορίσει το σύνολο της πληροφορίας που περιέχουν. Για τις μεταβλητές που κάθε μοντέλο αναδεικνύει ως περισσότερο σημαντικές, εξάχθηκαν τα διαγράμματα μερικής επίδρασης τους.

Τα αποτελέσματα δείχνουν ότι οι μη παραμετρικές μέθοδοι αναδεικνύουν μη γραμμικές επιδράσεις οι οποίες μπορούν να έχουν πολύ σημαντική επίπτωση στην χάραξη πολιτικής ή στην δημιουργία εστιασμένης στρατηγικής μάρκετινγκ εταιριών σε ειδικότερες ομάδες πληθυσμού. Στις μεθόδους των RF και KCDMD ο ερευνητής δεν χρειάζεται να θέσει καμία υπόθεση σχετικά με την διάρθρωση του μαθηματικού υποδείγματος καθώς επίσης ούτε για την ενδεχόμενη κατανομή που ακολουθούν τα σφάλματα, ενώ αξιοποιούν τις πληροφορίες που παρέχουν τα δεδομένα.

Κεφάλαιο 3: Διαφθορά και επιδότηση τιμής: Μια διαφορετική οπτική στην διάχυση τεχνολογιών παραγωγής ηλεκτρισμού από Ανανεώσιμες Πηγές ενέργειας

Το τρίτο κεφάλαιο μελετά τους παράγοντες εκείνους που επηρεάζουν την διάχυση των τεχνολογιών μεγάλης κλίμακας που παράγουν ηλεκτρική ενέργεια μέσω ΑΠΕ, δίνοντας ιδιαίτερη βαρύτητα στα άμεσα μέτρα πολιτικής υποστήριξης των, καθώς και στον θεσμικό παράγοντα της διαφθοράς που ορίζει το πλαίσιο δραστηριοποίησης και αλληλεπίδρασης των οικονομικών φορέων. Με την χρήση διαμήκη διαστρωματικών δεδομένων (panel data) για 48 χώρες για τα έτη 2005-2012, πραγματοποιείται ανάλυση των βασικών παραγόντων που επηρεάζουν τις επενδύσεις σε νέες εγκαταστάσεις ανεμογεννητριών. Τα δεδομένα που αφορούν το επίπεδο της πολιτικής επιδότησης τιμής (Feed-in-tariffs, FIT) συλλέχθηκαν από διαφορετικές πηγές για κάθε χώρα και για το σύνολο των ετών που ερευνάται, ενώ παράλληλα συμπεριλαμβάνονται στοιχεία από άλλους εθνικούς λογαριασμούς για περιβαλλοντολογικά και άλλα δεδομένα. Από μεθοδολογικής σκοπιάς αυτή η έρευνα αντιμετωπίζει το πρόβλημα ενδογένειας που μπορεί να υπάρχει στα αναλυόμενα δεδομένα και μπορεί να επηρεάσει την πιστότητα των αποτελεσμάτων της. Συγκεκριμένα, ακολουθώντας την σχετική βιβλιογραφία η οποία υποστηρίζει ότι οι πολιτικές καθορίζονται ενδογενώς σύμφωνα με τους αντίστοιχους στόχους των κυβερνήσεων για το επίπεδο της ενέργειας από ΑΠΕ (Söderholm and Klaassen, 2007, Jaffe and Stavins, 1995; Maza and Winden, 2004), το μέτρο άμεσης πολιτικής υποστήριξης επιδότησης τιμής, αντιμετωπίζεται ως ενδογενής μεταβλητή. Παράλληλα, η παρούσα έρευνα μελετά τον σύνθετο τρόπο με τον οποίο η διαφθορά μπορεί να επηρεάσει τις επενδύσεις σε ΑΠΕ, και ελέγχει αν αυτό το αποτέλεσμα αλλάζει για διαφορετικές γεωγραφικές περιοχές. Τα αποτελέσματα της παρούσας έρευνας αναδεικνύουν την σημαντική συνεισφορά της επιδότησης τιμής στην ανάπτυξη των επενδύσεων σε ανεμογεννήτριες. Παράλληλα, υποστηρίζεται ότι η διαφθορά επηρεάζει αρνητικά τις επενδύσεις σε ανεμογεννήτριες, εκτός από τις χώρες που βρίσκονται στην ανατολική Ασία, όπου η επίδραση είναι θετική. Με αυτό ως δεδομένο, η παρούσα έρευνα παρέχει εμπειρικές αποδείξεις για την ύπαρξη αυτού του παράδοξου, που μελετάται στην βιβλιογραφία ως «East Asian paradox» (Olson, 1993; Rock and Bonnett, 2004; Wedeman, 2002).

Για την μελέτη της επίδρασης των μέτρων πολιτικής αλλά και του θεσμικού παράγοντα της διαφθοράς στις επενδύσεις σε ανεμογεννήτριες, προσεγγίσαμε τις επενδύσεις ως την κατά κεφαλήν ετήσια αύξηση της εγκατεστημένης ισχύος (EIA). Επιλέχθηκαν 48 χώρες οι οποίες κατέχουν το 98% της παγκόσμιας εγκατεστημένης ισχύος ανεμογεννητριών, προερχόμενες από τις γεωγραφικές περιοχές της ανατολικής και νότιας Ασίας, βόρειας Αφρικής, λατινικής Αμερικής και χώρες του OECD που δεν συμπεριλαμβάνονται στις παραπάνω γεωγραφικές περιοχές. Τα δεδομένα αφορούν την περίοδο 2005-2012, ενώ αποκλείστηκαν άλλες τεχνολογίες όπως των SPV, βιομάζας, κ.α., λόγω της πιο πρόσφατης εισαγωγής τους στην αγορά και λόγω της έλλειψης δεδομένων. Επιπλέον, συλλέχθηκαν στοιχεία για το επίπεδο επιδότησης τιμής των χωρών που μελετώνται, καθώς επίσης και στοιχεία για την ύπαρξη άλλων πολιτικών μέτρων άμεσης υποστήριξης των ανεμογεννητριών (IRENA 2016; REN21 2016). Η επιδότηση τιμής εισήλθε στο υπόδειγμα ως μη σταθμισμένος μέσος των διαφορετικών επιπέδων επιχορήγησης που παρέχονται σε κάθε χώρα, ανάλογα με το μέγεθος της εγκατάστασης. Παράλληλα, συλλέχθηκαν και δεδομένα που αφορούν το επίπεδο της αντιλαμβανόμενης διαφθοράς (TI 2005-2008), το επίπεδο της μόλυνσης της κάθε χώρας (εκπομπές διοξειδίου του άνθρακα), το μερίδιο άλλων πηγών ενέργειας στην παραγωγή ηλεκτρικής ενέργειας μιας χώρας καθώς και το επίπεδο εξάρτησης κάθε χώρας από εισαγωγές ηλεκτρικής ενέργειας (EIA).

Για την επίτευξη των στόχων της έρευνας χρησιμοποιήθηκε η μέθοδος των σταθερών επιδράσεων (Fixed Effects) (Wooldridge 2002) σύμφωνα με την οποία, μη παρατηρούμενα στοιχεία των υπό μελέτη χωρών, τα οποία είναι και σταθερά ανά έτος, μπορούν να αλληλεπιδρούν με τις μεταβλητές εντός του υποδείγματος. Αυτή είναι μια βασική υπόθεση για την αξιοπιστία της εν λόγω έρευνας καθώς για παράδειγμα τα καιρικά φαινόμενα που επικρατούν σε μια χώρα ή οι γεωγραφικές της ιδιαιτερότητες δρουν ως παράγοντες που επηρεάζουν το επίπεδο παραγωγικότητας των ανεμογεννητριών και μπορεί να επηρεάζουν το επίπεδο ή το σύνολο των πολιτικών μέτρων υποστήριξης των τεχνολογιών ΑΠΕ. Για τον έλεγχο αυτής της υπόθεσης, διεξήχθη ο εύρωστως έλεγχος Hausman (Wooldridge, p288, 2002), του οποίου το αποτέλεσμα απορρίπτει την μηδενική υπόθεση και επιβεβαιώνει την χρήση της προσέγγιση του FE μετασχηματισμού.

Παράλληλα, όπως αναφέραμε και παραπάνω, η μεταβλητή που αφορά το επιδότηση τιμής μπορεί να είναι ενδογενής καθώς μπορεί να συναντώνται προβλήματα ταυτοχρονισμού (simultaneity) η προβλήματα σφάλματος εξειδίκευσης (omitted variables) (Wooldridge 2002). Συγκεκριμένα, λαμβάνοντας υπόψη ότι το κόστος εγκατάστασης δεν ήταν δυνατό να συμπεριληφθεί στην εξειδίκευση του υποδείγματος λόγω έλλειψης στοιχείων και το επίπεδο επιδότησης τιμής εφαρμόζεται για να υποστηρίξει το υψηλό κόστος εγκατάστασης, η παράλειψη του μπορεί να οδηγήσει σε αναποτελεσματικούς εκτιμητές. Παράλληλα, μπορεί να υπάρξει πρόβλημα ταυτοχρονισμού το οποίο εμφανίζεται καθώς το επίπεδο επιδότησης τιμής μπορεί να καθορίζεται ως αποτέλεσμα της ανάδρασης μεταξύ των στόχων για ΑΠΕ και των υπαρχουσών εγκαταστάσεων ανεμογεννητριών. Για την αντιμετώπιση του εν λόγω φαινομένου έγινε χρήση δύο εξωγενών βοηθητικών μεταβλητών για το επίπεδο τιμών επιδότησης, οι οποίες είναι α) η ύπαρξη της πολιτικής επιδότησης τιμής για υποστήριξη άλλων πηγών ΑΠΕ εκτός των ανεμογεννητριών εντός της χώρας, και β) ο μέσος όρος του επιπέδου επιδότησης τιμής που χρησιμοποιούνται από χώρες που βρίσκονται στα ίδια επίπεδα οικονομικής κατάστασης. Πραγματοποιήθηκε ο έλεγχος Hausman (1978), οποίος δείχνει ότι το επίπεδο επιδότησης τιμής είναι ενδογενής μεταβλητή, ενώ ο έλεγχος Sargan (1975) (OIR test) αποτυγχάνει να επιβεβαιώσει ότι οι βοηθητικές μεταβλητές συσχετίζονται με τον διατακτικό όρο του υποδείγματος. Λαμβάνοντάς υπόψη τα παραπάνω, προχωρήσαμε στην χρήση της μεθοδολογίας εκτίμησης βοηθητικών μεταβλητών σταθερών επιδράσεων (Fixed effects two-stage least squares, FE 2SLS). Τα εμπειρικά αποτελέσματα της μεθοδολογίας FE 2SLS δείχνουν ότι μια αύξηση της τιμής επιδότησης για την διάθεση ηλεκτρικής ενέργειας στο δίκτυο αυξάνει τις επενδύσεις σε ανεμογεννήτριες.

Προκειμένου να γίνει έλεγχος σχετικά με την επίδραση της διαφθοράς σε διαφορετικές γεωγραφικές περιοχές δημιουργήθηκαν νέες γεωγραφικές μεταβλητές ως αποτέλεσμα του γινομένου ψευδοταβλητών ανά γεωγραφική περιοχή και του επιπέδου αντιλαμβανόμενης διαφθοράς για κάθε χώρα. Ειδικότερα, έγινε ο διαχωρισμός των χωρών ανατολικής Ασίας, νότιας Ασίας, βόρειας Αφρικής, λατινικής Αμερικής και των υπολοίπων χωρών του OECD. Τα εμπειρικά αποτελέσματα της παρούσας έρευνας αναδεικνύουν τον αποτρεπτικό ρόλο που έχει η διαφθορά στο επίπεδο των επενδύσεων σε ανεμογεννήτριες. Παράλληλα όμως δείχνουν ότι για τις χώρες της Ανατολικής Ασίας, το υψηλό επίπεδο διαφθοράς ενισχύει τις επενδύσεις σε ανεμογεννήτριες.

Για την αξιοπιστία του παραπάνω αποτελέσματος, χρησιμοποιήθηκαν διαφορετικές μεταβλητές που μετρούν το μέγεθος της αντιλαμβανόμενης διαφθοράς από πολίτες και επιχειρηματίες (TI, 2005-2012; WGI, 2005-2012). Τα αποτελέσματα για τα εν λόγω δύο μέτρα διαφθοράς δε διαφοροποιούνται. Σε αυτό το σημείο είναι κρίσιμο να αναφερθούμε στην ερμηνεία αυτού παραδόξου στις Ανατολικές Ασιατικές χώρες. Συγκεκριμένα, η σχετική βιβλιογραφία η οποία έχει προσπαθήσει να ερμηνεύσει αυτό το παράδοξο, τόσο σε επίπεδο επενδύσεων και ανάπτυξης, αναφέρει ότι αυτές οι χώρες διέπονται από οργανωμένη διαφθορά η οποία οφείλεται σε δύο βασικούς παράγοντες (Olson, 1993; Rock and Bonnett, 2004). Οι κυβερνήσεις αυτών των χωρών έχουν μακρόχρονους ορίζοντες διακυβέρνησης και έχουν μονοπωλήσει τις δομές του κράτους και τις δημόσιες υπηρεσίες με αποτέλεσμα να δημιουργούν περισσότερο σταθερά περιβάλλοντα, μειώνοντας τον κίνδυνο για νέες επενδύσεις. Όμως παρόλο που η επίδραση μια αύξησης της διαφθοράς είναι θετική σε αυτές τις χώρες, αυτό που δεν απαντάται στην παρούσα έρευνα είναι, «με ποιο κόστος;». Ποιος τομέας της οικονομίας ή του κοινωνικού ιστού επιβαρύνεται προκειμένου να υπάρξει αυτή η αύξηση των επενδύσεων σε ανεμογεννήτριες, καθώς η έννοια της διαφθοράς αφορά την παραβίαση κανόνων με σκοπό το προσωπικό κέρδος.

Στην παρούσα μελέτη χρησιμοποιήθηκαν και άλλες μεταβλητές σχετικές με την ύπαρξη επιπλέων άμεσων μέτρων πολιτικής υποστήριξης των επενδύσεων σε ανεμογεννήτριες, όμως μόνο το μέτρο που αφορά την επιχορήγηση του κόστους (Investment subsidies) βρέθηκε να έχει σημαντική επίδραση στην αύξηση των εγκαταστάσεων ανεμογεννητριών. Παράλληλα, η αύξηση του επιπέδου μόλυνσης δεν οδηγεί σε αύξηση των επενδύσεων σε ανεμογεννήτριες.

INTRODUCTION

This Ph.D. thesis empirically analyzes the factors that act as facilitators or impediments of Renewable Energy adoption by economic agents. Within three interrelated chapters, this thesis focuses on the adoption process of micro and large-scale Renewable Energy Technologies (RETs).

The first chapter of the thesis entitled "Modelling Heterogeneity of Consumer Preferences for Microgeneration Renewable Energy Technologies," analyzes household preferences for renewable micro-generation technologies using a stated preference choice experiment and data gathered from 187 homeowners in the island of Crete. In the arguments set forth in the analysis, micro-generation is considered as an innovation whose diffusion depends on its characteristics as exposed in the Diffusion of Innovations Theory. Based on the aforementioned theory, the attribute of compatibility is introduced as a latent construct within an Integrated Choice Latent Variable model. The results indicate that the innovation compatibility with homeowner's environmental values is an important factor explaining the choice of micro-generation technology and heterogeneity in preferences. Thus, devising policy instruments raising environmental awareness and the energy-saving attitudes of homeowners can result in reducing the overall implementation cost, as well as in increasing the efficiency of the instrument.

The first chapter contributes to the existing literature by pointing out important information concerning the on-grid renewable energy micro-generation technologies innovation, related to its attributes, for the appraisal of their adoption. This study makes the distinction between off-grid and on-grid micro-generation RET innovation, arguing that governments, which is the third unit in the latter innovation's social system, are responsible for initializing, facilitating, or act as an impediment to their diffusion process. This study also empirically analyzes Cretan homeowner's preferences for micro-generation technologies, and as a novelty, introduces the compatibility attribute as a latent variable in a discrete choice setting and uncovers it as a factor that explains unobserved heterogeneity. Additionally, within this study, a novel dataset of Cretan homeowners related to stated preference discrete choice on micro-generation RETs is created where more research implications on the Crete market can be extracted.

The second chapter of this thesis entitled, “A comparative study of parametric and nonparametric methodologies for modeling choice of Renewable Energy Micro Generation Technologies,” answers to the following two questions, namely, which modeling approach a researcher should use for predicting a household’s choice for micro-generation RETs, and whether off-the-shelf machine learning algorithms can be effective within a researcher-defined stated preference (SP) choice experiment dataset. In particular, this chapter examines two basic well-known logit models, namely the standard Multinomial Logit and the Random Parameter Logit model. It compares them with the state of the art machine learning algorithm (ML) of Random Forests (RF) and the nonparametric kernel multinomial model (KCDMD). The comparison is made in terms of the predictability and interpretability of the above models using low-dimensional stated preference data of Cretan homeowners’ choice over micro-generation RETs. The results indicate that when the training set used for the estimation of the data-driven models does not include valuable individual information, the nonparametric models of the RF and the KCDMD do not outperform traditional logit models in terms of accurate predictability. In terms of the variable importance used to build the estimated models, the nonparametric models draw their attention to the household’s socio-economic status rather than the alternative specific attributes designed by the researcher.

Although the literature mainly compares the standard parametric logit models with black-box machine learning algorithms, the second chapter of this study additionally uses the data-driven nonparametric KCDMD estimator and argues that the latter has similar results to the RF ML algorithm, where both nonparametric models identify nonlinear effects that would not otherwise appear. In particular, this research proposes the nonparametric kernel-based model as an effective alternative methodology for discrete response models. This research also points out that the accuracy of the nonparametric data-driven methodologies is stemming from the used training dataset. In contrast to the literature arguing that both the ML and KCDMD estimator model approaches outperform the standard parametric logit models, this study shows that within a low-dimensional dataset, when important information is excluded from the estimation of the models, none of them manage to predict new individuals’ choices.

In the third chapter of this thesis, entitled "Feed-In-Tariffs and Government Corruption: Another Look at the Diffusion of Renewable Energy Technologies", the primary interest is to explore how institutional factors and implemented supporting policy schemes influence the diffusion process of large-scale RETs investments in the case of wind energy. In an attempt to unravel the effect of government intervention through implemented policy mechanisms and the effect of corruption on RE investments, this research employs an empirical panel data analysis for investments on windmills in 48 countries. The data for Feed-in-Tariffs (FIT hereafter), which is a price policy mechanism for RES producers compensation level, was gathered for all countries in the sample from the International Energy Agency and the Renewable Energy Policy Network. The FIT policy mechanism is treated as endogenous following the intuition proposed from the diffusion literature, arguing that policymakers endogenously define policy instruments along with the RE electricity targets. This chapter also explores the possible directions in which corruption can affect investments over the deployment of Wind Technologies and further tests whether this effect changes within different geographic regions. Research results indicate the importance of the FIT in the growth of large-scale wind investments and provide empirical evidence on the different effects the perceived corruption has on wind investment development.

The third chapter has a three-fold contribution to the literature. The first is the creation of a database for 48 countries in the sample that combines data collected on feed-in-tariffs and other support policy mechanisms for each country, environmental statistics and accounts, and institutional corruption measures. From a methodological point of view, this study also tackles the problem of potential endogeneity of feed-in-tariffs, which, if not taken into account, could seriously affect the validity of the estimation results. This potential endogeneity can arise because installation cost has not been included in the model and also because of the feedback effect between feed-in-tariffs and renewable energy targets. In particular, support mechanisms such as feed-in-tariffs could be adjusted downward as the installed renewable energy capacity increases because investment costs are lower or adjusted upward whenever the capacity targets are not met. Another contribution of this study is that it explores the possible directions in which corruption can affect investments over the deployment of large-scale wind investments and gives empirical prominence to the east Asian paradox in the case of RE investments.

CHAPTER 1: MODELLING HETEROGENEITY OF CONSUMER PREFERENCES FOR MICROGENERATION RENEWABLE ENERGY TECHNOLOGIES

1. Introduction

A global switch to renewable energy sources (RES) is now more than ever essential to mitigate global warming and climate change severe impacts on humans, economies, and the environment. At the 21st conference of parties (COP21) held in Paris in 2015, countries holding over 55% of global emissions set a goal for this century to stop global temperature rise below 2°C compared to the increase made before the start of the industrial revolution. According to the International Energy Agency (IEA 2015), to achieve this target, more than USD 200 billion must be invested in RETs per year in the years to come. However, greenhouse gas emissions continue to grow despite political commitments, and only a few countries have set a longterm strategy to reduce them at the levels set in COP21 (UNEP 2019).

The residential sector and in particular cities are the main contributor to greenhouse gas emissions, accounting for more than 70% of the total human-made CO2 emissions, and the use of renewable energy is the way forward towards a sustainable energy system (IRENA 2016). There are two main directions for cities to achieve energy sustainability through the use of renewable energy for heating, cooling, and powering of appliances. However, it is the cities special conditions that invoke the mix between decentralized micro-scale building and centralized large-scale renewable energy production. In the EU, members of urban policymakers under the energy communities' policy framework are moving towards Remunicipalisation of the local energy markets and strengthening their strategic and political role in their country's energy policy (Gancheva et al. 2018). Given the ambitious goals of the COP21 agreement, the EU members have set up National Energy Climate Plans (NECP) for the sustainability of the EU cities' electricity powering mix between large-scale or micro-generation RETs installed capacity. In 2019, Greece, among other EU members, has set ambitious targets concerning the uptake of micro-generation RETs aiming at 5% of the overall installed capacity in 2030.

Because of the anticipated growing needs on micro-generation RETs, any decisions made for the future planning of the climate and energy policy framework need to build on a robust understanding of their adoption process. With this in mind, the objective of this study is to improve the understanding of the on-grid micro-generation RETs innovation borrowing elements by the Diffusion Innovation Theory (Rogers, 2003), and empirically analyze its adoption process by households in Crete, Greece. According to the DIT theory, innovation is diffused in a market through a five-step process, namely *knowledge*, *persuasion*, *decision*, *implementation,* and *confirmation* (Figure 1.1). In the *knowledge* stage, potential adopters become aware of the innovation characteristics, and that is the time that the decision process begins. The diffusion process of the on-grid micro-generation RETs innovation can not start unless the government regulates the possibility of connecting to the grid. As a next step, in the *decision* stage, potential adopters have evaluated the characteristics of the innovation and decide over adoption, taking into consideration their subjective decision risk. Thus, any implemented policy instrument that alters the characteristics of the innovation may add or reduce the risk of the potential adopters' decision process.

Related literature has opted for the crucial role of governments to change the motivation of potential adopters from just technical or environmental to also financial (Shelly, 2004; Claudy et al. 2011). However, this study argues over the crucial role of governments as a social system unit that can be a change agent responsible for initializing, facilitating, or act as an impediment to the micro-generation RETs innovation diffusion process. For instance, in the case of Greece, only solar photovoltaics can be considered as an on-grid micro-generation technology, although the prompt release and promotion of new micro-generation RETs, is set as a target for residential micro-scale installations (Greece NECP 2019). Greece is an economy that has gone through several economic turbulences, and the Greek governments imposed several pauses of their incentives policy in the micro-generation market once the EU2020 targets were achieved. Despite the changes in the economic situation in Greece, the provision of a consistent, long-lasting, and efficient policy strategy is a prerequisite for the micro-generation market to grow towards a sustainable energy system.

With the use of a stated preference choice experiment (CE) and data gathered from 187 homeowners on the island of Crete, this study analyzes household preferences for different renewable micro-generation technologies. In the arguments set forth in the analysis, a micro-generation RET is considered an innovation whose diffusion depends on its characteristics as exposed by the DIT. Based on this theory, the attribute of compatibility is introduced as a latent construct within an Integrated Choice Latent Variable model (Ben-Akiva et al. 2002b). The results indicate that the innovation compatibility with homeowner's environmental values is an important factor explaining the choice of micro-generation technology and heterogeneity in preferences. Also, the on-grid micro-generation RETs compatibility with homeowners' in-residence energy-saving past experiences, increases their propensity to adopt. Thus, from a policymaker point of view, devising policy instruments raising environmental awareness and the energy-saving attitudes of homeowners can result in reducing the overall implementation cost, as well as in increasing its efficiency.

This study makes a three-fold contribution to the existing literature. The first is by pointing out important information concerning the on-grid renewable energy micro-generation technologies innovation related to the social system and its attributes for the appraisal of their adoption. The second is that it introduces the compatibility attribute as a latent variable in a discrete choice setting in the empirical analysis of Cretan homeowner's preferences for micro-generation technologies and uncovers it as a factor that explains unobserved heterogeneity. Finally, within this study, a novel dataset of Cretan homeowners related to stated preference (SP) discrete choice on micro-generation RETs is created where more research implications on the Crete market can be extracted.

In what follows, the next section places this study within the broad literature studying the adoption of micro-generation RETs. Section 3 provides an overview of the Greek micro-generation RETs energy market in order for the reader to have a clear view of the market under study. Section 4 presents the DIT and analyzes the micro-generation RET Greek market and the innovation itself in light of the DIT framework. Section 5 provides an analysis of the methodology followed both in terms of structuring the SP survey but also analyzing the econometric models used. This section also presents the final administration of the survey and description of the data gathered. Section 6 presents the empirical findings of this study, and Section 7 discusses the findings, identifies possible limitations, and proposes future research directions.

2. Willingness to pay for renewable energy and household heterogeneity: a literature review

There is a rich literature focusing on the valuation of large-scale RE project investments eliciting consumers' willingness to pay (WTP) for green electricity (Bergman et al. 2006; Borchers et al. 2007; Sardianou and Genoudi, 2013; Kontogianni et al. 2013; Yoo and Ready, 2014; Karakaya et al. 2015; Murakami et al. 2015; Sundt et al. 2015; Ntanos et al. 2018 among others). The above scholars' main argument is that electricity consumers are willing to pay a premium for green electricity in order to reduce CO2 emissions. On the other hand, only a small strand of the literature has given attention to evaluating the factors driving the adoption of micro-generation RETs by households. In this direction, two sub-strands of research have emerged. The first sub-strand using stated preference methods deals with the estimation of homeowners' WTP and the identification of the sources of heterogeneity when adopting micro-RETs, namely electricity micro-generation and thermal RE (Scarpa and Willis 2010; Rai and Robinson, 2013; Rouvinen and Matero, 2013; Ruokamo 2016; Su et al. 2018; Dong and Sigrin 2019 among others). Another sub-strand of research, using stated or revealed preference methods, studies the diffusion of micro-RETs adoption and uses the DIT as a means of interpretation (Claudy et al. 2011; Bjørnstad 2012; Schelly 2014; Yamamoto 2015; Franceschinis et al. 2017) or as a mean of forecasting their diffusion rate (Islam 2014).

In the first sub-strand of literature, the pioneering study of Scarpa and Willis (2010) assess WTP for several attributes of different micro-generation alternatives by conducting a choice experiment directed to households in England, Wales, and Scotland. The results of their study show that respondents that are middle-aged and highly educated have a higher propensity to adopt micro RETs, and additionally draw important policy implications since they show that although respondents positively value the adoption of renewable micro-generation systems, this value might not cover the capital costs that adoption would entail. In an attempt to analyze the decision-making process of homeowners in Texas for adopting SPVs, Rai and Sigrin (2013), using a revealed preference study, evaluate the financial merits of deciding either for self-adoption or a lease scenario and find the latter as more effective. The scholars' findings also suggest that, in both case scenarios, adopters do not differ concerning socio-demographic characteristics. In a more recent study, Su et al. 2018, using an unlabeled choice experiment related to the choice among alternative micro-generation systems by Lithuanian homeowners, find respondents to have a high WTP value for the SPV option compared to the other alternatives. Finally, Dong and Sigrin (2019), use the estimated WTP from two choice experiment surveys conducted in different periods and forecast the market demand for residential SPV in the United States.

Within the second sub-strand of the literature, Claudy et al. (2011) empirically analyzed the willingness to pay of Irish households for micro-generation technologies by applying the double bounded Contingent Valuation method. For the four examined technologies, micro-wind, wood pellet boilers, SPVs and solar water heaters, the results in their paper suggest that despite the slow uptake of renewable energy technologies due to the low willingness to pay level, homeowners' purchase or investment decisions are not entirely based on cost-benefit evaluations but are influenced by other factors. These factors are homeowners' beliefs about product characteristics, social norms, and socio-demographic characteristics. Their findings show that perceived compatibility with habits and routines has a positive effect on WTP only for wood pellet boilers. In the same line, Franceschinis et al. (2017) results indicate that the perceived characteristics of the thermal RET system innovation act as factors of taste heterogeneity for homeowners in Italy provinces. Other researchers further investigate the diffusion process of micro-generation RETs using different aspects of the DIT. For instance, Yamamoto (2015), using a survey of SPV adopters in Japan, shows that opinion leaders positively influence the adoption process and the WTP level of other adopter categories.

On the other hand, Islam (2014), goes one step further from the previously described research and, through the innovation diffusion model, investigates whether and when households in Ontario, Canada, are going to adopt SPVs. The author shows that awareness of consumers concerning relative advantage and environmental impact constitutes an essential factor for increasing the probability of adoption. He further argues that policy instruments, such as communication campaigns that enhance technological awareness, may accelerate the diffusion process. The present research belongs to the second sub-strand of the literature, analyzing the factors affecting the diffusion process of micro-generation RETs in the market of Greece, borrowing elements of the DIT. In order to delve into the factors influencing the diffusion process of micro-generation technologies, the next two sections present a thorough discussion of the Greek RE market, followed by an overview of the DIT with a focus on its application to the adoption of micro-generation technologies.

3. Overview of the Greek micro-RETs market

Renewable energy technologies were introduced in the Greek market over 30 years ago in the form of large-scale wind farms (IEA Wind TCP, 2017). Later on, in 2006, investments on large-scale solar photovoltaic (SPV) technologies emerged in the Greek energy market. Although SPVs entered the market after wind, their total cumulative capacity went from below 1Mwp in 2007 to 2445Mwp in 2016 (Kyritsis et al. 2017), reaching the one from wind installations (IEA 2019). This high increase of large-scale SPV capacity compared to the wind is mainly due to the different supporting policy levels. The appearance of the SPV technology in the Greek Market marked the introduction of the legal framework of laws 3468/2006 and 3851/2010 that supported RET electricity generation with the Feed-in-Tariff (FIT) mechanism. The FITs mechanism provides a substantially high guaranteed sales price to RET electricity producers. Within the 3468/2006 law, similar guaranteed FIT levels were set for Wind and Solar electricity generation, where for the former, the price was approximately 0.1€ per KW for capacity power over 50KW and 0.25€ for lower capacities. The 3851/2010 amendment, discriminated in favor of on-grid SPV with the prices of FITs exceeding 0.4€ per KW.

The implemented legal framework resulted in a high large-scale capacity installation rate, which in turn led the country to fulfill its 2020 RE targets. Greece had to meet the 20% target, whereas 20% of energy in gross consumption had to come from renewable energy (3851/2010 law), split into at least 40% for Renewable Energy Sources electricity, 20% for RES-heating and cooling, and 10% for RES-transport. Following the expansion of large-scale RETs, residential micro-generation RETs had become the next target in the Greek energy production map. In this direction, Greece, with the Ministerial Decree OG B1079/4.6.2009, gave incentives to micro-scale rooftop SPVs, whereas high FITs of over 0.5€ per KW were given to residential producers. Until that moment, micro-generation RETs had been introduced in the market as an off-grid appliance allowing residences to be independent of the public utility and at a relatively high installation cost. Through the law mentioned above, residential SPV energy was introduced in the Greek market as an on-grid solution where homeowners could sell their electricity production to the grid administrator. Under this law, households were provided with a more profitable choice, avoiding the significant and costly issue of energy storage faced by the off-grid scenario. The increased FIT implemented to support micro SPVs increased the overall net profit and decreased the payback time of the overall investment.

The implementation of the Ministerial Decree OG B1079/4.6.2009 can be considered as the starting point for the on-grid micro-generation SPVs to set foot in the Greek market and resulted in a substantial increase of micro-generation SPVs installations. The total micro-generation SPVs power installed in Jan 2012 was approximately 121,33 MWh and almost tripled in 2019 (Deddie 2019). However, it is important to note that in 2012, the accumulated applications reached the number of almost fifty thousand, and only one in three has been successfully connected to the grid (Deddie 2019). In addition to the great bureaucratic delays, feed-in-tariffs suffered two successive reductions for new installations, the first by almost 50% following the Ministerial Decree OG B14/11.01.2012 whereas the new FIT for all micro-generation technologies was set at 0.25€/Kw. A second reduction ensued in 2013 through the Ministerial Decree B1103/02.5.2013. Furthermore, in many cases, grid saturation, especially in areas not connected to the central electricity grid, has caused the pause of new installations. At present, the FIT policy mechanism has evolved to net metering (Ministerial Decree 1547B/5.5.2017), where the utility offsets electricity production and consumption. Within net-metering, any possible power difference is compensated with the price that the power utility sells electricity to the building. All in all, following the degradation of policy support mechanisms along with the insecure market environment, the demand for building owners to install micro SPVs continues to remain low relative to the 2030 target set in the country's NECP, of installed power greater than 1Gwh.

Besides the SPV technology, which has been a target of the policy framework in Greece, several micro-generation alternative RETs exist, and although they are not yet supported, they can play an important role in the domestic electricity generation. Micro-wind turbines, available for domestic use under certain wind conditions, can have a substantial impact on domestic generation (Bahaj et al. 2007; Allen et al. 2008). However, the lack of predictability for wind resources in an on-grid configuration is presented as a barrier for its diffusion by Allen et al. (2008) and Eleftheriades et al. (2015). Furthermore, Kyritsis et al. (2017), argues that efficiency and safe operation of the Greek electricity grid can be controlled only from more steady and predictable sources such as thermal and hydropower plants. Another technology that produces both heat and electricity using solar energy is the solar micro CHP (combined heating and power), which through solar heating and the use, for instance, of sterling engines, produces both hot water for heating and electricity. This technology, although not supported by the Greek policy scheme, can produce a clearly greater advantage to its end-users compared to the micro-wind and SPV technologies. The main requirement for exploiting the heating advantage of micro solar CHP is the existence of a waterborne heating system. Similar to the micro-wind, solar micro-CHP technology is not yet supported as an on-grid installation in independent buildings (HACCHP 2015).

In addition to micro-generation, solar energy has also been used by solar thermal systems in order to provide hot water. The solar thermal systems market in Greece has experienced a remarkable increase in the number of installations, and Greece ranks third in cumulative installed capacity per capita in the EU-27 countries, from 2008 to 2017 (CRES 2008; ESTIF 2017). The above indicates that solar thermal systems have become a key product -if not a necessity- within a dynamic and mature open market, although they did not receive any financial support from the Greek government. At this point, it is worth mentioning that the on-grid SPVs diffusion process takes place in a high state-regulated market, while this is not the case for solar thermal water systems. However, the two technologies are similar both in a) installation requirements and b) investment payback period taking as granted the implemented FIT/or net-metering policy mechanisms supporting micro-SPV. Despite this fact, the up-take of SPVs is still at an early stage and did not follow the evolution of the solar thermal systems market. This might be due to the fact that the diffusion of micro-generation RET in Greece is taking place in an unstable environment, whereas although incentives exist, the lack of clear strategy in their implementation may have caused the underdevelopment of the market.

4. Diffusion of Innovation Theory Literature

In this section, we briefly present some of the basic elements of the DIT and borrowing on Roger's (2003) categorization on innovation main characteristics we analyze them in the case of renewable energy micro-generation technologies.

4.1. Definitions and elements

Rogers (2003) defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system." In other words, diffusion consists of four essential elements, namely, innovation, communication, time, and the social system. Following Rogers (2003), we view an innovation as "an idea, practice, or object perceived as new by potential adopters." Innovation can arise either through a new technological breakthrough or through a product or procedure improvement and adjustment to fit in new needs (EU Green Paper on Innovation 1995). In the same line, Garcia and Calantone (2002, p. 112) defines innovation as the evolution of an idea that reaches the market as a product or a service. The diffusion process begins right after the innovation reaches the market, and it is the differences among the innovation characteristics that influence the pace at which it will diffuse. Under the DIT, these characteristics are classified into five elements, namely, a) Relative advantage, b) Compatibility, c) Complexity, d) Trialability, and e) Observability (Rogers 2003). Potential adopters' knowledge and understanding of innovation characteristics mitigate the risks and increase the propensity of adoption, while perceptions are formed subjectively.

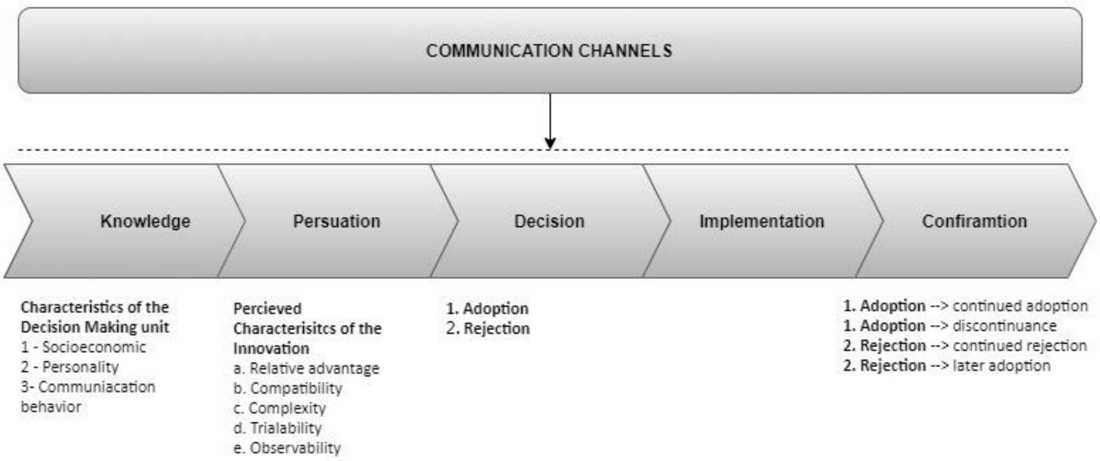


Figure 1.1: A model of stages in the innovation-decision process (Rogers 2003)

According to the DIT theory, innovation is diffused in a market through a five-step process, namely *knowledge*, *persuasion*, *decision*, *implementation*, and *confirmation*. The decision process begins in the *knowledge* stage, where potential adopters become aware of the new technology (see Figure 1.1). Following the awareness stage, potential adopters, who are interested in the innovation, actively seek information and form a favorable or unfavorable attitude towards it. In this stage, individuals take into consideration all surrounding uncertainties and risks regarding the adoption of an innovation. The weighting of all available information to decide for it or against it follows at the *Decision* stage. The last stages are the *Implementation* and *confirmation* stage, and it is when adopters evaluate their decision in terms of continuing using the innovation. In any of the diffusion stages mentioned above, potential consumers can be exposed to different communication messages stemming from either individuals or organizations. The communication process for the diffusion of innovations has many aspects that should be taken into account by researchers. For instance, Claudy et al. (2010) argue that in order for the communication of a micro-generation RET innovation to be efficient, it must be targeted to a specific audience. Eventually, the majority of the information exchanged between the members of a social system is associated with the innovation's characteristics affecting, therefore, potential adopters' perceptions.

Following the previous discussion, one should also take into account the social system within which an innovation is diffused. The social system is defined as a "set of interrelated units that are engaged in joint problem-solving to accomplish a common goal" (Rogers 2003). The social system sets the boundary for the diffusion process, and the latter can be affected by the social norms and the interaction between units of the system. In this direction, one should first define the structure of the social system or, in other words, the units of the social system and its characteristics, their organizational structure, the unit's innovativeness, and the channels through which the individuals communicate with each other, in order to unravel the possible interrelated factors affecting the diffusion process of innovations.

4.2. The innovation of on-grid micro-generation RETS

This study distinguishes on-grid from off-grid micro-generation RETs and discusses how underlying characteristics of the former assist in its diffusion process. The on-grid micro-generation RET, use inverters instead of expensive batteries, and the produced electrical energy is directly exported into the grid (Allen et al. 2008; RETScreen 2004). The decision to adopt on-grid micro-generation RETs results in a) a significant reduction of the overall cost of the installed system, and b) the transformation of homeowners into producers with a financial support advantage. Also, great environmental benefits are gained from reducing local grid energy losses and meeting the grid peak demand periods (RETScreen 2004).

In contrast, in the case of off-grid micro-generation, installers save money from the cost of the electricity consumed. In addition, off-grid micro-generation RETs installations present as merit the full independence of buildings from electric utilities but are subject to potential issues with the continuity of the power supply caused by the degradation and damages of the equipment. Also, in the off-grid case, energy consumption habits must adapt to the power supply or production. Importantly though, one of the main differences between off-grid and on-grid micro-generation RETs is that the latter can only exist when governments provide the legal framework for the produced electricity to be sold to the grid. In this direction, on-grid micro-generation is subject to the implemented energy policy strategy and the level of the underlying support mechanism, which accordingly alter the innovation characteristics.

4.2.1. Innovation characteristics

We continue our discussion by analyzing the characteristics of innovation, that potential adopters become aware of in the *knowledge* and *persuasion* stages of the diffusion process and concentrate on the particular characteristics of the on-grid micro-generation RETs innovation.

Relative Advantage

The DIT defines the *Relative Advantage* characteristic as the individuals' perceived advantages of the innovation, in comparison to the state that it supersedes. In this direction, Tornatzky and Klein (1982) define the relative advantage as economic, social, and or personal benefit. Thus, one can argue that advantages from adopting micro-generation RETs consist of economic motivation (Claudy et al. 2011; Simpson and Clifton, 2017; Wolske et al. 2017), satisfaction over environmental benefits

(Simpson and Clifton, 2017) or any other personal satisfaction. Taking into consideration the impediment of the high installation cost for micro-generation technologies (Balcombe et al. 2013; Claudy et al. 2011, Scarpa et al. 2010; Baskaran et al. 2013; Islam, 2014; Korcaj et al. 2015; Simpson and Clifton, 2017) the policy mechanisms used to promote micro-generation RETs can be considered as an important factor influencing their financial “relative advantage”.

For instance, the FIT scheme undoubtedly contributed to the spread of micro-generation RETs adoption by ensuring lower investment payback periods (Baulcombe et al. 2017; Simson and Clifton, 2017; Schelly, 2014; Scarpa et al. 2010; Claudy et al. 2011). Nevertheless, the issue of the high up-front capital cost is not addressed through FITs but mainly from the implementation of an investment subsidy mechanism (Andor et al. 2015). The FITs mechanism is a production price subsidy that shifts the financial advantages of installation through time rather than once at the beginning. In this case, the perceived relative advantage of the innovation is subject to risk if potential adopters do not trust that the government unit will keep the contracted level of FITs.

Continuing our discussion concerning the relative advantages of micro-generation RETs, Claudy et al. (2011) argue that there are environmental benefits, additionally to the financial ones. The researchers’ findings indicate that the reduction of the environmental impact and the sense of independence from conventional fuels adds up to the magnitude of homeowners’ willingness to pay. Following Homer and Kahle’s (1998) value-attitude-behavior hierarchical model, personal values on the subject of environmental pollution shape the attitude and, consequently, the behavior of individuals towards environmentally friendly technologies. Thus, one could argue that the perceived environmental benefit stems from the compatibility of the innovation with the potential adopter’s environmental values. In this direction, a more thorough discussion about the formation of the perceived environmental advantage follows later on.

Compatibility

Another critical characteristic of innovation, defined form the DIT, is *compatibility*, which, under a broad definition, means that potential adopters’ existing values, past experiences, and needs, come in agreement with the innovation. The literature studying micro-generation RETs adoption identifies mainly two types of compatibility. The first one has to do with potential adopters' past experiences and values towards the environment, and the second one focuses on operational compatibility defined either as changing daily habits or modifications in the residence infrastructure. Tornasky and Klein (1982), firstly identified the latter type of compatibility, along with normative compatibility.

By using operational compatibility in a study of micro-generation RETs adoption, Claudy et al. (2011) find that homeowners are more willing to pay for micro-generation technologies when they perceive them as more compatible with their daily habits and routines. They further argue that significant modification of existing infrastructure when installing micro-generation technologies may result in changes in homeowners' daily practices and routines. In the same line are the findings of Franceschinis et al. (2017), that use a discrete choice experiment methodology to study the effect of thermal RET system's characteristics on the WTP of homeowners in Italian provinces and point out that compatibility concerning fewer perceived changes in habits (past experiences) and less perceived household modifications (operational compatibility) positively influences homeowners WTP. Wolske et al. (2017) studied domestic on-grid SPV adoption in the United States and proposed a theoretical framework based on three theories, namely, the DIT, the theory of planned behavior (Ajzen, 1985), and the value-belief-norm theory (Stern 2000). The researchers introduce the compatibility construct defined as homeowners' riskiness regarding possible household damages resulting from SPV installation. They find that less perceived riskiness increases the on-grid SPVs adoption.

As we have pointed out in section 3, on-grid micro-generation SPVs have the same requirements as a solar thermal installation in terms of space and house modifications. In the same line, this seems to be the case for other micro-generation technologies, such as a vertical axis micro-wind turbine, where the only caveat for the latter installation is that its profitability is subject to the site wind conditions (Allen et al. 2008). Thus, in the case of the on-grid micro-generation RETs, there is no need for significant household modifications or changes in the resident's daily habits. The literature that studies the adoption of solar thermal technologies focuses on compatibility with values and past experiences (Labay and Kinnear, 1981; Berkowitz and Haines, 1980) and not on operational compatibility. Thus, in the present study, our interest focuses on the environmentally friendly aspect of micro-generation RETs and whether they fit potential adopters' values and past experiences.

Indisputably, micro-generation RETs are environmentally friendlier than any other conventional electricity-producing technology. Thus the perceived environmental benefits of installing such a technology is an essential factor of its adoption process. (Schwarz and Ernst, 2009; Balcombe et al. 2013; Rai 2013; Islam et al. 2014; Schelly 2014). Scholars, using behavioral theories such as Theory of planned behavior (Ajzen 1981) and Theory of Reasoned Action (Ajzen and M. Fishbein's 1980), analyze the environmental values of potential adopters as a factor influencing behavior intentions. For instance, Leehner (2011) finds that environmental concern is a significant factor for Dutch households to switch to own-power generation. Also, Korcaj et al. (2015), through the use of a survey of potential adopters, finds that environmental attitudes positively influence intentions of SPV adoption. In the same line, Dharshing (2017) argues that environmental attitudes are the stepping stone for the adoption of SPVs in Germany. Based on these pieces of evidence, and following Homer and Kahle's (1998) value-attitude-behavior hierarchical model, this study upholds that the compatibility of the innovation with a homeowner's environmental values influences the perceived environmental benefit discussed previously and, in turn, the innovation adoption process.

Complexity

Another important characteristic of the diffusion process of the innovation is its c*omplexity* or, in other words, whether it is regarded as simple in understanding and use by potential adopters. Scholars find that complexity in the form of perceptions on required knowledge from potential adopters is negatively associated with the adoption of micro-generation RETs (Claudy et al. 2011; Labay and Kinnear, 1981). The present study argues that complexity can take more forms, and a comprehensive overview of the social system of innovation is a requirement for its identification. The social system in the case of an on-grid micro-generation RETs installation is composed of the following units, homeowners, installers, and the state. Under an introduced policy scheme, the state may subsidize micro-producers with a high electricity price to sell their electricity production into the grid. In order to proceed in with installation, potential adopters must submit a proposal in an open call, and subsequently, the state following its regulatory procedures carries out an audit for each application. Thus, the on-grid micro-generation produces complexity through the time and the paperwork involved in the procedures needed for subsidization (Wolske et al. 2017). Following this approach, we can expect that the risks associated with bureaucratic cost, act as a weight against the adoption of micro-generation RETs.

Trialability

Besides the previously discussed characteristics, potential adopters of micro-generation RETs cannot try (*Trialability*) out the innovation, thus producing more uncertainty in their choice. If they had the chance to try it before adoption, their uncertainty concerning many aspects of the innovation would be lessened. For instance, a software innovation can be easily tried out by potential adopters with a free trial period. Even an off-grid micro-generation system could be used as a small-scale product sample. Although the DIT considers trialability as the perceptions of the members of the social system to try an innovation, literature on the topic of micro-generation technologies uses as a proxy either the desire to try (Wolske et al. 2017) or the ability to obtain information from family, relatives, friends, and acquaintances (Claudy et al. 2011). However, according to the DIT, the latter approach approximates the definition of the observability attribute where others can observe the effect and impact of an innovation.

Observability

Observability, which consists of the fifth attribute of innovations, is defined as “the degree to which the results of an innovation are visible and communicable to others” (Rogers, 2003, p.16). Installations of micro-generation RETs can be easily observed by potential adopters, thus stimulating peer influence. One would expect micro-generation RET installed in the outside of the building, to be diffused more easily among neighbors, friends, and acquaintances (Rogers 2003; Wolske et al. 2017). Additionally, we should note that when referring to the o*bservability* of micro-generation RETs, a question that arises is the extent to which it is confounded with the other attributes of micro-generation RETs. Tornasky and Klein (1982), in their meta-analysis on studies related to innovation characteristics, argue that although *observability* is positively related to the rate of adoption of an innovation, an important aspect of this dimension is related to the other attributes of innovations. In other words, incompatibility, low relative advantage, and the complexity of innovation may be communicated to potential adopters and result in a dampening effect on the diffusion of an innovation.

4.2.2. Time of adoption

Governments' role is to design stable policy schemes inspiring confidence in adopters. Increased financial incentives for the adoption of micro-generation RETs expand the motivation of potential adopters from just technical or environmental incentives to also financial ones (Shelly, 2014) by increasing their perceived relative advantage. The level of support influences the rate of adoption through its effect on the characteristics of the micro-generation RETs innovation. In order to analyze the innovation rate of adoption, the DIT categorizes potential adopters according to the time they adopt an innovation, namely, innovators, early adopters, early majority, late majority, and laggards. The first two categories, innovators and early majority, do not attach great value to the attribute of trialability and observability since they do not have the benefit to learn from others' experiences. On the other hand, the other three categories of adoption groups are significantly affected by observing the behavior of former adopters. In this direction, Moore (2014) identifies a chasm between the first two groups and the early and late majority, whereas the latter groups need more time to understand the relative advantage of the innovation.

Thus, the communication channels of the innovation's social system play a key role for the latter groups to apprehend the relative advantage and the policy mechanisms that influence it and consequently achieve a critical mass. Simpson and Clifton, (2017) survey different groups of adopters of SPVs in Australia and find that early majority's primary motivation was financial benefits, rather than technical and environmental values of the early adopters' group. This finding is further supported by the literature (Baskaran et al. 2013; Leehner et al. 2011), indicating that homeowners with stronger environmental values are classified in the first groups concerning the time of adoption.

Among the groups of early adopters and innovators, DIT recognizes opinion leaders as the individuals that are able to influence other individuals over adoption. For instance, Schelly (2014) interviewed 48 early adopters of solar electricity technologies from the state of Wisconsin and finds that demographic characteristics and the desire to transfer their know-how are common characteristics among this group. Yamamoto (2015), using a survey of adopters of SPVs in Japan, identifies the significant role of opinion leaders for the influence of the decision to adopt. From this point of view, policymakers should devise stable and multi-dimensional policy mechanisms that broaden the pool of adopters. In particular, enhancing the awareness and knowledge of potential adopters on the micro-generation RET, as well as increasing the understanding of the implemented policy mechanisms, can have a pivotal role in the market to reach the required critical mass and take off.

5. Methodology and Data

The island of Crete is located in the southern part of the EU, where solar radiation is among the highest. Even though this means that Crete would be a place where large-scale and micro-generation RETs would have a vital role in the electricity generation map, this does not seem to be the case yet. The island of Crete is not connected to the national electricity grid, and it is highly energy-dependent on conventional polluting energy sources. However, the interconnection of islands and the further promotion of micro-generation renewable technologies constitutes a strategic priority for the Greek NECP for 2030. Still, at present, SPVs is the only available technology for on-grid building micro-generation installation in the Greek electricity market, and potential adopters have gone through several vicissitudes of the national policy strategy. In order to elicit consumers' preferences towards micro-generation technologies, we use a stated preference choice experiment for different on-grid micro-generation RETs.

This section firstly presents the SP methodology, focusing on the selection of attributes, the pilot testing, and the experimental design. We continue with the description of the data gathered from the conducted stated preference questionnaire final administration. Lastly, this section presents the econometric models used, focusing on the Multinomial Logit, the Mixed Logit, and the Integrated Choice Latent Variable model.

5.1. Survey questionnaire

5.1.1. Choice Experiment methodology

Within the class of SP methods, there are two main alternative groups of techniques, namely, choice modeling (CM) and contingent valuation (CV). Contingent valuation concentrates on the valuation of a good or service as a whole, while choice modeling seeks to elicit people's preferences for the individual characteristics or attributes of these goods and services. Therefore, since the relative valuation of the different attributes of the alternative technologies is of interest in the present study, the CM approach was adopted. In a CM questionnaire, the respondents are presented with a set of choice cards where each choice card presents a set of alternatives with different levels of the attributes. The respondent then has to choose an alternative for each choice card, and by varying the levels of the alternative attributes, it is possible to obtain an estimate of how much they value specific attributes.

In order to better define the subject of RETs in Greece, we gathered information on the topic of micro-generation technologies through face to face interviews with local suppliers and from the press. The information gathered in combination with the study of the existing literature indicated the three following on-grid micro-generation alternative technologies: Solar Photovoltaic systems, Wind Generators, and Solar Cogeneration Systems as the most common on-grid micro-generation technologies for adoption by households at the time of the study in the case of developed electricity markets such as the UK, Germany and other countries. At the time the choice experiment was designed, solar cogeneration was an emerging micro-generation and heat-producing system, whereas along with micro-wind, homeowners still cannot install it on-grid. As is customary in choice experiments, we used a fourth alternative, representing the Status Quo allowing respondents to remain within their present situation.

In order to gain some more insights into the types of attributes that are the most relevant to households, we carried four focus groups, consisting of seven to ten individuals each. The participants were homeowners aged between 25 and 65. The focus groups gave prominence to five attribute categories related to the installation and maintenance cost of such technologies, overall benefits, product guaranty, and the lack of trust in the government's commitment to RES. We chose a labeled alternative CE rather than an unlabelled one since labeled choice experiments are less abstract and may increase the validity of the estimated results (Kløjgaard et al. 2012).

5.1.2. Pilot testing and Attributes selection

In the present study, we carried out two rounds of pilot testing of the questionnaire to fine-tune the levels and attributes of our experiment. During this process, we administered the questionnaire to two small samples of twenty and forty-five randomly selected homeowners, respectively, with ages between 25 to 65 years. Respondents were first contacted by phone, and a short interview was conducted in order to check whether they met the basic requirements (Non-adopter[1], Homeowner[2], Aged between 25 and 70, Decision Maker[3], Central Heating[4], Solar Water Heater installation[5]). If the respondents met the requirements, we arranged an in-person interview. The selected attributes for the present study are installation cost, annual savings from the electricity sold to the power utility, heating bill savings, maintenance cost, years of guaranty, aesthetics, and the time required for the grid connection approval. Table 1.1 below presents the attributes as mentioned above together with their levels.

The installation cost and the annual savings attribute levels were formed for the installation of one kWh of micro-generation RETs alternatives. At the time of the survey, the roof-top installations of SPVs connected to the grid were promoted with a fixed FIT price of 0.55 euro per kWh. Thus, we simulated real scenarios of the annual saving attribute regarding three different levels of prices per installed kWh. The levels are computed as the product of the electricity production and the electricity price levels, where for the highest level, we used the FIT level mentioned above and for the lowest the actual electricity market price, representing the net-metering policy scheme. In each case, the level of electricity production was estimated with information taken for local wind and solar conditions. In addition to the above, we have set four different installation cost scenarios according to the current market cost for installing a micro-generation SPV and Wind technology. As far as the cost of solar cogeneration is

[1] Respondents must not have already installed a micro-generation SPV in their residences.
[2] Not all homeowners have the ability to install RES technologies since the installation most of the times must take place at the roof of a building might be communal space, as for example in the case of a block of apartments. Homeowners that cannot install any of the alternatives due to this restriction were excluded from the sample.
[3] It is important for our research to record the views and choices of respondents who participate in the decision making so as to reduce bias in our estimation results.
[4] Without Central Heating - water radiators, Solar Co-generation system is not able to provide heat for the residence, thus limiting this technology effectiveness. For this reason homeowners without central heating were excluded.
[5] Solar water heater installation is a prerequisite for new homeowners installing a RES technology (i.e. Solar Photovoltaic) in order to be price subsidized.

concerned, the hypothetical values used were based on quotations taken from foreign enterprises selling it, and by also adding the extra cost of installation. With the scenarios mentioned above, the investment payback periods reproduced in the CE spans from 4.5 years under the increased applied FIT mechanism of 0.55 per kWh, to 10 years, for the net-metering scheme.

Table 1.1: Attributes and Attribute levels – final administration

Solar PV and Wind micro-generation alternatives				
Attribute	Level 1	Level 2	Level 3	Level 4
Installation Cost	2.500 €	3.250 €	4.000 €	4.750 €
Annual savings	400 €	500 €	600 €	
Heating Savings				
Maintenance Cost (Effects coded)	50 € (base level)	100 €		
Guaranty years	2 years	6 years	10 years	
Aesthetics (Effects Coded)	Unstylish (base level)	Neutral	Stylish	
Time required for approval	3 months	9 months	15 months	
Solar Co-generation micro-generation alternatives				
Attribute	Level 1	Level 2	Level 3	Level 4
Installation Cost	10.000 €	11.500 €	13.000 €	14.500 €
Annual savings	400 €	500 €	600 €	
Heating Savings	30%	50%	70%	
Maintenance Cost (Effects coded)	50 € (base level)	100 €		
Guaranty years	2 years	6 years	10 years	
Aesthetics (Effects Coded)	Unstylish (base level)	Neutral	Stylish	
Time required for approval	3 months	9 months	15 months	

In the case of Solar Cogeneration, the installer, in addition to selling their production to the grid, has an additional benefit that comes from the reduction of her annual residence heating bill. The levels chosen for this attribute, are reported as percentages of their previous heating bill. The maintenance cost is chosen to be the same amongst the three alternatives and not more than 20 percent of the annual savings. In the case of guaranty, we selected three values spanning from two to ten years that represented the market conditions at the time of the implementation of the choice experiment. Concerning the time required for issuing a permit for installing micro-generation RET, the present research took as a proxy the time needed for Solar Photovoltaic electricity production permit to be issued, which at that time was approximately nine months. Two additional values were selected, one lower and one greater in order to study whether the complexity induced by the simplification or the deterioration of bureaucratic procedures affects the choice to adopt micro-generation RETs. Finally, we introduced the aesthetics with three levels where respondents, based on example images, were asked to imagine how their residence would look like in each situation of unstylish, neutral, and stylish intervention. We chose all attributes to be independent of one another (Train 2000), and the number of levels, except the up-front installation cost, are three or less to reduce complexity in our experiment (Louviere et al. 2000). Furthermore, in order to enhance the decision-maker understanding of the choice process, we informed them of taking into consideration the variability of attributes levels among the different choice tasks and further rank the attributes under the priority given in each choice situation (Louviere et al. 2000 p.275).

5.1.3. Experimental Design

Having identified the alternatives, attributes, and their levels, we proceeded with the design of the choice experiment. The literature on choice experiments identifies mainly two types of designs, namely, orthogonal and efficient designs (Pearmain et al. 1991; Louviere, Hensher and Swait 2000; Ferrini and Scarpa 2007; Rose and Bliemer 2008; Bliemer, Rose and Hensher 2008). Efficient designs optimize the design to reduce standard errors with or without using former knowledge of the parameters (priors). It is also the case that the bulk of the recent literature using choice experiments has opted for efficient designs, mainly for two reasons. The first one is that although the property of orthogonality avoids multicollinearity and minimizes the variance-covariance matrix of the estimated model parameters in linear models (Rose and Bliemer, 2009), it is not always preserved when the estimation of the actual model takes place (Rose and Bliemer, 2009). The second one arises from the fact that discrete choice models, which are used in the present study, are not linear.

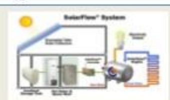
Respondents in the present survey were called to trade-off six attributes for two alternatives and seven attributes for the third alternative, with different levels each as it is shown in Table 1.1. For efficiency reasons, only a fraction of all possible treatment combinations is selected either based on the property of orthogonality or by minimizing the standard error for the estimated model (D-efficiency). The property of orthogonality requires all estimate effects to be uncorrelated and loses statistical power for unbalanced designs such as the one used in the present study (Louviere et al. 2000). On the other hand, within the D-efficient designs, the most commonly used measure of efficiency criterion is the D-error, which is based on the determinant of the asymptotic variance-covariance matrix. Different choices for D-error are the Dz-error when no information is available about the values or signs of the parameters and the Dp-error when we have a good guess about the values of the parameters. Taking into account the above, in the present study, we implemented a D_z-error efficient design for a Multinomial Logit model. Thus, 12 different choice combinations subject to non-dominance were produced. Each choice set contained all four alternatives, and each respondent was called to answer six choice cards. The implementation of the pilot study produced priors that led to the construction of a new D_p error blocked efficient design, a sample of which is presented in Figure 1.2. We produced the design using Ngene – ChoiceMetrics, a specialized software in generating experimental designs.

CHOICE CARD

Taking into account

- **The level of your financial restrictions and**
- **the attributes of the aforementioned environmental friendly micro-generation Renewable Energy Technologies**

Would you proceed to installing one of the below systems (using your own savings or borrowing money) or would you choose none of the systems and remain at your present situation? Please choose one option.

	 ***Solar photovoltaics***	 ***Micro-wind***	 ***Solar Cogeneration***	***None***
Initial capital cost	4.750 e	2.500 e	13.000 e	
Annual revenues from electricity sold	600 e	400 e	400 e	
Heat savings	-	-	50%	
Annual maintenance cost	50 e	100 e	100 e	
Guaranty time	2 years	10 years	2 years	
Aesthetics	Unstylish	Neutral	Stylish	
Time for issuing a permit	3 months	15 months	9 months	
Choose only one option	○	○	○	○

Which attributes did you use for your choice? Please rate them in order of priority

	Initial capital cost		**Guaranty time**
	Annual profit from electricity sold		**Aesthetics**
	Heat savings		**Time for issuing a permit**
	Annual maintenance cost		**Other? Please Mention**

Figure 1.2: Choice card example

5.2. Final Administration and Data Description

5.2.1. Final Administration

In addition to the choice experiment section, the questionnaire included three additional parts related to a) the household's living space and energy operational information, b) the respondents' environmental attitude and behavior, and c) the socioeconomic and demographic information of homeowners. The final survey took place from the winter of 2012 until the spring of 2013, in Heraklion and Rethymnon administrative districts for a randomly selected stratified sample of these cities population. We conducted the survey in two stages. In the first stage, we contacted respondents through either phone or in-person interviews and checked whether they met the requirements, as discussed previously in section 5.1.2. In the second stage, we called respondents to fill in an internet-based or hard copy questionnaire. As far as the internet-based questionnaire is concerned, we ensured respondents unique answers through creating personal email tokens. Altogether, with a response rate of 51%, approximately 600 persons were reached to participate in the survey, and only 236 of them met the criteria as mentioned above. Forty-nine questionnaires were dropped out of the sample since important information concerning their choices and demographic data were missing, so we were left with 187 valid questionnaires with a total of 1122 observations.

5.2.2. Data Description

Table 1.2 shows the on-grid micro-generation choice distribution among alternatives for the 1122 choice situations, and Table 1.3 presents the frequency of choices over the six choice cards for the 187 respondents. The status quo (SQ) alternative is the most frequently chosen, followed by SPV, Wind, and Solar Cogeneration (see Table 1.2). This comes in agreement with the current situation in the Greek energy market, where only micro SPVs are available as on-grid installations. A legitimate concern about our data is that it could be subject to selection bias as it could be the case that those respondents that are more interested in the subject of RET micro-generation are also more likely to participate in the survey (Banfi et al. 2008). However, the frequent selection of the status quo alternative, namely 24,6% of respondents chooses SQ in all choice cards, in a choice experiment where there is high variation among the alternatives' attributes can be used as an argument against it.

Table 1.2: Micro-generation choice distribution

Variable	Frequency	Percentage
Solar Photovoltaic	327	29,15%
Wind Generator	239	21,30%
Solar Cogenaration	121	10,78%
Status quo	435	38,77%

One would expect the choice to depend on the levels of the attributes, but in some cases, respondents show their preference over specific alternatives. In particular, over three-quarters of the respondents choose between one or two alternatives. One out of four respondents selects only the SQ alternative, 18% show their preference over only SPVs and Wind alternatives, and another 10% only select either an SPV technology or the SQ alternative. In total, more than two-thirds of the respondents show their preference over the most known alternatives of SPVs and wind technologies or staying at their state level (SQ). A smaller percentage of around 6% shows its preference for the Solar Cogeneration alternative or the SQ alternative, and only 13% choose among all the three adoption options. As expected, SPV and wind alternatives confirm their reputation as a known on-grid and off-grid, respectively, installed technologies.

In order to further analyze respondent’s choice, we compare how often they select the adoption option according to their education level (see Table 1.4) and according to their family income (see Table 1.5). The higher the education level of respondents, the more they select the adoption option. Also, more than half of individuals with an educational level higher than a high school degree selected more than four adoption choices on the provided choice cards. Individuals with family incomes higher than 10,000 euros tend to select more the adoption option. It is worth noting that more than half of the families with an income level between 10,000 and 30,000 euros state that they would adopt a micro-generation RET. Taking into consideration the fact that the 1 KW installation cost lies between 2,500 and 4,750 euros for SPV and wind and 10,000 and 14,500 euros for solar cogeneration, we can argue that almost 55% of the families with income level in between 10,000 and 30,000 euros are willing to spend a rather high percentage of their annual family income to adopt a micro-generation RET in their residence.

Table 1.3: Frequency of respondents choice-combinations

Solar Photovoltaic	Wind Generator	Solar Cogeneration	Status quo	Frequency	Percentage
■	■	■	■	7	3.74%
■	■	■		17	9.09%
■	■		■	23	12.30%
■		■	■	4	2.14%
	■	■	■	3	1.60%
■		■		4	2.14%
	■	■		1	0.53%
■	■			33	17.65%
■			■	18	9.63%
	■		■	**3**	1.60%
		■	■	**8**	4.28%
■				**7**	3.74%
	■			**4**	2.14%
		■		**4**	2.14%
			■	46	24.60%

Table 1.4: Choice on micro–generation RETs and Education level

Adoption frequency	< high school	high school	>= University degrees
0 times	37,50%	26,92%	20,43%
1-2 times	18,75%	7,69%	8,60%
3-4 times	25,00%	8,97%	12,90%
5-6 times	18,75%	56,41%	58,06%

The descriptive statistics of the explanatory variables used in the study are presented in Table 1.6. The table presents the variables in three parts. The first part consists of the socio-economic status of individuals, where 79% of the respondents are married, 53% are males, and the average age of the respondents is around 45 years old. Moreover, the family income seems to be concentrated in the levels of 10,000 to 30,000 euros, containing more than 60% of the total sample. Also, the education level of 70% of the participants is High school and University degree holders. The second part consists of information regarding the homeowner’s residences, where the average residence size, owned by the survey participants, is 114 square meters, and the average annual electricity and heating bill is 1.150 and 908 euros, respectively.

The third part presents individual characteristics that can be related to important aspects of the DIT. A large number of our sample respondents, around 55%, have previously searched for information over on-grid micro-generation RET installation and did not proceed with adoption. This means that 55% of respondents have already reached the first three stages of the adoption process, namely, Knowledge, Persuasion, and Decision, and decided against adoption. Analyzing the communication channels through which these respondents acquired knowledge on the innovation, around 43% took information from the press or the internet. Moreover, around 34% have been informed by relatives or acquaintances, and only 23% have taken advice from experts. Also, it is important to notice that, at the time that the survey took place, 75% of our sample homeowners reported that they have seen (observability) an on-grid micro-generation RETs being installed on residences of relatives, friends, or acquaintances.

Table 1.5: Choice of on-grid micro-generation RETs and family income levels

Adoption frequency	Less than 10.000€	10.000-20.000€	20.000-30.000€	>30.000€
0 times	41,18%	28,18%	14,00%	10,00%
1-2 times	5,88%	8,18%	8,00%	30,00%
3-4 times	11,76%	9,09%	18,00%	20,00%
5-6 times	41,18%	54,55%	60,00%	40,00%

Table 1.6: Descriptive statistics

Variable	Mean	Std.Dev	Minimum	Maximum	N.Cases	Missing
		Demographics				
Married						
0: no married	0.7914	0.4065	0	1	39	0
1: married					148	
Gender						
0: woman	0.5294	0.4994	0	1	88	0
1: man					99	
Age	43.85	11.94	25	65	187	0
Education Level						
Classes:						
1: illiterate						
2: Elementary School					16	
3: Secondary School	4.3476	1.0812	2	6	18	0
4: High School					60	
5: University degree					71	
6: Master or higher					22	

Variable	Mean	Std.Dev	Minimum	Maximum	N.Cases	Missing
Family Inc						
Classes:						
1: 0 to 10.000					17	
2: 10.001 to 20.000	3.0107	1.2755	1	6	57	0
3: 20.001 to 30.000					53	
4: 30.001 to 40.000					37	
5: 40.001 to 50.000					13	
6: > 50.000					10	
	Residence inforamtion					
Annual Electrical Bill	1.1505	0.6288	0	3000	187	1
Annual Thermal Bill	0.9080	0.6600	0	3500	187	0
Residence Square Meters	114.69	35.19	45	256	187	0
Residence age						
1: <1950					7	
2:1950-1975	3.1390	*0.7330*	1	4	19	0
3: 1975-1999					106	
4: >2000					60	
	DIT Profiling					
Homeowners previously searched for RETs					187	
0: No	0.5561	0.4971	0	1	83	0
1: yes					104	
Known					35	
MME / Internet					45	
Specialist					24	
Micro-generation RETs observability	0.7433	0.4370	0	1	187	0
Maintenance of heating and cooling systems						
1:never					1.60%	
2:seldom	4.1711	0.8916	1	5	2.67%	0
3:often					14.97%	
4:almost always					38.50%	
5:always					42.25%	
Efficient use of excessive energy (temperature)						
1:never					0.00%	
2:seldom	4.1230	1.0142	1	5	1.07%	0
3:often					6.95%	
4:almost always					31.55%	
5:always					60.43%	
Replacement of home appliances with more environmentally friendly						
1:never					0.00%	
2:seldom	4.5027	0.7270	2	5	1.07%	0
3:often					10.70%	
4:almost always					25.13%	
5:always					63.10%	
Efficient use of excessive energy (lights)						
1:never					0.00%	
2:seldom					1.07%	
3:often	4.6203	0.6545	2	5	6.42%	0
4:almost always					21.93%	
5:always					70.59%	
Recycling frequency						
1:never					2.14%	
2:seldom	4.3262	1.0001	1	5	5.88%	0
3:often					8.56%	
4:almost always					24.06%	
5:always					59.36%	

Variable	Mean	Std.Dev	Minimum	Maximum	N.Cases	Missing
Interested for the planet pollution 1:no 2: Slightly 3:Fairly 4: important 5: very important	4.3369	0.7595	1	5	1.07% 0.53% 9.63% 41.18% 47.59%	0
Interested for the pollution of air and water in their city 1:no 2: Slightly 3:Fairly 4: important 5: very important	4.5134	0.6734	2	5	0.00% 1.07% 6.95% 31.55% 60.43%	0
Interested in garbage management 1:no 2: Slightly 3:Fairly 4: important 5: very important	4.2246	0.8977	1	5	1.60% 3.74% 10.70% 38.50% 45.45%	0

Aiming at capturing the compatibility of respondent's environmental values with the innovation, we further measure their environmental attitudes and energy-efficient usage past experiences (see Table 1.6). The energy-usage past experiences behavioral questions were focused on how often homeowners carry out actions to reduce the energy they use through either buying environmentally friendly home-appliances or actions towards the efficient use of energy in their residences. In particular, within the latter, the questions included are related to the proper and regular maintenance of their heating and cooling systems, efficient regulation of their house temperature, and the efficient use of lights. In order to measure the environmental attitudes of the respondents, we asked questions regarding their interest in the pollution of the planet, water, their city, and the garbage management in the area of their residence. The answers were structured with a Likert scale from 1 (never or not important) to 5 (always or very important). It is worth noting that more than 80% of the respondents always or almost always implement actions to reduce their in-residence energy consumption for appliances such as lights and heating and cooling systems. While 88% of the respondents always or almost always replace their house appliances with environmentally friendly ones. Recycling is an important habit for more than 80% of the respondents, and almost 90% state that the planet pollution is important to them. In the same line, more than 85% of the respondents state that garbage management in their city is an important priority for them.

5.3. Econometric Models

This section describes the different parametric modeling approaches used in the present research for analyzing the preferences of Cretan homeowners. In particular, we analyze the Multinomial Logit and the Mixed Logit models along with the extended Integrated Choice Latent Variable Multinomial Logit model, which allows the introduction of latent attitudinal variables. However, we firstly model an individual's decision-making process under the Random Utility Theory (RUT) (Marschak, 1960; Manski, 1977), that the above models are built upon.

5.3.1. Random Utility Theory (RUT)

A decision-maker (individual) must decide among a finite set of mutually exclusive and exhaustive alternatives and enjoy an overall utility that depends both on the alternatives and on their characteristics. Thus, if we define X_{ij} as a vector of the characteristics of alternative j, as faced by individual i and Z_i a vector of a person's i characteristics, then we can write the utility function of the decision-maker as

$$U_{ij} = U\left(X_{ij}, Z_i\right),\ j = 1, \cdots, J; i = 1, \cdots, n, \tag{1.1}$$

where J is the set mutually exclusive alternatives. Thus individual i will choose the alternative that provides the highest utility. Or in other words, alternative j will be chosen if

$$U_{ij} > U_{ik}, \text{ for all } k \text{ in } J, \tag{1.2}$$

or $U\left(X_{ij}, Z_i\right) > U(X_{ik}, Z_i)$, for all k in J. (1.3)

Note that the choice set J could be individual specific, but for the present application, all individuals face the same choice set. If we assume a specific function V of respondents' characteristics and alternative's attributes, Eq. (1.1), can be written as follows:

$$U\left(X_{ij}, Z_i\right) = V\left(X_{ij}, Z_i, \beta\right) + e_{ij}, \tag{1.4}$$

where $V()$, denotes the observed part of the utility, β is a vector of unknown parameters and e_{ji}, the random or unobserved component of the utility function. Then, the probability that individual i will choose alternative j as can be written follows:

$$P_{ij} = Prob(U_{ij} > U_{ik}, \forall \ k \neq j), \tag{1.5}$$

$$P_{ij} = Prob(V_{ij} + e_{ij} > V_{ik} + e_{ik}, \forall k \neq j), \tag{1.6}$$

$$P_{ij} = Prob(e_{ij} - e_{ik} > V_{ik} - V_{ij}, \forall \ k \neq j). \tag{1.7}$$

The estimation of the unknown parameters β, is what follows in the next sub-sections.

5.3.2. The Multinomial Logit Model

A base model for the estimation of discrete choice experiments is the Multinomial Logit models, which assumes that the error term in Eq. (1.1), e_{ij} follows a type I extreme value distribution, and it is independently and identically distributed. Then the density of each ε_{ij} can be written as

$$f(\varepsilon_{ij}) = exp(-\varepsilon_{ij}) \exp(-\exp(-\varepsilon_{ij})), \tag{1.8}$$

and its cumulative distribution as

$$F(\varepsilon_{ij}) = \exp(-\exp(-\varepsilon_{ij})). \qquad \text{Have} \tag{1.9}$$

Inserting the extreme value distribution and dropping the individual index for simplicity, then the probability of choosing alternative j in Eq. (1.7) becomes:

$$P_j = \frac{\exp(V_j)}{\sum_{k=1}^{J} \exp(V_k)}. \tag{1.10}$$

Then the ratio of the choice probabilities for two alternatives j and k can be written

$$\frac{P_j}{P_k} = \frac{\frac{exp(V_j)}{\sum_{k=1}^{J} exp(V_k)}}{\frac{exp(V_k)}{\sum_{k=1}^{J} exp(V_k)}} = \frac{exp(V_j)}{exp(V_k)} = exp(V_j) - exp(V_k), \tag{1.11}$$

where the ratio of the two probabilities does not depend on the observed utility of the characteristics of other alternatives. This property is called Independence of Irrelevant Alternatives Property (IIA) (Luce, 1959; Train, 2000), which is a quite restrictive condition to impose on the behavior of consumers and might fail to hold in many real choice situations. The unknown parameters β can then be estimated by maximum likelihood methods. Noting that the true probability of a person to choose an alternative is

$$\prod_{i\epsilon(1,\dots J)} P_{ij}^{y_{ij}}\ , \tag{1.12}$$

where y_{ij} is one if individual i chose alternative j, and zero otherwise. Then, the likelihood function L for a random sample is given by:

$$L = \prod_{i\epsilon(1,\dots.n)} \prod_{j\epsilon(1,\dots.J)} P_{ij}^{y_{ij}} = \prod_i \prod_j P_{ij}^{y_{ij}}, \tag{1.13}$$

Finally, the log-likelihood function can be written:

$$LL(\beta) = \sum_{i\epsilon n} \sum_{j\epsilon J} y_{ij}\ ln\ P_{ij}, \tag{1.14}$$

The main limitation of the MNL model arises from the IIA property (see Eq. (1.11)). If the IIA holds the cross elasticities for each alternative are equal (Hausman 1978). Three tests have been developed in the literature to test the IIA property (McFadden et al. 1977; Small and Hsiao, 1985; Hausman and McFadden, 1984) and all of these tests compare estimates from the restricted and unrestricted models where one of the alternatives is excluded. Another limitation of the MNL model is that although it can capture taste variations within a system of observed variables, random tastes among individuals cannot be handled. The MNL model can incorporate a systematic variation of tastes among the individuals; however, when this variation has a random component, the iid assumption does not hold (Train, 2003). A model that relaxes IIA and allows estimated parameters to vary among individuals is the Mixed Logit (MXL) (McFadden & Train, 2000) model that is analyzed in the next subsection. Under the existence of an unobserved random taste, the MNL may capture the average tastes, but it cannot capture the heterogeneity of the tastes.

5.3.3. Mixed Logit Model

The Mixed Logit model (MXL) (Train, 2003) can overcome the limitations mentioned above, by allowing substitution and correlation among alternatives and simultaneously allowing for individual random taste variation. A desirable property of the MXL model is that it comes from RUT. In the MXL model, the error term is assumed to be iid, and the coefficients in the vector β, vary over decision-makers in the population with density $f(\beta)$, therefore allowing for the presence of individual heterogeneity. If we assume that a) the coefficients of β, vary over decision-makers in the population with density $f(\beta)$, and b) that the decision-maker knows the values of his β_i and ε_{ij}, and c) for all J alternatives, the rule for the choice decision follows Eq.(1.4), the probability of individual i choosing alternative j is given by:

$$P_{ij} = \int \frac{exp(\beta\prime X_{ij})}{\sum_{j=1}^{J} exp(\beta' X_{ik})} f(\beta) d(\beta), \tag{1.15}$$

Models estimated in the above form are called mixed logit models. In order to estimate β_i the distribution of the parameters must be specified. If a normal distribution is assumed for β_i, Eq. (1.15) now becomes:

$$P_{ij} = \int \frac{exp(\beta' X_{ij})}{\sum_{k=1}^{J} exp(\beta' X_{ik})} \varphi(\beta|b, W) d(\beta), \tag{1.16}$$

where $\varphi(\beta|b, W)$ is the normal density with mean b and covariance matrix W. Note that one disadvantage of using a normal distribution for the parameters is that it can give rise to very large estimates of some of the coefficients since it is not bounded. The unknown parameters in β and W can be then estimated by maximum simulated likelihood methods. The reader is advised to see McFadden and Train (2000), for more information on the estimation of a mixed logit model using the maximum simulated likelihood method.

Although the MXL is a state of the art extension of the MNL overcoming the IIA restrictions (Train 2000) and incorporating heterogeneity of preferences, it does not point out the source of this heterogeneity. However, the present study borrowing latent element characteristics of the DIT aims at shedding light on the factors affecting the heterogeneity of choices on on-grid micro-generation RETs. In this direction, the discrete choice modeling literature proposes two approaches. The first is to follow a two-step sequential process where the estimated latent variables are included in the specification of the models (Ben-Akiva et al. 2002b; Ashok et al. 2002) and the second is to integrate a structural equation model (SEM) in a discrete choice model (Ben-Akiva et al. 2002b; Temme et al. 2008; Hess and Behhary-Borg 2011). In any of the two cases, extending traditional choice models to incorporate latent factors proposed from behavioral or innovation theories can shed light on important aspects of consumer's choice and on interpretation (Ben-Akiva et al. 2002a). Under the two-step sequential process of estimating separate models of SEM and choice, the estimated latent variables are introduced directly in the utility of the discrete choice model. However, such an estimator is not statistically efficient, and it is preferable to use the second approach of the full information estimators (Ben-Akiva et al. 2002a; Temme et al. 2008; Bierlaire et al. 2009). Thus, in the next subsection, we analyze the case of the full information model, namely the Integrated Choice Latent Variable model.

5.3.4. Integrated Choice Latent Variable (ICLV) Model

The ICLV MNL model merges the classic MNL choice model with structural equation modeling (SEM) for latent variables. Thus, if we add up a vector of latent variables η's to Eq. (1.4), the utility function becomes:

$$U(X_{ij}, Z_i) = V(X_{ij}, Z_i, \eta_i; \beta) + e_{ij} \tag{1.17}$$

where X_{ij} is a vector of alternative j's characteristics as faced by person i, and Z_i the vector of person's i characteristics, and we regard η_i as a vector of the person's i latent characteristics. At this point, it is useful for the reader to distinguish two ways that the latent variables vector η_i enters the above equation. It can be either introduced directly into the utility function or as a coefficient shifter for some β. For instance, an individual that perceives a micro-generation RET as more compatible with their values and past experiences might be less affected by increases in the installation cost.

If we assume that the e_{ij} is independently, identically distributed (i.i.d) extreme value, the probability of respondents to choose alternative j, within the MNL model is as follows:

$$P(y_{ij} = 1 | X_{ij}, Z_i, \eta_i, \beta) = \frac{exp(V(x_{ij}, Z_i, \eta_{ij}, \beta))}{\sum_{j=1}^{J} exp(V(x_{ij}, Z_{ij}, \eta_i, \beta))}, \tag{1.18}$$

The latent variables in vector η_i are not observed and are a function of explanatory variables X_i. A simple structural model for the latent variable is as follows:

$$\eta_i = \Gamma x_i + \zeta_i, \tag{1.19}$$

where Γ is a vector of unknown coefficients of the observed variables x_i, and ζ_i is the i.i.d normal random term. Since η_i is not observed, under a multiple indicator multiple cause (MIMIC) model, the identification of Eq. (1.19) requires that we obtain information about the latent variable from multiple indicators, specifying their relationship in the measurement part of the structural equation model (Ben-Akiva et al.

2002a; Temme et al. 2008; Bierlaire et al. 2009). In the simplest linear case the indicator measurement equations can be written as

$$I_i^* = \Lambda\eta_i + \varepsilon_i, \tag{20}$$

where, I_i^* is a vector of indicators, Λ is a matrix of factor loadings and ε_i is a vector of measurement errors which are i.i.d. multivariate normal. The additional indicators are useful to overcome identification problems but also for the efficiency of the SEM estimation (Ben-Akiva et al. 1999). One should, however, distinguish among continuous and discrete indicators when estimating an ICLV model. When indicators are discrete, as it is the present study case since we use Likert scale variables, the probability of a given response is given by an ordered probit model as follows:

$$P(I_i = j_l) = P(\tau_{l-1} \leq I_i^* \leq \tau_l) = P(\tau_{l-1} \leq \Lambda\eta_i + \varepsilon_i, \leq \tau_l) =$$

$$P(\tau_{l-1} - \Lambda\eta_i \leq \varepsilon_i \leq \tau_l - \Lambda\eta_i) = \Phi(\tau_l - \Lambda\eta_i) - \Phi(\tau_{l-1} - \Lambda\eta_i) \tag{1.21}$$

where I_i is an ordered discrete variable taking values $j_1,\ldots,j_M$, when the indicator takes M distinct values, τ_l are the cut-off points which are parameters to be estimated with $\tau_0 = -\infty$ and $\tau_M = \infty$, and Φ the normal conditional density function.

Addressing the identification issue of Eq. (1.19), with the use of Eq. (1.20) and Eq. (1.21), and by assuming that the random errors of the above equations are independent, the probability of observing a specific alternative being chosen is given by the following multidimensional integral:

$$P(y_j = 1 | x, \theta) = \int P(y_j = 1 | x, z, \eta, \beta) \times f_I(I|\eta; \Lambda, \Sigma_\varepsilon) f_\eta(\eta | x; \Gamma, \Sigma_\zeta) d\eta, \tag{1.22}$$

where **θ** represents the model parameters, $P(.)$ is the probability function of observing the choice of a specific alternative conditional on the latent variable, $f_I(I|\eta, \Lambda, \Sigma_\varepsilon)$ is the density function of the latent variable indicators related to the measurement model and $f_\eta(\eta | x; \Gamma, \Sigma_\zeta)$ is the density function of the latent variable that corresponds to the structural model. Finally, Σ_ε and Σ_ζ are the covariance matrices of the errors and the individual subindex has been dropped for simplicity. Thus, using full information maximum likelihood techniques for efficiently estimating θ, we obtain the likelihood function for a particular individual,

$$L = \prod_j P\left(Y_j = 1, I\middle|x, \theta\right)^{Y_j} = \int \prod_j P\left(Y_j = 1\middle|x, z, \eta, \beta, \Sigma_e\right) \times$$
$$f_I(I|\eta; \Lambda, \Sigma_\varepsilon)\, f_\eta\left(\eta\middle|x; \Gamma, \Sigma_\zeta\right) d\eta, \tag{1.23}$$

If more than one latent variable is used, random numerical integration is not as efficient as Monte-Carlo integration for predicting latent estimators (Bierlaire 2018). Monte Carlo integration involves simulating chosen probabilities in a large number of cases and obtain the maximum likelihood, whereas, in a multidimensional integral, the use of Monte Carlo simulation is more efficient (Judd 1998).

6. Model specification and estimation results

In this study, we introduce two latent factors in an ICLV MNL and compare its results with the MNL and the MXL model. The ICLV model incorporates two sub-models, namely the discrete choice model and the latent structural equation model, as shown in Figure 1.3. Rectangular boxes represent observed variables such as attributes, demographics, attitudinal and behavioral indicators, and choices, and ovals represent the latent variables such as the utility and the attitudinal variables. The direction of the arrows shows the dependence between latent variables, indicators, other factors, and demographics.

The structural equation model links the latent variable with the indicators, the demographic, and other factors. In order to decide the indicators used in the SEM model, we performed an exploratory factor analysis (see Table 1.7). The results of the explanatory factor analysis indicate the existence of two latent variables, specifying the homeowners' environmental values (Factor 1) and their past experiences on electricity energy-saving (Factor 2). The indicators for Factor 1 are the homeowners' recycling attitudes, their interest in waste management, and the planet and city pollution. Factor 2 indicators are efficient energy use actions such as management of lights, thermal appliances, maintenance of heating and cooling systems, and the replacement of home appliances with more environmentally friendly ones.

The results of the factor analysis indicate that there are two distinct latent constructs, one is environmental, and the other is financial. We posit that these two latent constructs affect the utility derived from the different alternatives and, therefore, the choice of different technologies. Micro-generation RETs inextricably contribute to the conservation of the environment (Schwarz and Ernst, 2008; Balcombe et al. 2013; Rai 2013; Islam et al. 2014; Schelly 2014; Korcaj et al. 2015; Dharsing 2017) since less CO_2 emissions are produced from their use. Although there is a dispute between scholars about the negative impacts of large-scale RETs on damaging or consuming natural resources (Hadian and Madani, 2015; Burkhard et al. 2012, Helfenstein and Kienast, 2014 among others), micro-generation RETs installed in buildings do not pose similar issues. In addition to the micro-generation RETs environmental aspect, homeowners may install them only due to overall savings (Simpson and Clifton, 2017; Baskaran et al. 2013; Leehner et al. 2011). For instance, the same thing happens with economy light bulbs or solar water heaters, where some people use them not only for their environmental friendliness but because they perceive there is an economic gain.

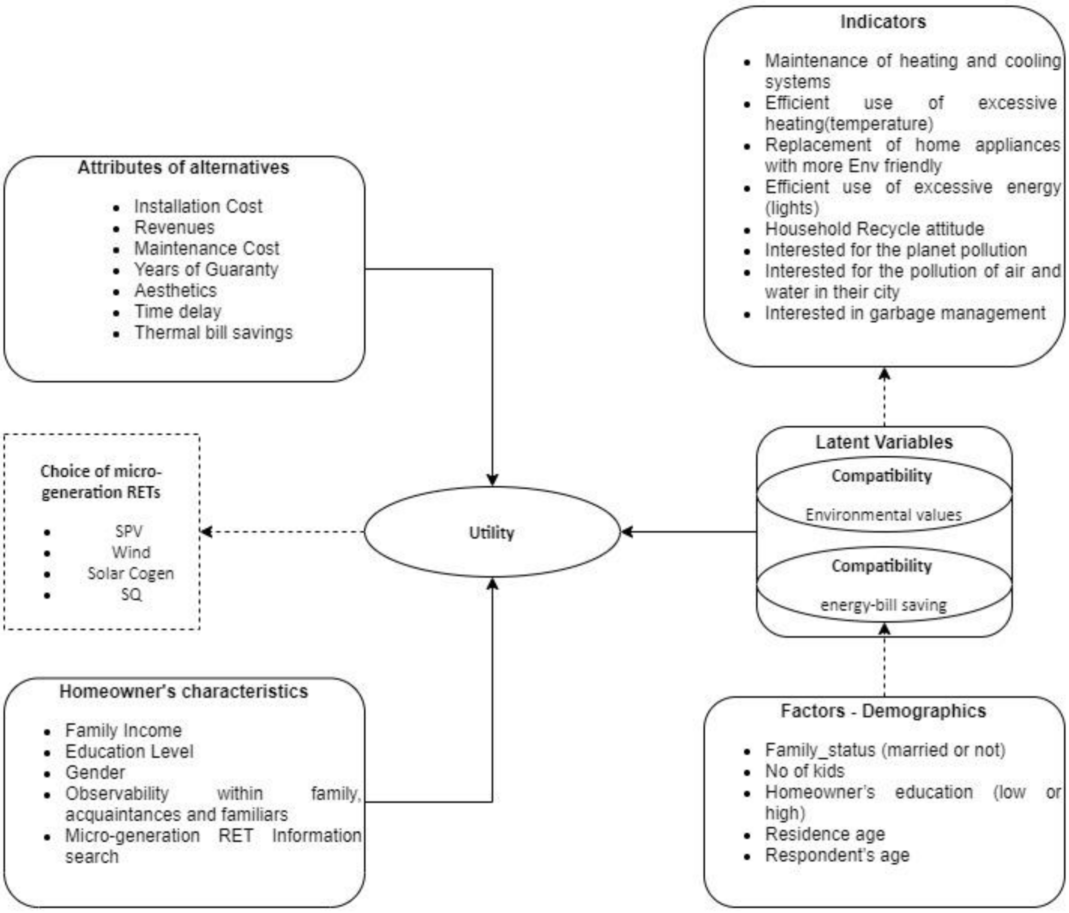


Figure 1.3: Discrete and latent structural equation model

We can then expect that the higher the environmental interest, the higher the compatibility with micro-generation RETs (environmental values compatibility). We can also expect that potential adopters with a more active electricity-bill saving behavior will have greater motivation for adoption since such behavior will be rewarded more if, for instance, higher FITs are implemented (energy-bill saving compatibility). According to Homer and Kahle (1998), that proposed the value-attitude-behavior hierarchical model, values which are presented as a set of longlasting beliefs directly affect attitudes, and in turn, attitudes affect behaviors. According to this model, both individual attitudes and behaviors are, in principle, more numerous and context-specific than values. Thus, within the above setting, individuals with strong environmental values will show a bigger interest in several environmental issues such as garbage management and pollution, and individuals with an electricity-saving attitude will engage in different energy-saving actions in their residence. Given the above causation, both latent structures are assumed reflective, or in other words, the latent variables cause the indicators' variation.

Table 1.7: Explanatory factor analysis

Indicators	Factor 1 Environmental values	Factor 2 Energy-bill saving attitude
Maintenance of heating and cooling systems 1 (never)-5 (Always)	-0.024	**0.604**
Efficient use of excessive (temperature 1 (never)-5 (Always)	-0.063	**0.751**
Replacement of home appliances with more 1 (never)-5 (Always)	0.072	**0322**
Efficient use of excessive energy (lights) 1 (never)-5 (Always)	0.094	**0.268**
Household Recycle attitude 1 (never)-5 (Always)	**0.417**	0.069
Interested for the planet pollution 1 (none)-5 (very much)	**0.761**	0.073
Interested for the pollution of air and water in their city 1 (none)-5 (very much)	**0.769**	0.092
Interested in garbage management 1 (none)-5 (very much)	**0.796**	0.012

6.1. Structural and Utility Models Equations

Starting from the specification of the utility functions for the four alternatives in the MNL model, we extend it for the case of the ICLV model in order to accommodate the inclusion of latent variables and for the MXL model to allow for random parameters.

6.1.1. Specification of the utilities in Multinomial and Mixed Logit model

We formulated the homeowner's utilities of the different choice alternatives for the estimation of the base MNL model using the attributes described in Table 1.1, and the observed individual socio-economic, residence, and DIT characteristics, shown in Table 1.6.

$$U_{spv} = asc_{spv} + b_1 * Cost_{spv} + b_2 * Revenues_{spv} + b_4 * MaintenanceCost_{spv} + b_5 * Guaranty_n + b_6 * D_1Aesthetics_{spv} + b_7 * D_2Aesthetics_{spv} + b_8 * Timedelay_{scogen}$$

$$U_{wind} = b_1 * Cost_{wind} + b_2 * Revenues_{wind} + b_4 * MaintenanceCost_{wind} + b_5 * Guaranty_n + b_6 * D_1Aesthetics_{wind} + b_7 * D_2Aesthetics_{wind} + b_8 * Timedelay_{wind}$$

$$U_{SCogen} = asc_{Scogen} + b_1 * Cost_{Scogen} + b_2 * Revenues_{Scogen} + b_3 * HeatSavings_{scogen} + b_4 * MaintenanceCost_{Scogen} + b_5 * Guaranty_{scogen} + b_6 * D_1Aesthetics_{scogen} + b_7 * D_2Aesthetics_{scogen} + b_8 * Timedelay_{scogen}$$

$$U_{SQ} = asc_{sq} + \alpha_1 * Observabillity + \alpha_2 * Family\ Income + \alpha_3 * Gender + \alpha_4 * Infosearch \tag{1.24}$$

For identification purposes, the alternative specific constant of the wind choice is set to zero. The deterministic part of the utility of SQ contains only observability and variables described in Table 1.7. The experimental attributes used in the formation of the above utilities are the amount of the installation cost for each alternative (*Cost*), the annual revenues obtained from selling the electricity produced from each of the three alternative RETs (*Revenues*), the annual maintenance cost of the installation (*MaintenanceCost*), the number of years that the manufacturer guarantees the functionality of the product (*Guaranty*), two effect coded variables for aesthetics (*Aesthetics*) using as reference group the bad aesthetics, the time needed for a potential installer to acquire a permit (*Timedelay*) and savings from using the solar cogeneration heating system (*HeatSavings*). The latter is defined as the last annual household heating bill savings for each residence, or in other words, the percentage of heat savings reported in each choice card multiplied with the respondents' last annual heating bill in euros. In order to avoid the estimated coefficients of the *MaintenanceCost* and the

Aesthetics variables to be confounded with the alternative specific constants, we used effects coded for their introduction in the utilities.

Following DIT, we introduce a dummy variable (Observability), taking the value of 1 if homeowners had observed installations of micro-generation RETs from acquaintances or relatives. We include this variable in the SQ utility to test whether the visibility of installations of micro-generation RETs affects adoption propensity. Also, we included in the SQ utility the level of family income ($Family\ Income$) and the gender (Gender) of each individual to recognize possible demographic variations in our sample. The Family Income is dummy coded with four different levels unifying family income levels greater than 40,000 euros. In order to test whether the existing variability on the stage of the decision process among the individuals in our sample has an effect on the adoption choice over micro-generation RETs, we also introduce a dummy variable taking the value of 1 if respondents have previously searched for information ($Infosearch$) and 0 otherwise.

The specification of the utility model for the Mixed Logit model is also given by Eq. (1.24) above, but the parameters of the alternative specific attributes ($b_l, l = 1, \cdots, 8$) are assumed to be random. Normal distribution was assumed for the random parameters, and the t-statistic of the deviation of the random parameter test was used to select random parameters. Based on the above testing procedure, we selected the coefficients of $Cost$ (b_1), and the $Timedelay$ (b_8) as random parameters. Both the MNL and the MXL models have been estimated with the software Biogeme (Bierlaire, 2018).

6.1.2. Specification of the utilities for the ICLV model

Since there are different ways to introduce latent constructs in the utility functions, namely as variables entering the utility or as parameter shifters, different specifications were tried. However, we report below the three final specifications that were chosen based on the log-likelihood ratio test for the comparison of the different specification scenario. The first specification (ICLV_MNL1) is the same as Eq. (1.24) where the coefficient of cost, b_1 is specified a

$$b_1 = b_C * \exp\left(b_{\eta_1} * \eta_1\right) \tag{1.25}$$

where η_1 is the first latent factor related to compatibility of innovation with environmental values and b_C, b_{η_1} are parameters to be estimated. This specification allows for heterogeneity since the effect of the estimated parameter of the $Cost$ attribute depends on the compatibility with environmental values. Given a value for b_C, the absolute value of b_1 will be increasing in "compatibility" whenever b_{η_1} is positive and decreasing otherwise. As we expect installation cost to have a negative effect, b_C is anticipated to be negative. In addition, it is expected that higher levels of compatibility with environmental values will "soften" the negative effect of cost on the utility of the micro-generation alternatives, therefore we expect $b_{\eta_1}$to be negative as well.

The second specification (ICLV_MNL2) introduces the second latent construct η_2, compatibility with energy-saving behavior, in the utility of the status quo as an additional explanatory variable in Eq. (1.24). We would expect that the probability of choosing the SQ decreases with the level of η_2, as potential adopters whose actions are compatible with energy saving are expected to prefer the new RET based technologies to the SQ. The third specification (ICLV_MNL3) combines the two previous models and introduces both latent variables simultaneously in Eq. (1.24), whereas η_1 is again a shifter of the cost coefficient and η_2 is added to the status quo utility equation as an additional explanatory variable. The above models have been estimated with the Biogeme (Bierlaire, 2018), which is a Python open-source software. Full information maximum likelihood has been used for the three models handling the calculation of integrals with numerical integration for models ICLV_MNL1 and ICLV_MNL2 and Monte-Carlo integration from model ICLV_MNL3.

6.1.3. Specification of the Measurement and Structural Equation Models

In the SEM model, the number of indicators defines the number of equations used. In order to capture the two latent variables and following the exploratory factor analysis, we formed eight equations, four for each latent variable as follows:

$$I_{kj} = a_{kj} + \lambda_{j\kappa} * \eta_j + u_{\kappa j}, \tag{1.26}$$

for $k = 1,2,..4$, the number of indicators and $j = 1,2$, the number of latent variables. η_j denotes the latent variables and I_k denotes the indicators used for each latent variable, as shown in Table 1.7. The error term u_κ follows a normal distribution with zero mean and variance$\sigma^2_{u_\kappa}$.

Following Eq. (1.19), the latent variables structural model is given by:

$$\eta_1 = c_{11} + c_{12} * ResidenceAge + c_{13} * Higheducation$$

$$\eta_2 = c_{21} + c_{22} * HighAge + c_{23} * Higheducation \tag{1.27}$$

The control variables used for the structural equation of η_1, which represents the compatibility of micro-generation RETs with respondent's environmental values, are a dummy variable for a respondent's education level greater than highschool ($Higheducation$) and a categorical variable of their residence age ($ResidenceAge$). Also, for the structural equation of η_2, which represents the compatibility of micro-generation RETs with the respondent's financial motive to save energy, we used again the $Higheducation$ variable, and a dummy variable indicating if the respondent age is above the mean ($HighAge$). We can expect that respondents with higher education will have a higher interest in saving the environment and more active behavior concerning saving money from energy-saving actions.

6.2. Utility and Structural Models Estimation Results

Table 1.8 presents the estimation results of the MNL and MXL models in the first and last columns, respectively, while the remaining columns display the results for the three ICLV models. Note that the variables Annual Savings, Installation Cost, and Thermal Savings have been measured in thousands of euros when estimating the different models. The log-likelihood values for the ICLV_MNL_1, ICLV_ MNL_2, and ICLV_ MNL_3 models are calculated for only the choice probabilities in order to be comparable to the MNL, and MXL models. The ICLV models provide significantly better fit compared to the MNL and Mixed Logit model according to McFadden's pseudo R^2, where the latter is five times bigger for the ICLV models than for the MNL and more than twice as big than the one for the MXL models. We also note that the AIC, BIC criteria, again calculated only for the choice probabilities, report the lowest values for the ICLV models.

As it is shown in Table 1.8, the ICLV models are the same with respect to MXL, in terms of overall fit, but in terms of estimation results, the difference of the estimated coefficients is moderate. The estimation results of the MNL model, show that all estimated attribute coefficients have the expected signs. For instance, higher installation cost is a deterrent to the choice of respondents to adopt one of the three technologies. Confirming related literature (Claudy et al. 2011, Scarpa et al. 2010; Islam, 2014; Simpson and Clifton, 2017; Su et al. 2018), our results indicate that the installation cost acts as a barrier for the diffusion process of micro-generation RETs. Also, greater expected revenues positively influence the probability of adopting all three technologies (1% significance level) and heating savings positively and significantly (at 5%) affect the deployment of Solar Cogeneration technology. Furthermore, expanding the years of guaranty has a significant positive effect on the probability of adoption. Also, an increase in the time needed for a state approval will negatively and significantly effect (at the 1%) new installations. This indicates that homeowners perceive the extra time waiting for a permit to be issued as a complexity (Wolske et al. 2017) and need to be compensated for any delay caused by inefficient bureaucratic procedures.

Homeowners positively and significantly value stylish installations to unstylish ones, whereas the effect from unstylish to neutral aesthetics level is greater in magnitude than from neutral to stylish. In contrast to the findings of Rai and Sigrin (2013) indicating that adopters of micro-generation RETs do not differ with respect to their socio-demographic characteristics, our result indicates that higher family income positively and significantly affects the decision for the deployment of each of the three technologies, while lower-income agents seem to prefer the SQ alternative. Our results also indicate that men are less likely to choose the SQ option. Furthermore, confirming the DIT, respondents that have observed installations of micro-generation RET in their social circle have a higher propensity to adopt a micro-generation RET. Our results are in the same line as the ones from Wolske et al. (2017) that find observability to have a direct effect on the relative advantage of micro-generation RETs and, in turn, to increase homeowner's interest for adoption. Also, our results indicate that the respondents that have searched for information about micro-generation RETs, have a negative and significant effect on the SQ alternative, or in other words, they have a higher propensity to decide over adoption.

Table 1.8: Models Estimation results (standard errors in parenthesis)

Variable	MNL Coef/se	ICLV_ MNL_1 Coef/se	ICLV_ MNL_2 Coef/ se	ICLV_ MNL_3 Coef/ se	MXL Coef/ se
spv: ***asc***	0.345*** 0.0884	0.331*** 0.0888	0.330*** 0.0888	0.331*** 0.0888	0.405** 0.1082
scogen: ***asc***	2.04*** 0.410	1.86*** 0.417	1.96*** 0.414	1.87*** 0.417	2.112*** 0.5228
sq: ***asc***	0.321 0.396	0.386 0.398	-0.529 0.506	-0.543 0.505	-0.448 0.5556
D1aesthetics	0.137** 0.0607	0.137** 0.0613	0.139** 0.0612	0.139** 0.0613	0.282** 0.1127
D2aesthetics	0.0949* 0.0553	0.0951* 0.0557	0.0938* 0.0557	0.0943* 0.0557	0.058 0.0694
Guaranty	0.0325*** 0.0126	0.0335*** 0.0127	0.0336*** 0.0127	0.0335*** 0.0127	0.034** 0.0142
MaintenanceCost	-0.0732** 0.0409	-0.0871* 0.0413	-0.0878** 0.0412	-0.0879** 0.0413	-.099** 0.0448
Revenues	1.72*** 0.497	1.69*** 0.501	1.69*** 0.501	1.69*** 0.501	1.974*** 0.6038
ThermalRevenues	0.446** 0.224	0.584** 0.229	0.470** 0.225	0.569** 0.229	0.713** 0.3370
Observabillity	-0.287*** 0.146	-0.354*** 0.147	-0.367*** 0.148	-0.390 0.149	-0.465*** 0.1973
Gender	0.285*** 0.128	0.309*** 0.130	0.378*** 0.135	0.399 0.136**	0.3706 0.1693**
Family Income 1	1.11*** 0.263	0.889 0.277***	0.903*** 0.279	0.913 0.280***	1.077*** 0.3613
Family Income 2	0.555*** 0.215	0.572*** 0.216	0.567*** 0.217	0.585 0.218***	0.648** 0.2746
Family Income 3	0.195 0.221	0.179 0.223	0.142 0.223	0.154 0.225	0.252 0.2801
Family Income 4	-0.0239 0.241	-0.0126 0.241	-0.0546 0.243	-0.07 0.245	0.089 0.3035
Info_search	-0.789*** 0.131	-0.752*** 0.133	-0.750*** 0.134	-0.777*** 0.135	-0.925*** 0.1933
Cost	-0.348*** 0.0432		-0.342 0.0434		-0.449*** 0.0760
sd_Cost					0.149*** 0.0594
Timedelay	-0.0216*** 0.0084	-0.0225*** 0.0084	-0.0222*** 0.0084	-0.0224*** 0.0085	-0.06** 0.0279
Sd_timedelay					0.121** 0.0518
$\mathbf{b_c}$		-0.272** 0.0486		-0.275** 0.0486	
(b_{η_1}) Factor 1: Environmental Values		-0.168** 0.671		-0.160*** 0.0662	
(b_{η_2}) Factor 2: Energy-bill saving attitude			-0.482*** 0.165	-0.489*** 0.162	
Log Likelihood	-1380,45	-1353.60	-1355.89	-1352.71	-1355.67
Akaike Information Criterion	2798.9	2743.2	2747.78	2745.42	2751.34
Bayesian information criterion	2818.85	2762.1	2766.68	2766.42	2772.34
McFadden Rho	0.13	0.21	0.21	0.21	0.21
Sample size	1122	1122	1122	1122	1122

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The ICLV_MNL_1, ICLV_ MNL_2, and ICLV_ MNL_3 model results are similar in terms of the sign of the estimated coefficients to the MNL model. However, we find differences in the magnitude of the estimated coefficients, in particular, regarding the installation cost for the ICLV models that includes the environmental values latent variable as its variant (ICLV_ MNL_1, ICLV_ MNL_3). Within these models, we can retrieve valuable information regarding the effect of environmental values compatibility on the perceived value of installation cost. In particular, our results indicate a negative and significant (at the 1%) effect of the latent variable of environmental values in the *cost* attribute. In other words, the higher the compatibility of the homeowner's environmental values with micro-generation RETs, the smallest the negative effect of *Cost* attribute, or in other words, homeowner's heterogeneity in preferences changes according to their environmental concern. Also, the inclusion of the latent variable of energy-bill saving attitude (ICLV_MNL_2) indicates that the higher it is, the smaller is the probability of selecting the SQ alternative or the higher the probability of adoption. In both cases, we confirm the DIT and find that the higher the level of the latent constructs, the higher the probability of adoption. This means that the more environmentally conscious a homeowner is and/or the more concerned about energy savings, the more likely they are to choose one of the micro-generation technologies.

The MXL model estimation results are the same in terms of signs and significance but are higher in absolute value than for the other models. The estimated random parameters of $Cost$ and $Timedelay$ indicate that there is significant heterogeneity among respondent's preferences concerning the magnitude of the installation cost and the time they are willing to wait for issuing a permit or in other words to be compensated. However, the small mean of time delay, together with the high standard deviation, indicates that for some homeowners, the effect of time delay is positive. Thus, we can argue that the MXL model does address unobserved heterogeneity, providing different estimates for each individual, however, it does not provide information regarding its source as the ICLV_MNL_1 and ICLV_MNL_3 models.

Table 1.9: Latent variable part of the ICLV models

	ICLV_MNL_1		ICLV_ MNL_2		ICLV_ MNL_3	
	Coef	se	Coef	se	Coef	se
	Measurement Equation					
Maintenance of heating and cooling systems (λ_{11})			1.39	0.161***	1.37	0.159***
Efficient use of excessive temperature (λ_{12})			2.04	0.251***	1.93	0.232***
Replacement of home appliances with environmental friendly (λ_{13})						
Efficient use of excessive energy (lights) (λ_{14})			0.700	0.123***	0.719	0.123***
Household Recycle attitude (λ_{21})						
Interested for the planet pollution (λ_{22})	1.06	0.0970***			1.06	0.098***
Interested for the pollution of air and water in their city (λ_{23})	1.13	0.107***			1.15	0.109***
Interested in garbage management (λ_{24})	1.33	0.120***			1.33	0.120***
	Structural Equation					
ResidenceAge (c_{12})	-0.092	0.026***			-0.093	0.026***
Highage (c_{21})			-0.017	0.004**	-0.016	0.043
HighEducation (c_{13})	0.101	0.049***			0.102	0.048**
HighEducation (c_{23})			0.157	0.054***	0.162	0.057***
Intercept (c_{11})	-1.70	0.107***			-1.70	0.108***
Intercept (c_{11})			-1.75	0.082***	-1.76	0.084***

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

The results of the SEM part of the ICLV model are presented in Table 1.9. For identification purposes in the structural equation model estimation, we kept constant one indicator for each latent variable used (Bierlaire 2018). Thus the replacement of home appliances regarding Factor 1 and the household recycle attitude for Factor 2 is kept constant and not reported in Table 1.9. The coefficients of the indicators are presented for each estimated ICLV model. We should note that the reported results show the effect of the latent variables on the indicators. The structural equation model confirms the results of the explanatory factor analysis, and we find that the higher the environmentally friendly values of a homeowner, the more they are interested in the planet, city pollution, and garbage management programs. In the same line, increased interest in savings from energy consumption causes the actions towards it.

The independent variables used for explaining the latent factors are a dummy variable for a respondent's education level greater than highschool and a categorical variable of their residence age. Thus, the results indicate that homeowners with a higher than high-school education level have formed strong, environmentally friendly values and also an energy-efficient attitude in their residence. Interestingly enough, we also find that homeowners that built their household more recently belong in the former category. This could be an indication of a direct effect of the implemented policy towards this direction. For instance, the mandatory implementation of energy certificates (law 4111/2012 or past building code laws) in every transaction involving buildings, may have driven homeowners that have recently built their residences towards this direction. It could also be the case that the eco-friendly technological advancements are forging ahead, and homeowners that constructed their residence recently are informed of them and, in turn, cultivate both their environmental values and energy-efficient attitudes. Finally, as expected, the saving behavior from energy consumption is more likely to be met withn aged respondents.

6.3. Willingness to Pay for micro-generation RETs

6.3.1. Willingness to Pay estimation

The measurement of the economic value of micro-generation RETs characteristics is made through estimating homeowner's willingness-to-pay (WTP). Following Eq. (1.4), the WTP for an additional unit of an attribute x_k is

$$w_k = -\frac{\partial V_j / \partial x_{jk}}{\partial V_j / \partial x_{jcost}}, \tag{1.28}$$

where, x_j represents the known attribute levels of attribute k for alternative j, and $\partial V_j / \partial x_{jcost}$ is the marginal utility of installation cost. For the MNL model, when the attributes appear linearly in the utility function as is for the present case, we obtain the WTP measures by computing the negative ratio of the estimated attribute coefficients to the installation cost coefficient (Train 2000). For instance, following Eq. (1.24), the mean WTP for the annual revenues attribute is estimated as the ratio of $-b_2/b_1$. However, when an attribute is effect coded and it has only two levels, as it is the case for *Maintenance Cost*, the WTP is estimated as twice the ratio $(-b_4/b_1)$.

On the other hand, for the estimation of the WTP for the ICLV models, and when the $\partial V_j / \partial x_{jcost}$ is related to the latent variable η_1 (ICLV_MNL_1 and ICLV_MNL_3 models) we need to use Eq. (1.25). Thus the WTP measure follows a normal distribution as the latent variable is assumed to be normal. Following, Hess and Behhary-Borg

(2011), we simulated 10.000 draws for the latent variable η_1 for each individual. Using the estimated output of Table 1.8 and Table 1.9, we obtain the respective values of the coefficients for each draw and divide each attribute coefficient with the price coefficient.

Furthermore, for the case of the MXL model, since we have assumed the price coefficient to follow a normal distribution, we can write the parameter of installation cost β_p as

$$\beta_p = \mu_p + \sigma_p z_p, \tag{1.29}$$

where z_p follows a standard normal distribution $N(0,1)$, μ_p represents the mean, and σ_p represents the standard deviation. Then the WTP can be written as follows:

$$w_k(z_p|\theta_p) = \frac{\beta_\kappa}{\beta_p(z_p|\theta_p)}, \tag{1.30}$$

where $\theta_p = (\mu_p, \sigma_p)$. Then the unconditional WTP estimate for an additional unit of an attribute K is the following:

$$\widehat{w_k} = \int_{z_p} \widehat{w_k}(z_p|\theta_p)\, dF_c(z_p). \tag{1.31}$$

While, in the case of *Timedealy*, the distribution z_k and the parameter vector θ_k, is also introduced in Eq. (1.31). We estimated Eq. (1.30) by simulation methods using 100 pseudo-random draws (Train 2000). An issue that can arise from Eq. (1.30) is that it is not defined at $\beta_p = 0$ (Bliemer and Rose, 2013). However, in the present case, the individual estimation results of $\hat{\beta}_p$ for the MXL model are different from zero.

6.3.2. Willingness to Pay results

A positive value of WTP means that a respondent is willing to pay more for a relative increase of the attribute under study, everything else held equal. On the other hand, a negative value means that respondents need to be paid for a corresponding increase in the concerned attribute. The mean WTP estimated values for each of the estimated models are reported in Table 1.10, recall that Installation Cost and Revenues are measured in thousands of euros. The means of the WTP measures derived from all models are quite similar but, in some cases, different from the MXL model. In particular, the MNL and ICLV models indicate that homeowners are willing to pay 400 euros more for changes in the aesthetics of micro-generation RETs from unstylish to neutral, whereas this value is estimated at 583 euros for the MXL model.

Table 1.10: WTP estimation results

	MNL	ICLV_MNL_1	ICLV_MNL_2	ICLV_MNL_3	MXL
D1aesthetics (€ for changes from unstylish to neutral)	393.7	399.2	405.1	405.4	583.1
D2aesthetics (€ for changes from neutral to stylish)	272.7	277.3	274.3	274.7	179.6
Timedelay (€ for one month delay)	-62.0	-65.7	-65.0	-65.1	-11.34
Guaranty (€ for one extra year of guarranty)	93.4	97.7	98.2	97.4	93.5
MaintenanceCost (€ for changing from 50€ to 100€ per year)	-42.07	-50.75	-51.34	-51.19	-34.08
Revenues (€ for a 100€ more savings annualy)	494.25	491.76	493.98	491.74	535.46
ThermalRevenues (€ for an increase of 100€ annualy)	128.16	170.11	137.30	165.69	170.14

However, for a change in aesthetics from neutral to stylish, the estimated homeowners' WTP is 275 euros for the MNL and ICLV models and substantially lower for the MXL model at 179.6 euros. As far as the time needed for a permit to be accepted from the state, Cretan homeowners require a compensation fee for each month of delay. In particular, all models mean estimates for the compensation is between 62 and 65 euros except from the MXL model that provides a substantially lower value of 11 euros. Also, homeowners are willing to pay approximately an additional amount of 100 euros for an extra year of guaranty on top of the installation cost. The MNL and the ICLV models indicate that for an increase in the annual maintenance cost from 50 euros to 100 euros, homeowners require a reduction of 50 euros in the total installation cost of 1kWh. The MXL mean WTP estimations provide a lower value of the compensation at 34 euros per installed kWh.

Concerning the annual revenues from selling the electricity production into the grid, homeowners in Crete are willing to pay the additional amount of approximately 490 euros (MNL and ICLV models) in the installation cost of 1kWh, for 100 euros annual increase. Again the MXL model provides a higher mean estimate of the WTP at 535.46

euros. This result can have important implications concerning policy-making. Taking into consideration a 1kWh installation, an increase in the FIT measured as an increase of 100 euros in the household's annual income, can compensate for a total of 500 euros of the innovation capital cost. In the same line, Cretan homeowners are willing to pay a higher price for installing a micro-generation, which increases their annual thermal revenues. The MXL, ICLV_MNL_1, and ICLV_MNL_3 models provide a substantially higher mean estimate of the WTP compared to the other models. In particular, the results indicate that homeowners are willing to pay an extra amount of around 170 euros for 100 euros for an annual increase in heating savings. At this point, we should note that the thermal savings attribute is only relevant for the Solar Cogeneration alternative, where the installation cost is already higher than the SPV and Wind, and as expected, the WTP is smaller than the previously discussed results in the annual savings.

7. Discussion and conclusions

The present study's goal is to analyze household preferences for renewable micro-generation technologies using a stated preference choice experiment and data gathered from 187 Cretan homeowners. In the arguments outlined in the analysis, micro-generation is considered as an innovation whose diffusion depends on its characteristics as exposed in the DIT of Rogers (2003). Based on the aforementioned theory, the attribute of compatibility is introduced as a latent construct within an Integrated Choice Latent Variable model (Ben-Akiva et al. 2002b). The results indicate that the latent compatibility construct upholds a key role in explaining Cretan homeowner's heterogeneity in preferences for micro-generation RETs.

With the use of the DIT, this study makes the distinction between off-grid and on-grid micro-generation RETs innovation, arguing that governments are responsible for initializing, facilitating, or act as an impediment to their diffusion process. In particular, through policy-making, governments can influence the micro-generation RETs innovation characteristics in several ways, and accordingly, their diffusion process. For, instance a price-based mechanism supporting a micro-generation technology can provide a substantial financial relative advantage for potential adopters (Claudy et al. 2011; Simpson and Clifton, 2017; Wolske et al. 2017). However, a complex bureaucratic structure of a policy mechanism requiring a vast amount of time or paperwork for issuing a permit may raise the perceived complexity of homeowners' decision process. In addition to the above, increased risks may be invoked from an unstable implemented policy strategy pausing new installations or abruptly decreasing the previously provided financial incentives.

Another important characteristic of the micro-generation RET innovation diffusion is its compatibility with potential adopter's values, past experiences, and needs. As such, a contribution of the present study compared to related literature studying the diffusion process of micro-generation RETs (Simpson and Clifton, 2017; Claudy et al. 2011) lies in the fact that compatibility is handled as a latent structure, and the homeowner's environmental attitudes are used as indicators for estimating it. Although the literature studying the adoption of micro-generation RETs, finds the perceived environmental benefits of the micro-generation RETs as an important factor for their adoption process (Leehner 2011; Korcaj et al. 2015; Dharshing 2017), this research recognizes the innovation compatibility with environmental values as a variant of the relative advantage of the innovation. This study also considers an additional latent construct of compatibility with "savings" influencing the adoption process. Beyond the micro-generation RETs environmental aspect, homeowners may install a micro-generation RET only due to overall savings (Simpson and Clifton, 2017; Baskaran et al. 2013; Leehner et al. 2011), which is similar to the case of solar water heaters, or economy light bulbs. Our results indicate that the probability of adopting is higher as the innovation is more compatible with the homeowner's "savings" attitude. Thus, from a policymaker point of view, policy designs supporting micro-generation RETs should also focus on devising instruments that raise environmental awareness and the energy-saving attitudes of homeowners, to reduce the overall implementation cost, as well as to increase its efficiency.

Based on a novel dataset of Cretan homeowners related to stated preference discrete choice on micro-generation RETs, this research provides an empirical evaluation of supporting mechanisms characteristics, especially useful for the uptake of new micro-generation RETs in the Greek market. For instance, a potential increase in the FIT level, measured as an increase of 100 euros in the household's annual income, can compensate for a total of 500 euros of the innovation installation cost. In addition, simplification of permits' procedures also can pave the way for the diffusion process of micro-generation RETs where homeowners want to be paid an extra amount of 60 euros for an extra month of waiting for their application to be approved. This means that a ten-month delay induced by the government's bureaucratic structures can raise the initial cost of the investment by around 600 euros. From a marketer point of view, this study's results show that Cretan homeowners have higher WTP for aesthetics rather than an extra year of guaranty. Also, homeowners with higher family income are more prone to adopt microgeneration technology.

A limitation of the present research lies in the small sample size of 187 respondents, which did not allow us to use more DIT attributes as latent, and this is the case for the observability characteristic, which may induce measurement error in the utility function estimation. Also, the validity of the SP survey that took place in 2012 and 2013 could not be enriched with the use of RP data since alternative micro-generation RETs to SPV, are not yet available in the Greek energy market. However, it would be of interest to implement a related RP survey as soon as the market evolves (Greek NECP for 2030), and new on-grid micro-generation RETs innovations will be introduced in the market. Finally, aiming at further confirming the DIT, it would be interesting to use nonparametric methodologies, such as Boltzmann machine (Wong et al. 2017), which is a data-driven approach, to apprehend potential latent factors and analyze the behavioral structure between them.

8. References

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CHAPTER 2: A COMPARATIVE STUDY OF PARAMETRIC AND NON-PARAMETRIC METHODOLOGIES FOR MODELLING CHOICE OF RENEWABLE ENERGY MICROGENERATION TECHNOLOGIES

1. Introduction

Economic agents are often faced with situations in which they are required to choose among a set of existing alternatives. Predicting and interpreting the behavior and the decision-making process of economic units is of great importance not only for scholars but also for policymakers. Until recently, the most widely used discrete choice models to explain choice among a set of distinct and mutually exclusive alternatives are models relying on the theoretical framework of utility maximization (Ben-Akiva et a., 1985). However, there is a growing interest given to the prediction and interpretation abilities of the so-called black-box Machine Learning (ML) algorithms. Black-box is a metaphor that mainly arises because ML algorithms approach data without a well-defined theoretical framework.

The parametric logit model's theoretical foundation, along with the monetary value measurement of willingness-to-pay, has given prominence to its broad application by researchers[6]. Using as a workhorse, the base Multinomial Logit model (MNL) (McFadden, 1973), and the advanced Mixed Logit (MXL) (McFadden & Train, 2000) models, researchers perform empirical and theoretical analyses on different economic discrete choice settings, useful for both marketers and policymakers. However, within an emerging literature studying modal choice, some scholars argue that the so-called black-box algorithms outperform the traditional parametric logit models in terms of predictability of accurate classification of choice and more recently in terms of interpretation (Chen et al. 2019; Lhéritier et al. 2018; Alwosheel et al. 2018; Brathwaite et al. 2017; Hagenauer and Helbich, 2017; Tribby et al. 2017; Sekhar et al. 2016; Wang et al. 2016; Vafeiadis et al. 2015; and Mohammadian and Miller, 2002 among others). Another nonparametric approach for predicting and analyzing consumer choice is the

[6] There are also semiparametric estimators of multinomial models that assume a linear utility function but no assumption on distribution of errors, however their application so far is quite limited.

nonparametric conditional mode model (Racine, 2019) based on the Kernel conditional density estimate for mixed data proposed by Hall et al. (2014). This estimator, hereafter KCDMD, is based on the nonparametric kernel family of estimators that researchers use for both continuous and discrete response variables (Pagan and Ullah 1999; Pagan and Ullah 1999), and its application has been so far quite limited.

Taking into consideration that there are alternative ways to model consumer choice, this study's aim is to shed some light on whether nonparametric ML or other approaches can be used for studying the household's choice for micro-generation RETs. So far, the literature dealing with modeling of the choice of households towards the adoption of RETs, using a set of parametric logit models, focusses either on the identification of the sources of households' heterogeneity (Scarpa and Willis 2010; Rai and Sigrin, 2013; Rouvinen and Matero, 2013; Ruakamo 2016; Su et al. 2018) or in the evaluation of the diffusion rate (Claudy et al. 2011; Bjørnstad 2012; Schelly 2014; Franchscini et al. 2017).

Within this relatively open field, this study intends to add up to the underlying literature and answer to the question of which modeling approach a researcher should use, for predicting and evaluating households' micro-generation RET's choices. Additionally, this study is interested in whether off-the-shelf machine learning algorithms can be effective within a researcher-defined stated preference (SP) choice experiment dataset. In particular, we examine two basic well-known logit models, namely Standard Multinomial Logit and Random Parameter Multinomial Logit, and compare them to the state of the art machine learning algorithm of Random Forests and the nonparametric kernel multinomial model. We compare the predictability and interpretability of the above models using low-dimensional stated preference data of Cretan consumer choice over micro-generation technologies. The results indicate that when the training set used for the estimation of the data-driven models does not include valuable individual information, because random selection for the training set is individually-based, the nonparametric models of RF and KCDMD do not outperform traditional logit models in terms of accurate predictability, and none of the models used has the ability to transfer their experience to new individuals whose experience is not used in the estimated model.

We additionally compare the models in terms of the importance given to each variable. We find that both the RF and the nonparametric models draw their attention to the household’s socio-economic status rather than the alternative specific attributes designed by the researcher. This research also shows that both the ML and kernel nonparametric models identify nonlinear effects that would not otherwise appear, thus giving them an additional advantage over their use. The KCDMD estimator is found to have similar results to the RF ML algorithm, indicating that a nonparametric kernel-based model is also an effective alternative methodology for discrete response models.

In what follows, the next section provides a review of the literature describing alternative ways of modeling discrete choice. Section 3 gives an exposition of the fundamentals of the models used, and section 4 describes the data used. Section 5 presents the evaluation of the different models in terms of accuracy in the prediction of choice and estimation evaluation, and section 6 summarizes the comparison findings, identifies the gaps, and suggests future research directions.

2. Review of related literature

The main goals of the literature dealing with modeling renewable energy technology household choice lie either in the identification of the sources of households’ heterogeneity (Scarpa and Willis 2010; Rai and Sigrin, 2013; Rouvinen and Matero, 2013; Ruakamo 2016; Su et al. 2018) or in the evaluation of their diffusion rate (Claudy et al. 2011; Bjørnstad 2012; Schelly 2014; Franchescini et al. 2017). All the researchers above follow the standard approach of modeling households’ choice through parametric logit type models. Within the framework of logit models, the researcher decides first which variables should be potentially included in the model and then estimates the relevant variables, usually following a “trial and error” procedure. Then the estimated parameters can be used to elicit household preferences for the different alternatives, sources of heterogeneity, and willingness-to-pay estimates. Relying on the theoretical framework of utility maximization (Ben-Akiva et a., 1985), the class of the parameter parametric logit model estimators can provide a valuable toolkit for choice analysis. The parametric logit models' theoretical foundation, along with the monetary value measurement of willingness-to-pay, has given prominence to their broad usage by researchers.

The most well-known logit model widely used by researchers is the MNL model proposed by (McFadden 1973). The MNL model received severe criticism for its strong underlying assumptions, namely, the IIA property, which implies that the probability of choosing one alternative over another one, is independent of other alternatives. Researchers pointed out several ways to relax either IIA or to introduce taste variations in the parametric logit models. The Mixed Logit (MXL) model (McFadden & Train, 2000), which is considered as the "state of the art" within discrete choice models (Hensher and Greene, 2011), fully relax the IIA assumption and allows for heterogeneity by allowing parameters to be individual specific and random. Scarpa and Willis (2010), through the use of the MXL model, assessed willingness to pay for several attributes of different micro-generation alternatives using SP of households in England, Wales, and Scotland. Franchscini et al. (2017), using a latent class random parameter model for SP data, evaluate the factors affecting households to decide for a renewable heating system.

An alternative approach to parametric logit modeling is to handle all the above choice cases as a consumer classification problem skipping the modeling part and predicting choice behavior using data-driven algorithms. A recent strand of literature argues that newly developed non-parametric supervised[7] learning ML algorithms outperform traditional parametric models in terms of predictive power (Chen et al. 2019; Lhéritier et al. 2018; Alwosheel et al. 2018; Brathwaite et al. 2017; Hagenauer and Helbich, 2017; Tribby et al. 2017; Sekhar et al. 2016; Wang et al. 2016; Vafeiadis et al. 2015; and Mohammadian and Miller, 2002 among others). For example, Mohammadian and Miller, (2002), empirically examine households' choice for automobile and find that the predictive power of the Artificial Neural Network (ANN) algorithm outperforms the parametric nested logit model. Vafeiadis et al. (2015) empirically compare ML methods with the logit model for predicting choice of churning in the telecommunication market and show that the Support Vector Machines has the highest predictive accuracy among Neural Networks (NN), Decision Trees, Naïve Bayes, and MNL. Also, in a travel mode choice setting, some researchers find that the RF algorithm provides advantageous predictive ability against the traditional MNL model (Tribby et al. 2017; Sekhar et al. 2016). In the same line, in a comparative study of ML algorithms

[7] Supervised learning refers to the classification problem where the researcher observes both the response and the independent variables.

and the MNL model for the Dutch travel mode choice, Hagenauer, and Helbich, (2017), finds the RF algorithm to be superior. The researchers above, find evidence that the predictive ability of ML algorithms for demand forecasting is superior to a base MNL or Nested Logit model although Hensher and Ton (2000) find that ANNs equally predict mode choice to a nested logit model.

So far, most researchers argue over the superiority of the ML algorithms for predicting demand and not for evaluating variables for choice interpretation, which is also essential for policymaking. Raising a rule of large sample size, Wang et al. (2016) find Neural Networks to be superior to the binary logit model both in terms of predictability and interpretation loss. They define interpretation loss as the difference between the true and the estimated choice probability, where an estimator of the first can incorporate all valuable economic information, namely market shares, utilities, and social welfare. Although it seems that NN can substitute parametric logit models in terms of both predictability and interpretability, Alwosheel et al. (2018) raised a rule of large sample size, and to further prove the above, NN also should be compared with more sophisticated and state of the art parametric logit models.

In a comparison study of the parametric MNL and MXL and several ML algorithms in travel mode choice, Zhao et al. (2019), find that RFs produce higher prediction accuracy and show that they can accommodate behavioral interpretability by using variable importance and partial dependence plots to identify causal relationships. Similarly, Chen et al. (2019), uses the RF algorithm to analyze travel mode choice and argues that RF can accommodate interpretability features that can lower its "black-box" criticism (Kotsiantis et al. 2007; Zhou et al. 2015). The predictive ability of the RF algorithm is also denoted by Lheritier et al. (2018), which predicts itinerary flight choice. The RF algorithm, similarly to the NN, provides better predictions with higher dimensionality feature space[8] (Chen et al. 2019; Matsuki et al. 2016), but also can easily handle and provides robust prediction in small sample sizes and high-dimensional datasets (Matsuki et al. 2016; Scornet et al. 2015). In addition to the prediction advantage presented in the literature, researchers can further interpret the causal effect of the variables forming the random trees using partial dependence plots (Friedman et al. 2001, Molnar, 2018). Partial dependence plots can be easily extended in multiple

[8] Feature space in the ML language refers to the complete set of explanatory variables to explain a target variable.

parametric and nonparametric models measuring the marginal effect of each predictor for choice analysis and policy-making purposes.

Scholars use RF (Breiman 2001a) along with NN algorithms as a workhorse for choice prediction and analysis. Thus, in order for ML algorithms to fully compete with traditional parametric logit models, a theoretical framework is left to be developed. There is a strand of literature arguing that machine learning decision trees can be represented from the non-compensatory microeconomic decision rule of Disjunctions-of-Conjunctions (DoC) (Hauser et al. 2010; Brathwaite, 2017). In contrast to Random Utility Theory, the DoC decision rule hypothesizes that the increase of a particular variable does not provide satisfaction for the loss of another one. In this direction, Brathwaite, 2017 formulated a bayesian tree model that reproduces the DoC rules, and empirically finds that their model supersedes the MNL model. Still, the RF algorithm produces numerous random decision trees which are not possible to interpret through DoC rules. In the context of the RF algorithm, Banjerjee et al. (2012) argues that a representative tree may be extracted from ensembling all produced trees. Considering that the representative RF algorithm output tree is of high complexity, cognitive simplicity is a prerequisite for its use (Hauser et al. 2010).

Another alternative approach for predicting and analyzing consumer choice is the nonparametric Kernel Discrete Choice Mixed Data (KCDMD) estimator proposed by Hall et al. (2004). This estimator is based on the nonparametric kernel family of estimators that researchers use mostly for continuous response variables (Pagan and Ullah 1999). However, according to Li and Racine (2007), this estimator can be used for multinomial choice analysis. Although the literature using this estimator in a discrete choice setting is scarce, the estimator under the minimum assumption of independent and identically distributed (IID) observations, outperforms the standard parametric MNL model (Elamin et al. 2019; Koch and Racine 2013). For example, Koch and Racine (2013) examined the effect of cutting down public healthcare fee policy measures on the choice of South African residents to visit a health facility. The authors find the nonparametric kernel estimator to outperform the parametric MNL model both in terms of in-sample and out-of sample predictive ability. In a comparative study of parametric MNL models and the KCDMD estimator, Elamin et al. (2019), argues that the later explains more unobserved heterogeneity in a study of women's choices of entering the UK labor force.

The KCDMD is a data-driven estimator that uses kernel smoothing techniques for estimating statistical density functions for both categorical and continuous variables, eliminating thus the possibility of functional specification (see Li and Racine 2007; Pagan and Ullah 1999 for more details). Furthermore, the KCDMD estimator can capture nonlinearities in both continuous and categorical variables, thus allowing for an explanation of unobserved heterogeneity in a discrete choice setting (Elamin et al. 2019; Li and Racine 2007). The caveat, contrary to parametric logit models, is that the KCDMD estimator is computationally complex and time-consuming and does not rely on a theoretical microeconomic framework.

3. Methodology

This section includes the different parametric and nonparametric modeling approaches used in the present research for predicting micro-generation RET choice. In the first subsection, the RF algorithm is discussed along with a single decision tree methodology. The single decision tree algorithm provides the basis for the construction of the RF algorithm, and the reader should apprehend first. This subsection continues with an overview of the Random Forest algorithm and its application in a discrete choice setting. It concludes with the extraction of partial dependence plots that will provide the ground to compare all models results. The next subsection presents a nonparametric Kernel estimator that can accommodate a multinomial discrete choice model with quite limited assumptions compared to parametric techniques. In the last subsection, the advantages and caveats of the two most used parametric logit models, namely the MNL, and the MXL models, are discussed.

3.1. Modeling choice through nonparametric Random Forest

3.1.1. Single decision tree

A decision tree can be defined as a set of successive yes/no questions asked within the respective analyzed data. According to the sequence of the questions asked, the decision tree creates mutual exclusive partitions in the dataset to classify responses. This sequential process resembles human choice behavior, where an individual asks questions on available data until she reaches a decision point. If we define by $F_x =$

$(x_{i1}, x_{i2}, x_{i3}, \dots\dots, x_{is})$ the feature space consisting of s independent variables for individual i, $i = 1, \dots.., n$, then a single decision tree model partitions this space in multiple mutually exclusive subcategories and classifies the available responses on the target variable y_i. The formed subcategories formulate a decision tree structure, whereas important information is presented at higher tree nodes. Figure 2.1 presents a decision tree example of the conditions under which a household will choose to install RET micro-generation technologies. The "Root" node represents the entire sample, which gets divided into "Decision" nodes. The nodes that do not split are called "leaf" nodes.

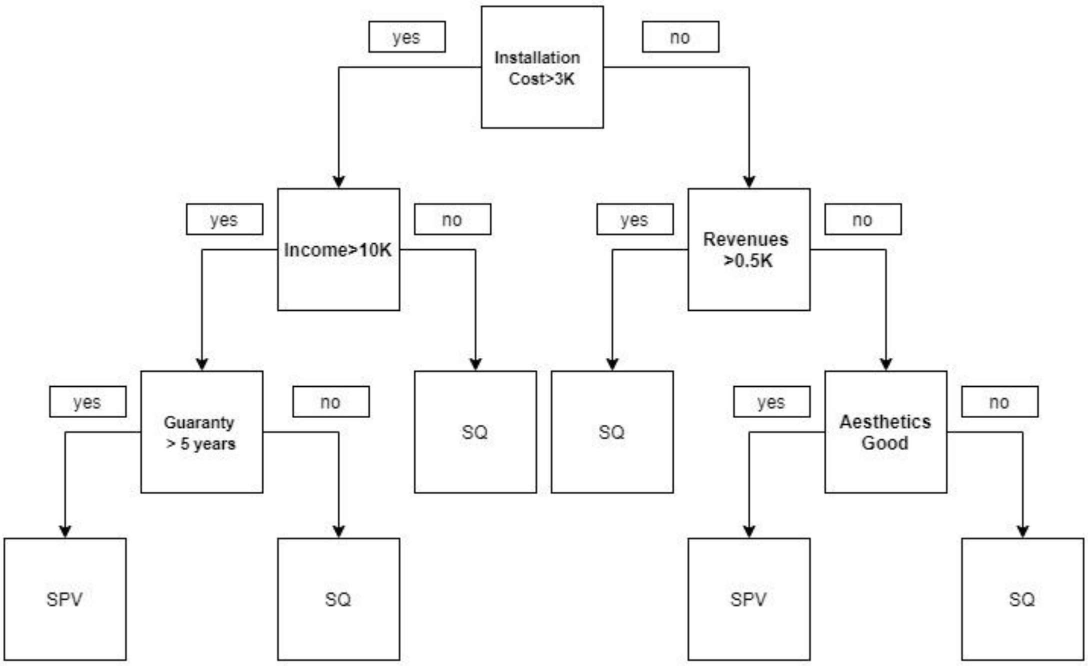

Figure 2.1: Example of a binary choice Decision Tree

The sequence of the information used for the construction of the tree is based on the available most crucial information. The importance of each exogenous variable, or in other words, the variable that the algorithm sets up in the higher nodes of the tree, and the splitting point is determined either with the Gini Impurity coefficient or the Information Gain Criterion (Suthaharan 2016; Breiman et al. 1984). At each node, starting from the parent node, the decision tree searches for the value to split, the latter being determined as the value giving the most considerable reduction of the Gini

Impurity. This process is repeated recursively until the tree reaches a point where each node corresponds to one class of the responses.

3.1.2. Random Forest modeling

The Random Forest algorithm constructs multiple decision trees using the procedure described above (Breiman, 2001a). RF is also a hierarchical machine learning algorithm that randomly performs variable renking for splitting nodes of each tree, using a random subset of variables to decide how the node will split. Also, the construction of each tree uses a different subset of the sample data. The predictions of all the extracted decision trees are averaged and produce the final prediction of the model.

Figure 2.2 below illustrates how the algorithm works. If N is the number of trees that the algorithm generates, then the steps followed for each of the *N* trees are as follows. The first step is to select the sample data and subsequently to calibrate the model. For this step, the algorithm uses bootstrapping methods, ensuring a different and uncorrelated sub-sample for each N tree. Then, the tree is fully grown using a random subset of variables of the sample selected in the first step. The classification result is an input that the forest uses when selecting the final tree through a voting procedure. The RF algorithm base its efficiency on the reduced correlation among the generated trees and from the magnitude of the selected N. In this respect, the algorithm presumably performs more effectively in large datasets where a higher number of trees chosen are not correlated.

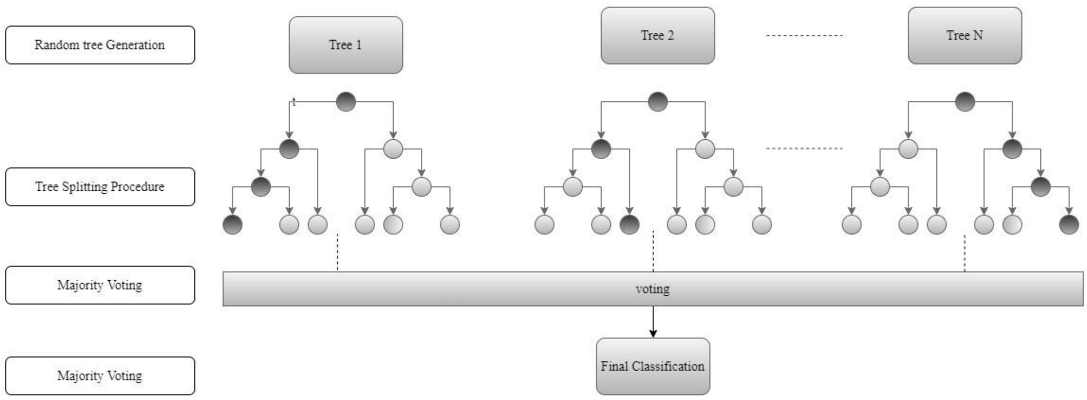

Figure 2.2: Random Forests algorithm

In supervised learning, the analyst defines an observed sub-sample of the feature space to train the RF. Then, given the test subsample left out of the training procedure, the trained model predicts the unseen responses or, in other words, assigns labels to the output. This is referred to as a hard-classification procedure, i.e., each observation is classified in one of the labels. A soft-classification procedure would instead produce an estimate of conditional probabilities for membership in each class, and then the estimated probabilities would be used to produce the final classification. In the present research, we use a hard-classification procedure.

3.1.3. Interpretation of Random Forests

The random forest algorithm generates numerous N_i trees and the decision of the classification outcome come through voting in the leaf nodes of the generated trees. However, the RF algorithm does not produce an estimate of the causal effect of exogenous variables as traditional parametric models. The RF algorithm provides a measure of variable importance calculated as the average decrease of the estimated Gini impurity index for each generated tree. In each tree, some variables are more important than others, and their node positioning depends on the degree under which they reduce impurity. Thus, for tree N_i, within an internal node, this index is calculated for the particular variable that the algorithm does the split. Then it is averaged across all N produced trees. For a single tree and a categorical target variable Y_i, taking values L_j, the Gini Impurity at node m is calculated as follows:

$$GImp_m = \sum_{j=1}^{J} P(Y_i = L_j)\left(1 - P(Y_i = L_j)\right), j = 1, \cdots, J, \tag{2.1}$$

The mean Decrease Impurity Index can rank the importance of the exogenous variables used in the model but still does not provide their casual effect. In an attempt to interpret "black-box" machine-learning algorithms, Friedman (2001), proposed the use of partial dependence plots to reveal this causal effect. Partial dependence plots, present the actual effect of an exogenous variable x_s, on the averaged predicted probability of selecting an alternative. A partial dependence plot depicts the average marginal effect of an independent variable on the prediction and can show if this effect is linear or more complex. The partial dependence function of an exogenous predictor x_s is modeled as follows:

$$f_s(x_s) = \int f(x_s, F_x(x_{-s}) dP(x_{-s}), \tag{2.2}$$

Where $f(x)$ is the output of the RF algorithm, and x_{-s} denotes all variables in the feature space other than x_s The partial dependence plot can be estimated by averaging over the observations in the training set keeping the value x_s fixed

$$\hat{f}_{x_s}(x_s) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}(x_s, F_x(x_{-s,i})), \tag{2.3}$$

where $F_x(x_{-s,i})$ represents all observations in training set for the variables in the feature space excluding x_s. Under the assumption that the x_s is uncorrelated with the rest of the variables in the feature space the above expression gives an estimate of the average marginal effect of x_s. Therefore, given the ease of implementation of the partial dependence plot, their use can be extended to multiple prediction methodologies.

3.2. Modeling choice through nonparametric Kernel Estimator

3.2.1. Kernel conditional probability estimator for a multinomial choice model

An alternative methodology for estimating a multinomial choice model without making assumptions on the functional form of the model is the nonparametric kernel family of estimators (Li and Racine, 2007). Rosenblatt (1956), first suggested the kernel estimator as a smoothing method for estimating the probability density function for one continuous variable. Within this approach, the kernel weighting function is used to estimate the density function of x, rather than using a histogram as a step function density estimation. A strand of literature extended the kernel smoothing methodology to discrete variables (Aitchison and Aitken, 1976; Habbema et al. 1978; Titterington 1980; Wang and Van Ryzin 1981, and Aitken 1983), overcoming the data limitations of the frequency-based approach used for continuous variables.

On the other hand, in a choice experiment setting, explanatory variables could be either discrete or continuous. Hall et al. (2004) developed a kernel-based nonparametric estimator of conditional densities for mixed data types. This nonparametric kernel estimator of the conditional density, KCDMD, can then be applied to estimate a conditional mode model of choice, as proposed in Racine (2019). In the present study, we also use the KCDMD estimator to model consumer choice for micro-generation RETs. Under the assumption that the observations are independent and identically distributed (IID), for $i \in (1,..,n)$, let Y_i denote the choice of consumer i and X_i the set of independent variables or set of explanatory variables of each individual i, containing q discrete variables $X_i^d = (x_{i1}^d, \cdots, x_{iq}^d)$ and p continuous variables $X_i^c = (x_{i1}^c, \cdots, x_{ip}^c)$. If we denote $f(y,x)$ the joint density of (Y,X) and $f(x)$ the marginal density of X respectively, following Racine (2019), the conditional density of y given x is given by:

$$f(y|x) = f(x,y)/f(x), \tag{2.4}$$

Following Hall et al. (2004), the estimators of the joint and marginal densities, $f(x,y)$ and $f(x)$, respectively, are given by:

$$\hat{f}(x,y) = \frac{1}{n}\sum_{i=1}^{n} K_{\gamma_{x,y}}\,(X_i, Y_i, x, y), \tag{2.5}$$

and

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} K_{\gamma_x}\,(X_i, x). \tag{2.6}$$

K_{γ_x}, $K_{\gamma_{xy}}$ denotes the product of the kernel functions for the discrete and continuous independent variables and with the dependent variable in the set of independent variables X_i as follows:

$$K_{\gamma_{xy}}(X_i, Y_i, x, y) = \{\prod_{s=1}^{p} w(X_{is}^c, x^c, h_s) \prod_{r=1}^{q} l^d(X_{ir}^d, x^d, \lambda_r)\} l^d(Y_i^d, y, \lambda_0), \tag{2.7}$$

$$K_{\gamma_x}(X_i, x) = \prod_{s=1}^{p} w(X_i^c, x^c, h_s) \prod_{r=1}^{q} l^d(X_{ir}^d, x^d, \lambda_r), \tag{2.8}$$

where $w(\cdot,\cdot,\cdot)$, is a kernel function used for smoothing the continuous variables of the set of the independent variables X_i. $l(\cdot,\cdot,\cdot)$, is a discrete variable kernel function. $\hat{\lambda}_0$, $\hat{\lambda}_r$ and $\hat{h}_s$ denotes the estimated bandwidths of the discrete dependent variable, the discrete independent variable, and the continuous variable kernels, respectively.

The kernel smoothing functions used for the discrete categorical unorder independent variables of the estimator l has the following form as proposed from Aitchison and Aitken (1976):

$$l(X_{jr}^d, X_{ir}^d, \lambda) = \begin{cases} 1-\lambda & if\ X_i^d = x^d \\ \frac{\lambda}{c-1} & if\ X_i^d \neq x^d \end{cases}, \lambda \in [0,1], \tag{2.9}$$

where $c \geq 2$ is the number of distinct values that the discrete variable takes.

The kernel function used for smoothing the continuous variables is as follows:

$$w(X_i^c, x_i^c) = w\left(\frac{X_j^c - X_{is}^c}{\hat{h}_s}\right), \tag{2.10}$$

Then Eq. (2.7) and Eq. (2.8) become

$$K_{\gamma_{xy}}(X_i, Y_i, x, y) =$$

$$\prod_{s=1}^{p} \frac{1}{h_s} w\left(\frac{x^c - X_{is}^c}{h_s}\right) \prod_{r=1}^{q} \left\{\frac{\lambda_r}{c-1}\right\}^{N_{ir}(x)} (1-\lambda_r)^{1-N_{ir}(x)}\} \left(\left\{\frac{\lambda_0}{r_j - 1}\right\}^{N_i(y)} (1-\lambda_0)^{1-N_i(y)}\right) \tag{2.11}$$

Where $N_{ir}(x) = I(X_{ir}^d \neq x_r^d)$, r_j is the number of distinct values Y can take and $N_i(y) = I(Y_i \neq y)$,

$$K_{\gamma_x}(X_i, x) = \prod_{s=1}^{p} \frac{1}{h_s} w\left(\frac{X^c - X_{is}^c}{h_s}\right) \prod_{r=1}^{q} \left\{\frac{\lambda_r}{c-1}\right\}^{N_{ir}(x)} (1-\lambda_r)^{1-N_{ir}(x)}\}. \tag{2.12}$$

The functions used for smoothing continuous variables in the set of independent variables X_i^c, are usually higher-order kernel functions that reduce the bias of the bandwidth selection (Li and Racine, 2007). Among them are the second-order Gaussian, Epanechnikov, and uniform, among others. Generally, these second-order kernels are found to produce more stable estimation functions in finite-samples (Li and Racine, 2007).

We then estimate the conditional mode of Y, conditional on $X = x$, as follows:

$$M(x) = argmax_{y \in D} f(y|x), \tag{2.13}$$

where $M(x)$ is the conditional mode of Y, D denotes the number of discrete outcomes and $f(y|x)$, the conditional density as defined above.

3.2.2. Bandwidth parameter selection

The bandwidth parameter selection is a common problem of all nonparametric curve methods. The magnitude of the bandwidth selected controls the smoothness of the kernel estimator, and it is of crucial importance. The underlying literature identifies two method categories for automatic bandwidth selection, namely the “plug-in” and the classical ones. Plug-in methods compute the optimal bandwidth by minimizing the

Mean Integrated Standard Error (MISE) (Hall and Marron, 1987;.Hal, Sheather, Jones and Marron, 1991). Classical bandwidth selection methods stem from existing parametric modeling approaches. One of the most popular methods used to select the kernel smoothing parameters is the Cross-Validation approach (Rudemo, 1984; Bowman, 1984). The two most popular data-driven smoothing parameter selection methods are the least square and the maximum likelihood Cross-Validation. As proposed by Hall et al. (2004) and Li and Racine (2007), both methods can be used when estimating conditional mixed-data densities.

The Least Squares Cross-Validation (LSCV) method uses the Integrated Squared Error (ISE) and selects the optimal smoothing parameter by minimizing the following function (Racine, 2004):

$$ISE = \int\{\hat{g}(y|x) - g(y|x)\}^2 f(x)dx, \tag{2.14}$$

where $f(x)$ is the marginal density function as defined before.

On the other hand, within the Maximum Likelihood Cross-Validation (MLCV) method, the parameters h, λ are selected through maximizing the following maximum likelihood function (Li and Racine, 2007):

$$L = \sum_{i=1}^{n} ln(\,\hat{g}_{-l}(Y_i/X_i), \tag{2.15}$$

where $\hat{g}_{-l}(Y_i/X_i)$ denotes the leave-one-out estimator. Although MLCV is computationally more efficient than LSCV, it tends to over smooth data for continuous variables drawn from fat-tail distributions (Li and Racine, 2007). The small sample size of the discrete choice setting under study and the existence of continuous variables led to the use of the LSCV method for choosing the smoothing parameters for the kernel density mixed data estimator.

3.3. Modeling choice through Parametric Logit Models

3.3.1. The simple Multinomial and the Mixed Logit models

The Multinomial Logit (MNL) model is a simple parametric model used for modeling multinomial choice that produces easily interpretable results in a utility maximization framework. However, the advantage above has the cost of restrictive assumptions about the unobserved part of the utility and the utility functional form. Under the Random

Utility Theory (Marschak, 1960; Manski, 1977), the utility of individual i's utility from choosing alternative j, out of J mutually exclusive alternatives is the following:

$$U\left(X_{ij}, Z_i\right) = V\left(X_{ij}, Z_i, \beta\right) + e_{ij}\ j = 1, \cdots, J; i = 1, \cdots, n, \tag{2.16}$$

or more succinctly $U\left(X_{ij}, Z_i\right) = V_{ij} + e_{ij}$,

where $V()$, denotes the observed part of the utility, β is a vector of unknown parameters and e_{ji}, the unobserved part of the utility function. The set of independent variables $X_s = (X_{ij}, Z_i)$ that enters in the observed part of individuals utility, consists of X_{ij}, a vector of attributes of alternative j as faced by individual i and of Z_i a vector of a person's i characteristics. To obtain the probability of individual i choosing alternative j, the error e_{ji}, follows a type I extreme value distribution, and it is iid. Then, dropping the individual index for simplicity, the probability, as mentioned above, is given by:

$$P_j = \frac{exp(V_j)}{\sum_{k=1}^{J} exp(V_k)}. \tag{2.17}$$

The MNL model has two severe disadvantages in contrast to its simplicity. The first is that it is subject to IIA property, implying that the relative probability of choosing one alternative over another alternative is independent of other alternatives, which in the real world rarely holds. The second limitation of the MNL model is that it cannot incorporate a random variation of tastes among individuals. The reader is advised to see p.5.3.2 in Chapter 1 for a more detailed analysis.

The MXL model (Train, 2003) can overcome the limitations mentioned above, by allowing substitution and correlation among alternatives and simultaneously allowing for individual random taste variation. A desired property of the ML model is that it comes from RUT. In the Mixed Logit model, the error term is assumed to be iid, and the coefficients in β, vary over decision-makers in the population with density $f(\beta)$. Within the latter attractive feature, the researcher can study individual choice heterogeneity. The reader is advised to see Hensher and Greene (2000) for a detailed discussion of the MXL model's merits. Under these assumptions, the unconditional choice probability, with the unknown β_i is:

$$P_{ij} = \int \frac{exp(\beta' X_{ij})}{\sum_{j=1}^{J} exp(\beta' X_{ik})} f(\beta) d(\beta). \tag{2.18}$$

Both parametric models, presented in the current subsection, are derived from RUT, and thus in both cases, the researcher can estimate the economic value of each attribute in the set of independent variables X_s. The ratio of the estimated coefficient of each attribute and the price attribute, namely, the willingness-to-pay measure, is a useful monetary valuation tool for policy analysis. This study does not report the WTP measure extracted from the parametric logit models since the used nonparametric methodologies cannot provide a similar measure for comparison.

4. Data for Empirical Comparison

The data used for the empirical comparison of the above methodologies came from a stated preference survey of homeowners in the region of Crete conducted in 2012 related to the preferences for installing micro-generation RETs. The survey asked the respondents to select among the following four micro-generation alternatives for their residence: *Solar Photovoltaic*, *Wind generator*, *Solar Cogeneration*, and the *Status Quo*. A total of 186 participants answered six hypothetical choice scenarios resulting in 1116 observations. Each choice scenario contained differentiated levels of the following attributes *Capital Cost*, *Annual savings*, *Thermal Bill Savings*, *Maintenance Cost*, *Guaranty years*, *Aesthetics*, and *Time required for approval* (see Table 2.2). Following the SP methodology (Hensher, 2005), four focus groups gave prominence to the above attributes, and their levels were determined to include both hypothetical but also realistic scenarios ensuring their independence and avoiding collinearity issues (Train, 2003). In the context of the SP survey, additional information was gathered regarding the participants' residence, environmental profile, and socioeconomic and demographic status. The SP survey also asked the respondents to rank the importance of each attribute in each choice situation. A more detailed description of the survey methodology can be found in the Methodology and Data subsection, in subsection 5.1 of chapter 1.

The dataset includes forty explanatory variables for predicting participants' micro-generation installation choice. Table 2.1 presents the choice frequencies for the different alternatives of micro-generation, while Table 2.2 presents a detailed description of the alternative specific attributes and their levels. According to Table 2.1, the status quo alternative (SQ) has the highest score (~40%), followed by the SPV and

Wind generation. As is expected, the percentage of SQ choices is the highest among all other alternatives, depicting the low infiltration of micro-generation RETs at that time. The first choice alternative that participants selected after the SQ is the SPV, which was to be expected as at the time the market share of the other two alternatives was negligible compared to that of SPV.

Table 2.1: Micro-generation choice distribution

Variable	Frequency	Percentage
Solar Photovoltaic	341	28,85%
Wind Generation	243	20,56%
Solar Cogenaration	127	10,74%
Status quo	471	39,85%

Table 2.2: Alternative specific attribute levels

Variable	Measurement	Level 1	Level2	Level3	Level4	Type
SPV Installation cost	Thousands euros	2.50	3.25	4.00	4.75	Categorical
Wind Installation cost	Thousands euros	2.50	3.25	4.00	4.75	Categorical
SCogen Installation cost	Thousands euros	10.0	11.5	13.0	14.5	Categorical
SPV Annual savings	Thousands euros	0.4	0.5	0.6		Categorical
Wind Annual savings	Thousands euros	0.4	0.5	0.6		Categorical
Scogen Annual savings	Thousands euros	0.50	0.08	0.40	0.60	Categorical
SPV annual maintenance cost	Thousands euros	0.5	1.00			Categorical
Wind annual maintenance cost	Thousands euros	0.5	1.00			Categorical
Scogen annual maintenance cost	Thousands euros	0.5	1.00			Categorical
SPV years of guaranty	Years	2	6	10		Categorical
Wind years of guaranty	Years	2	6	10		Categorical
Scogen years of guaranty	Years	2	6	10		Categorical
SPV aesthetics	Unstylish (1) Neutral (2) Stylish (3)	1	2	3		Categorical
Wind Aesthetics	Unstylish (1) Neutral (2) Stylish (3)	1	2	3		Categorical
Scogen Aesthetics	Unstylish (1) Neutral (2) Stylish (3)	1	2	3		Categorical
Scogen thermal bill savings	Percentage	30%	50%	70%		Categorical
SPV time required for approval	Months	3	9	15		Categorical
Wind Time required for approval	Months	3	9	15		Categorical
Scogen Time required for approval	Months	3	9	15		Categorical

Table 2.2 shows the descriptive statistics of the variables concerning the participants' demographics, information related to their residence, and their environmental profile. In particular, 79% of the respondents are married, 53% are males, and the average age

of the respondents is around 45 years old. We should note that the survey data concerns the answers given from the head of each household. Moreover, the family income ranges between the levels of 10,000 to 30,000 euros. Also, 70% of the participants hold either a High school or University degree. The average residence size is 114 square meters, and 81% plan to stay in their residence for more than 15 years. In the context of the present research, we gathered further information regarding the environmental profile of respondents. It is worth noting that most of the homeowners in our sample almost always implement actions to reduce their energy consumption, and most of them have stated a high interest in the environment.

Table 2.3: Demographics and environmental profile variables descriptive statistics

Variable	Levels	Mean	Std.Dev	Minimum	Maximum	No of Cases	Type
			Demographics				
Married	0: not married 1: married	0.80	0.40	0	1	228 888	Categorical
Gender	0: woman 1: man	0.53	0.50	0	1	281 835	Categorical
No of Kids		1.63	1.12	0	6		Categorical
Age		45.73	11.80	25	70		Continuous
Family Unemployment	0: No 1: Yes	0.33	0.47	0	1	744 372	Categorical
Family Income	1: 0 to 10,000 2: 10,001 to 20,000 3: 20,001 to 30,000 4: 30,001 to 40,000 5: 40,001 to 50,000 6: > 50,000	3.04	1.27	1	6	96 31 323 228 78 60	Categorical
Education Level	1: illiterate 2: Elementary School 3: Secondary School 4: High School 5: University degree 6: Master or higher	4.33	1.07	2	6	0 96 108 360 432 120	Categorical
			Residence Information				
Residence acquisition time (years)	1: <5, 2: 5-10 3: 10-20 4 >20	2.86	1.03	1	4	156 258 348 354	Categorical
Residence age	1: <1950 2:1950-1975 3: 1975-1999 4: >2000	3.14	0.73	1	4	42 108 618 348	Categorical
Residence sq meter		114,8	35.42	45	256		Continuous
Future stay (years)	1:<5 2: 5-10 3: 10-15 4: >15	3.56	0.91	1	4	90 60 60 906	Categorical
Annual Thermal Bill		1.53	0.75	0	2.75		Continuous

Variable	Levels	Mean	Std.Dev	Minimum	Maximum	No of Cases	Type
			Environmental profile information				
Maintenance of heating and cooling systems	1:never 2:seldom 3:often 4:almost 5:always	4.16	0.87	1	5	18 36 162 432 468	Categorical
Efficient use of excessive energy (temperature)	1:never 2:seldom 3:often 4:almost 5:always	4.11	1.04	1	5	48 48 114 426 480	Categorical
Replacement of home appliances with more Env friendly	1:never 2:seldom 3:often 4:almost always 5:always	4.53	0.67	2	5	0 12 108 276 720	Categorical
Efficient use of excessive energy (lights)	1:never 2:seldom 3:often 4:almost always 5:always	4.64	0.64	2	5	0 12 66 234 804	Categorical
Recycling frequency	1:never 2:seldom 3:often 4:almost always 5:always	4.36	0.97	1	5	24 54 90 276 672	Categorical
Interested for the planet pollution	1:no 2: Slightly 3:Fairly 4: important 5: very	4.36	0.75	1	5	12 6 96 462 540	Categorical
Interested for the pollution of air and water in their city	1:no 2: Slightly 3:Fairly 4: important 5: very	4.52	0.67	2	5	0 12 72 354 678	Categorical
Interested in garbage management	1:no 2: Slightly 3:Fairly 4: important 5: very	4.23	0.89	1	5	18 42 114 438 504	Categorical
Micro-generation RETs observability	1:none 2:few 3:some 4:many 5:a lot	2.15	0.92	1	5	276 510 228 90 12	Categorical
Micro-thermal RET observability	1:none 2:few 3:some 4:many 5:a lot	2.72	1.08	1	5	126 432 222 300 36	Categorical

5. Comparison of the Performance of Different Methods

This section presents the empirical results of a comparative analysis of the performance of the models described above. The models are compared first with respect to their predictive accuracy using a 10-fold cross-validation approach for random sub-sampling groups of the data, and the correct classification rate is computed for each model. A second comparison is carried out in terms of variable importance and interpretation analysis for each method using the estimates obtained from the full sample. All of the estimation results reported in the present research are made with the use of the R cran statistical software for data analysis and graphics. In order to estimate the parametric logit models, we made use of the “mlogit” package (Croissant 2020) for discrete choice analysis. We made the RF algorithm training and tuning with the use of “RandomForest” and “Caret” R packages, see Lia and Wiener (2002), and Kuhn (2020), for more details. Finally, we estimated the KCDMD estimator with the use of the “np” package developed by Hayfield and Racine (2008) for nonparametric kernel density estimation.

5.1. Predictive accuracy

In order to compare the predictive accuracy of the models used in the present study, we apply a 10-fold cross-validation approach. We randomly split the sample into ten equal size disjoint subsamples, and each time we exclude one subset from building the model. We then use the excluded subsample for validating (out of sample) the trained (in sample) model. In this way, we ensure that each model predictive accuracy results from independent subsets of data, thus reducing bias in performance estimation (Kohavi et al. 1995).

Table 2 4: 10-fold random-sampling cross-validation prediction accuracy

	MNL in sample	MNL out of sample	MXL in sample	MXL out of sample	RF in sample	RF out of sample	KCDMD in sample	KCDMD out of sample
Fold-1	49.801%	41.964%	48.506%	50.000%	65.550%	73.214%	99.120%	58.036%
Fold-2	49.203%	43.750%	50.000%	42.857%	67.275%	69.643%	98.190%	65.179%
Fold-3	50.697%	46.429%	50.199%	39.286%	66.976%	63.393%	97.800%	62.500%
Fold-4	50.498%	47.321%	50.100%	45.536%	63.493%	74.107%	98.200%	67.857%
Fold-5	50.896%	44.643%	49.701%	46.429%	67.044%	60.714%	98.250%	70.536%
Fold-6	50.498%	46.429%	49.602%	43.750%	67.204%	66.964%	99.500%	67.857%
Fold-7	50.149%	41.441%	49.453%	45.946%	68.221%	68.468%	97.200%	67.568%
Fold-8	51.841%	36.937%	48.856%	49.550%	65.801%	68.468%	98.600%	66.667%
Fold-9	49.851%	54.955%	49.254%	54.054%	66.860%	71.171%	97.700%	59.459%
Fold-10	49.652%	47.748%	49.950%	45.045%	66.065%	70.270%	98.500%	77.477%
Mean	**50.309%**	**45.162%**	**49.562%**	**46.245%**	**66.449%**	**68.641%**	**98.306%**	**66.314%**
SD	**0.00749**	**0.04766**	**0.00556**	**0.041393**	**0.01304**	**0.04138**	**0.00674**	**0.05580**

For each repetition of the procedure, we compute the correct prediction rate and average over repetitions. Within a stated preference discrete choice setting, there are two possible ways to partition the sample into subsets. The first is to partition the sample by individuals, along with their full set of answers, which may lead to dropping essential individuals' experience from the estimated model. The second is to treat all observations as a random sample and divide the sample into subsets. The second approach is a more generalized case where the trained model retains much more individuals' experience, and most frequently predicts a new decision from already acquired experience. Although related literature (Zhao et al. 2019; Wang and Ross, 2018 and Hagenauer and Helbich, 2017) applies the latter approach, in the present study, we apply both since we are interested in both testing the transferability of the models to different individuals but also to test the more general case of "known" individuals' behavior prediction.

Table 2.5: 10-fold individual-based cross-validation prediction accuracy

	MNL in sample	MNL out of sample	MXL in sample	MXL out of sample	RF in sample	RF out of sample	KCDMD in sample	KCDMD out of sample
Fold-1	48.902%	53.509%	48.802%	54.386%	67.438%	42.105%	99.500%	38.596%
Fold-2	52.495%	32.456%	51.896%	33.333%	69.212%	25.439%	97.200%	33.333%
Fold-3	51.297%	42.982%	50.499%	40.351%	66.592%	44.737%	98.600%	17.544%
Fold-4	53.493%	24.561%	52.994%	21.053%	68.245%	28.947%	99.120%	35.088%
Fold-5	50.798%	41.228%	50.599%	41.228%	67.250%	39.474%	98.190%	30.702%
Fold-6	50.299%	32.456%	50.998%	34.211%	67.693%	43.860%	97.800%	44.737%
Fold-7	50.595%	41.667%	50.595%	49.074%	66.359%	42.593%	98.200%	43.519%
Fold-8	50.298%	38.889%	50.496%	40.741%	70.308%	29.630%	97.700%	31.481%
Fold-9	50.397%	37.037%	49.504%	37.963%	69.129%	50.926%	98.500%	28.704%
Fold-10	50.794%	35.185%	50.893%	38.889%	67.187%	24.074%	97.500%	37.037%
Mean	**50.937%**	**37.997%**	**50.728%**	**39.123%**	**67.941%**	**37.178%**	**98.231%**	**34.074%**
SD	**0.01269**	**0.07753**	**0.01152**	**0.08982**	**0.01265**	**0.09333**	**0.00721**	**0.07845**

Applying a 10-fold random-sampling cross-validation approach, Table 2 4 presents the predictive accuracy of the estimated mean of the correctly classified individual's choice within (in-sample) and out of the training sample (out-of-sample). Both nonparametric approaches outperform the parametric model's accuracy. In all of the ten training subsamples, we tuned the RF algorithm concerning the number of variables used to split the sample and the number of trees. The out-of-sample predictive accuracy of the

RF algorithm and the KCDMD estimator is 68.6% and 66.3%, respectively. Instead, the parametric models of MNL and MXL accurately predict less than half of the out sample micro-generation choices with the latter to perform slightly better. The in-sample prediction accuracy of the parametric models reaches 50% and is close to unity for the KCDMD estimator. The RF in sample predictive accuracy is almost the same as its out-of-sample with a magnitude of 66.4%. Thus, we find that in a stated choice setting, well-trained nonparametric models of RF algorithm and the KCDMD estimator outperform the parametric logit models.

In order to test the transferability of the model to new individuals Table 2.5, presents the 10-fold individual-based cross-validation approach predicting model accuracy. The out-of-sample predictive accuracy of both data-driven methods, namely the RF algorithm and the KDCDM estimator has the same low prediction accuracy of the parametric logit models, and all models do not go beyond a predictive accuracy level of 40%. This result indicates that all of the used models fail to predict the choice of new individuals if their experience is not included in the training sample. Thus, datasets with a small number of observations may experience such phenomena whichever estimator a researcher uses. The supervised RF algorithm, along with the data-driven nonparametric kernel estimator, can have high predictive accuracy when new individual's experiences are used when building the model. If the above does not hold, we do not confirm the literature arguing that RF and the KCDMD estimator outperform parametric logit models but, under these circumstances, they can have a similar predictive ability (Hensher and Ton, 2000).

5.2. Model interpretability: a comparison

In this section, we try to compare the different models previously described concerning their assessment of variable importance on the one hand but also with their causal interpretation.

5.2.1. Parametric logit models

A simple way to assess variable importance in a parametric model is to look at the standardized coefficient estimates after the model has been estimated. The estimation of the parametric logit models took place using all the independent variables described earlier. In doing so, we formulated each individuals' utility function using Eq. (2.16). We formed the X_{in} vector of alternative specific variables using the variables presented in Table 2.2, where the beta estimated is the same for all alternatives. The Z_n is a vector of a person characteristics using the variables presented in Table 2.3, and is interacted with the alternative specific constant so that its coefficient varies in the model among alternatives. Under a testing formulation procedure, we selected the coefficients of *Installation cost*, *annual savings*, *thermal bill savings*, and the *time required for approval* as random parameters with a normal distribution in the case of the mixed logit model. The alternative specific constant for the SPV alternative was set to zero in both models.

The estimated beta and X-standardized coefficients of both models are presented in Table 2.6. We calculated the X-standardized coefficients by multiplying the beta coefficient for each variable that is statistically significant with the standard errors of this variable. The X-standardized coefficient indicates the relative importance of the independent variables (Menard 2004). Both models indicate that investment capital cost, the number of kids, the residence size, the education level, and the age as the most significant for households' choice of adoption. The McFadden R^2 for both models indicates a satisfactory model fit, however not providing a better result for the MXL model.

The output of both parametric models indicates that the alternative specific attributes do play a statistically significant role for households selecting a micro-generation technology. As expected, both the MNL and the MXL model indicate that installation costs negatively and significantly affect micro-generation installations. Maintenance costs and bureaucratic delays negatively influence the installation of the alternatives. In the same line, extended years of guaranty positively affect the deployment of micro-generation technologies. However, only the MNL model shows that increased expected revenues and thermal bill savings positively and significantly affect the probability of adoption. However, we should note that in parametric logit models, high multicollinearity between the explanatory variables may cause severe degradation of the estimated coefficients and reduce its overall statistical power.

Table 2.6: Parametric logit models estimation results (standard errors in parenthesis)

	Conditional Logit		Mixed Logit	
	beta coef	X-stand coef	beta coef	X-stand coef
wind:(intercept)	0.60 (1.43)		1.46 (2.21)	
cog:(intercept)	-3.48 (1.91) *		-12.55 (7.72)	
sq:(intercept)	0.16 (1.30)		-1.30 (2.57)	
Alternative Specific attributes				
Installation cost	-0.35 (0.04)***	-1.62	-0.62 (0.12)***	-2.87
Annual savings	1.64 (0.52)**	0.37	1.05 (1.20)	
Annual maintenance cost	-3.67 (1.68)*	-0.14	-4.77 (2.70) *	-0.19
Years of guaranty	0.04 (0.01)**	0.15	0.05 (0.02)*	0.19
Aesthetics	0.15 (0.06)*	0.17	0.26 (0.15) *	0.30
Thermal bill savings	0.67 (0.28)*	0.18	-0.15 (1.60)	
Time required for approval	-0.03 (0.01)**	-0.17	-0.06 (0.03)*	-0.35
Residence Information				
wind: Residence acquisition time	-0.04 (0.11)		-0.05 (0.15)	
cog: Residence acquisition time	0.17 (0.15)		0.31 (0.38)	
sq: Residence acquisition time	-0.11 (0.10)		-0.20 (0.20)	
wind: Residence age	-0.40 (0.15)**	-0.32	-0.53 (0.23)*	0.42
cog: Residence age	0.12 (0.21)		0.69 (0.68)	
sq: Residence age	-0.03 (0.13)		0.06 (0.26)	
wind: Residence sq meter	0.62 (0.30)*	0.62	0.76 (0.40) *	0.76
cog: Residence sq meter	-0.16 (0.38)		-1.16 (1.23)	
sq: Residence sq meter	0.42 (0.27)		0.72 (0.56)	
wind: Future stay	-0.17 (0.11)		-0.22 (0.14)	
cog: Future stay	-0.09 (0.15)		-0.11 (0.37)	
sq: Future stay	0.07 (0.10)		0.20 (0.21)	
Environmental Profile				
wind: Maintenance of heating and cooling systems	0.13 (0.12)		0.24 (0.18)	
cog: Maintenance of heating and cooling systems	0.12 (0.16)		0.48 (0.52)	
sq: Maintenance of heating and cooling systems	0.08 (0.11)		0.12 (0.20)	
wind: Efficient use of excessive energy (temperature)	0.03 (0.10)		-0.03 (0.14)	
cog: Efficient use of excessive energy (temperature)	0.14 (0.14)		0.27 (0.41)	
sq: Efficient use of excessive energy (temperature)	0.19 (0.10)*	0.20	0.35 (0.21)	
wind: Replacement of home appliances with more Env friendly	0.11 (0.14)		0.12 (0.19)	
cog: Replacement of home appliances with more Env friendly	0.44 (0.20)*	0.30	1.25 (0.74)	
sq: Replacement of home appliances with more Env friendly	0.51 (0.13)***	0.34	0.99 (0.36)**	
wind: Efficient use of excessive energy (lights)	-0.21 (0.16)		-0.38 (0.24)	
cog: Efficient use of excessive energy (lights)	-0.00 (0.21)		-0.16 (0.57)	
sq: Efficient use of excessive energy (lights)	-0.51 (0.14)***	-0.28	-1.00 (0.35)**	-0.55

	beta coef	X-stand coef	beta coef	X-stand coef
wind: Recycling frequency	0.32 (0.13)*	0.29	0.41 (0.17)*	
cog: Recycling frequency	0.32 (0.17) *	0.29	0.65 (0.51)	
sq: Recycling frequency	-0.27 (0.10)**	-0.25	-0.71 (0.29)*	-0.66
wind: Interested for the planet pollution	-0.36 (0.17)*	-0.27	-0.43 (0.26)	
cog: Interested for the planet pollution	0.12 (0.22)		0.65 (0.75)	
sq: Interested for the planet pollution	-0.13 (0.16)		-0.15 (0.30)	
wind: Interested for the pollution of air and water in their city	0.17 (0.21)		0.07 (0.30)	
cog: Interested for the pollution of air and water in their city	-0.73 (0.26)**	-0.10	-1.40 (0.84)	
sq: Interested for the pollution of air and water in their city	-0.21 (0.19)		-0.34 (0.33)	
wind: Interested in garbage management	0.10 (0.16)		0.19 (0.26)	
cog: Interested in garbage management	0.27 (0.21)		0.28 (0.56)	
sq: Interested in garbage management	0.59 (0.14)***	0.53	1.13 (0.37)**	
wind: Micro-generation RETs observability	-0.20 (0.12)		-0.19 (0.16)	
cog: Micro-generation RETs observability	0.07 (0.15)		0.43 (0.42)	
sq: Micro-generation RETs observability	-0.37 (0.10)***	-0.36	-0.67 (0.25)**	
wind: Micro-thermal RET observability	0.13 (0.10)		0.13 (0.13)	
cog: Micro-thermal RET observability	-0.13 (0.13)		-0.75 (0.51)	
sq: Micro-thermal RET observability	0.20 (0.09)*		0.34 (0.20)	
Demographics				
wind: Married	-0.10 (0.30)		-0.23 (0.45)	
cog: Married	0.22 (0.44)		-0.29 (1.04)	
sq: Married	-0.21 (0.24)		-0.43 (0.51)	
wind: Gender	0.32 (0.19)		0.36 (0.26)	
cog: Gender	-0.06 (0.24)		-0.61 (0.70)	
sq: Gender	0.50 (0.17)**	0.37	0.91 (0.41)*	0.68
wind: No of Kids	0.30 (0.11)**	0.27	0.44 (0.19)*	0.39
cog: No of Kids	0.31 (0.16)*	0.28	1.01 (0.55)	0.91
sq: No of Kids	-0.42 (0.10)***	-0.38	-0.93 (0.34)**	
wind: Age	-0.02 (0.01)		-0.02 (0.02)	
cog: Age	-0.02 (0.01)		-0.05 (0.04)	
sq: Age	0.04 (0.01)***	0.04	0.09 (0.03)**	0.09
wind: Family Unemployment	-0.24 (0.21)		-0.39 (0.31)	
cog: Family Unemployment	-0.08 (0.30)		0.38 (0.94)	
sq: Family Unemployment	0.11 (0.18)		0.24 (0.38)	
wind: Family Income	-0.17 (0.08)*		-0.24 (0.13)	
cog: Family Income	0.06 (0.11)		0.29 (0.38)	
sq: Family Income	-0.27 (0.07)***	-0.02	-0.54 (0.19)**	-0.36
wind: Education Level	0.03 (0.10)		0.08 (0.16)	
cog: Education Level	0.48 (0.15)**	0.43	1.05 (0.47)*	0.95
sq: Education Level	-0.39 (0.09)***	-0.35	-0.82 (0.28)**	-0.74
Random Parameters				
sd. Installation cost			0.29 (0.11)**	
sd. Annual savings			4.35 (2.08)*	

sd. thermal bill savings		5.51 (2.80)*
sd. time required for approval		0.13 (0.06)*
AIC	2638.75	2640.55
Log Likelihood	-1246.38	-1240.27
McFadden R2	0.1403	0.1452
Num. obs.	1116	1116

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

sq: Status Quo alternative specific coefficient

wind: Wind alternative specific coefficient

cog: Solar Cogeneration alternative specific coefficient

Other than the alternative specific variables, the estimated parametric logit models do not justify the usage of many individual-specific variables in the none SQ alternatives. For instance, only residence acquisition time and the size of the residence are significant and only explaining households' wind micro-generation utility. On the other hand, the parametric logit model output shows that an increased interest in garbage management results in an increased probability of not choosing a micro-generation alternative. Also, the more someone observes, micro-generation RET installations, the less likely she is of selecting the SQ alternative, compared to the SPV alternative, while the contrary holds for thermal RET installations. Concerning the demographic variables used, their signs are in accordance with intuition, and many of them are statistically significant. For instance, the models show that increased family income results in a lower likelihood of selecting SQ and wind alternatives relative to SPV. Elderly homeowners prefer the SQ in contrast to the SPV alternative, and higher education level has the exact opposite results. The outputs of the rest of the models will further prove or reject the above estimation results.

5.2.2. Nonparametric logit models

In contrast to parametric logit models, the RF algorithm and the Kernel Density estimator do not produce an estimate of the causal effect of exogenous variables as traditional parametric models. Within the RF algorithm, we use the variable importance tool to specify the importance of the independent variables, and the partial dependence plots, to analyze the effect of each variable on the classification probability.

Table 2.7: Nonparametric Models Independent Variables Importance

	Random Forests		KCDMD	
Variable Description	MeanDecreaseGini	Rank	Bandwidth	Rank
SPV Installation cost	13.231	22	0.7353	22
Wind Installation cost	13.282	21	0.4003	9
SCogen Installation vcost	9.964	24	0.6801	14
SPV Annual savings	7.523	31	0.6501	21
Wind Annual savings	7.403	33	0.6667	28
Scogen Annual savings	7.495	32	0.6667	33
SPV annual maintenance cost	3.771	40	0.5000	31
Wind annual maintenance cost	5.232	38	0.5000	36
Scogen annual maintenance cost	4.598	39	0.5000	37
SPV years of guaranty	7.869	29	0.6584	23
Wind years of guaranty	7.089	36	0.5344	13
Scogen years of guaranty	7.154	35	0.6413	20
SPV aesthetics	8.432	28	0.6667	29
Wind Aesthetics	7.076	37	0.6667	34
Scogen Aesthetics	7.289	34	0.4710	24
Scogen thermal bill savings	68.113	3	0.6600	2
SPV time required for approval	9.291	25	0.6667	16
Wind Time required for approval	9.063	26	0.6077	30
Scogen Time required for approval	8.722	27	0.6667	35
Residence acquisition time	27.418	10	0.7500	40
Residence age	21.763	14	0.7500	39
Residence sq meter	68.957	2	0.1070	1
Future stay	17.565	18	0.6074	12
Demographics				
Married	7.699	30	0.5000	38
Gender	14.246	20	0.5000	26
No of Kids	35.104	5	0.0748	5
Age	70.833	1	6.7036	3
Family Unemployment	12.892	23	0.1569	10
Family Income	37.048	4	0.0346	4
Education Level	32.927	6	0.8000	18
Maintenance of heating and cooling systems	24.259	11	0.8000	32
Efficient use of excessive energy (temperature)	29.032	8	0.4002	7
Replacement of home appliances with more Env friendly	19.731	15	0.7470	17
Efficient use of excessive energy (lights)	16.100	19	0.5311	11
Recycling frequency	23.349	12	0.7994	25
Interested for the planet pollution	18.368	16	0.3101	6
Interested for the pollution of air and water in their city	17.667	17	0.4340	8
Interested in garbage management	22.163	13	0.8000	27
Micro-generation RETs observability	28.031	9	0.7696	19
Micro-thermal RET observability	32.860	7	0.7386	15

Table 2.7 presents the variable importance, or in other words, the average decrease of the estimated Gini impurity index for each generated tree for each independent variable. Variable importance measure practically ranks variables according to how many times a particular independent variable is used to create nodes for all generated trees along with the node-level positioning, and can be used by the analyst as a variable selection tool. However, if the exogenous variables are correlated, the RF variable importance measure can be misleading (Gregorutti et al. 2017). In this study, we use all the independent variables presented in Table 2.2 and Table 2.3 for comparison purposes.

Except for *thermal bill* savings, the alternative specific variables do not seem to have the most crucial role in the classification process of the RF algorithm. Although the parametric logit models show that the installation cost has the most considerable importance, the RF algorithm places it nearly in the middle of the importance rank. On the contrary, the age of the head of the household, residence size, the level of the thermal bill savings, the financial state of each family, and the number of kids is between the five most important variables for the construction of the random trees.

In the nonparametric context, we further estimated the nonparametric kernel density conditional mode estimator for mixed data. We estimated the bandwidths of the nonparametric KCDMD using the Least Square Cross-Validation method (Hall et al. 2004), and we present the results in Table 2.7. Within the process of data-driven bandwidth selection, the LSCV method has the capability of excluding irrelevant or less important independent variables from the model specification by smoothing them out. The produced values of the estimated bandwidths for irrelevant independent variables are pushed to their upper bound which is ∞, for the continuous variables and and $(c_{x_i} - 1)/c_{x_i}$, for the categorical variables, where c_{x_i} is the number of the levels, for the categorical independent variable x_i. Estimated bandwidth close to its upper value causes the kernel density estimator of a particular variable to be constant across all sample observations. In the present study, we estimate the variable importance measure of categorical variables for the KCDMD estimator as the ranked difference between the estimated bandwidth and its upper bound. While, in the case of the continuous variables, lower values of bandwidths are given as a better rank. For continuous variables, the difference between the estimated bandwidth and their upper level ∞ will always be greater than the categorical ones. We present the KCDMD independent variable ranking in Table 2.7.

Within the above context, independent variables with a ranking value greater than 26, reach their upper limit bandwidth and are excluded from the model as if they were never included. As in the RF approach, the LSCV estimated bandwidths of the KCDMD estimator indicate that the most significant role for the classification process is played by the age of the head of the household, residence size, the level of the thermal bill savings, and the financial state of each family. Alternative specific independent attributes, such as maintenance cost and aesthetics, are excluded from the model as non-important. Also, the KCDMD estimator indicates that the SPV and the Solar Cogeneration alternatives installation cost is not of high importance for explaining the choice of micro-generation RETs. Continuing with the individual specific independent variables, the reader can see several differences concerning the ranking of alternatives between the two nonparametric models. However, the actual effect of each independent variable on the estimation result is not shown either by the mean decrease index or from the bandwidths estimation reported in Table 2.7. Thus, in the following section, we graphically present the effect of the most important, comparing the main results of the parametric and nonparametric models used, using partial dependent plots.

5.2.3. Models comparison

In the present study, we use partial dependent plots for comparing the produced causal effects of the parametric and nonparametric models. For brevity reasons, we compute and visualize the partial dependence of two alternative specific variables, namely, installation cost and the thermal bill savings (see Figure 2.3 and Figure 2.4), and the four most important variables indicated by the nonparametric models. (see Figure 2.5 - Figure 2.8). In order to avoid overinterpretation of the partial dependence plots in regions where no data exist, we add a rug distribution plot in all of the individual-specific variables presented plots. We further present the partial dependence plots of the rest alternative specific variables of Table 2.2 in Appendix I.

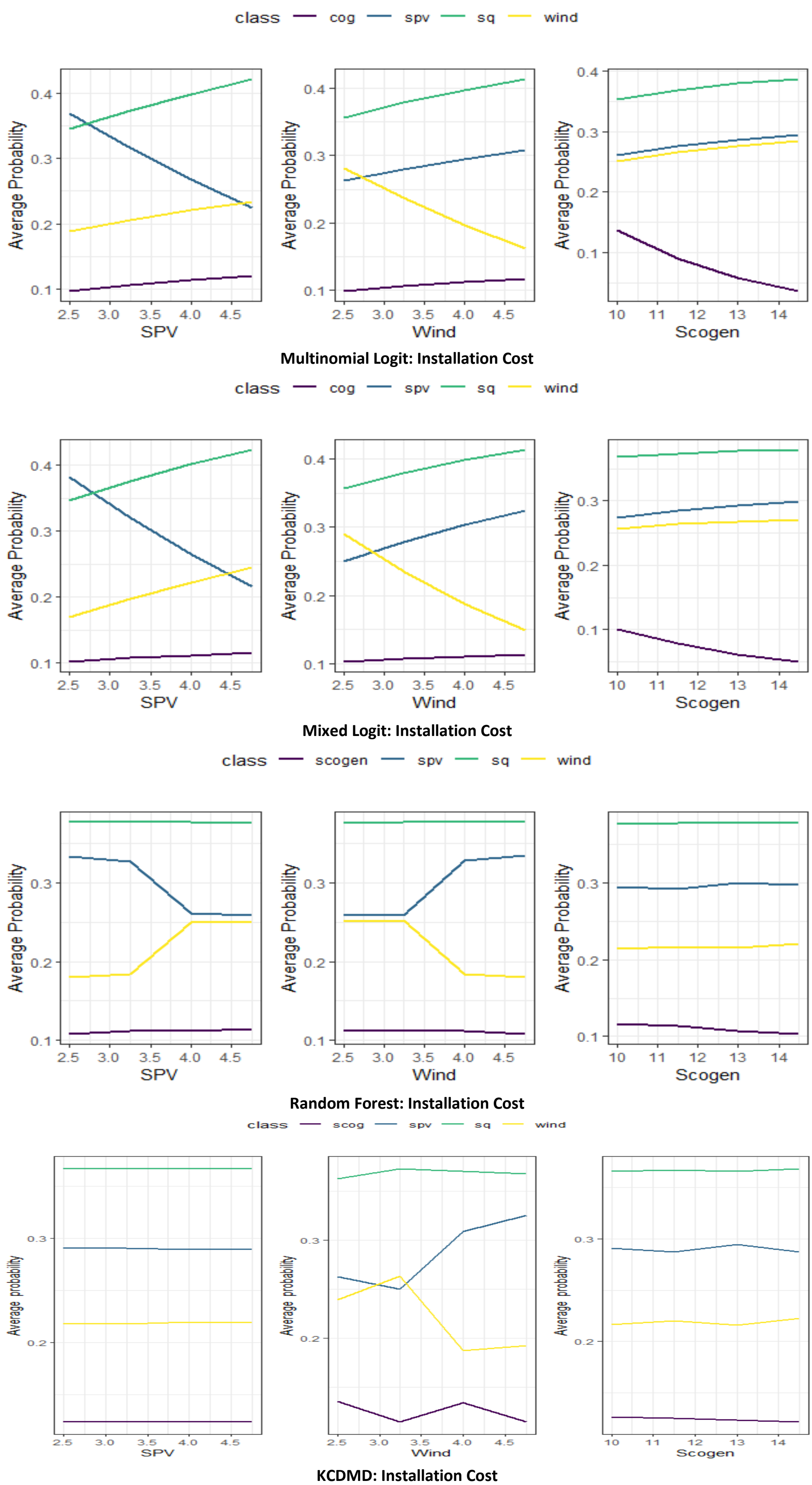

Figure 2.3: Partial Dependence Plots for the alternative specific Installation Cost variable

For both the parametric and nonparametric models discussed above, Figure 2.3 presents the predicted influence of installation cost on households' choice. As we discussed previously, both parametric logit models find that an increase in the installation cost of a technology results in a reduction of its propensity of being selected. The partial effect of the MNL and MXL model shows that this propensity decreases in a nearly linear way. The RF and the KCDMD methodologies show, however, a somewhat different perspective of this causal effect. In particular, the RF algorithm shows that the probability of choosing an SPV or a wind micro-generation technology decreases when its installation cost is between 3,250 to 4000 euros, and thereafter it is almost constant. This flattened curve may indicate that households become insensitive to installation cost levels above 4,000 euros. Also, the plot shows that when SPV installation cost affects the probability of choosing SPV negatively, it does so in favor of the wind technology mainly while when wind installation cost negatively affects the probability of choosing wind, it is the SPV technology that is favored.

The insensitivity to cost is further evidenced in the case of the solar cogeneration technology from the RF algorithm results, as increases in the installation cost of solar cogeneration, which is higher for the particular alternative, has a very small impact on the probabilities of selecting all choice alternatives. The KCDMD estimator produces a similar result to the RF algorithm in the case of wind installation cost, whereas only wind installation cost increases from 3,250 to 4,000 euros cause the probability of its adoption to fall. However, the installation cost of the other two alternatives is smoothed out of the estimated model as none important, a result that is confirmed from their estimated bandwidths presented in Table 2.7.

Within Figure 2.3, the parametric logit models further show that micro-generation alternatives act as competitors to each other since an increase in the installation cost of one alternative increases the probability of choosing all the other. However, the propensity to select the cogeneration alternative increases the least when the installation cost of other alternatives increases. Taking into consideration the higher installation cost of the solar cogeneration micro-generation alternative might exclude it from being a competitor. Contrasting with the above findings, the RF algorithm, and the KCDMD estimator indicate that only SPV and wind micro-generation technologies act as competitive technologies.

Turning now on interpreting the causal effect of thermal bill savings of the solar cogeneration alternative, all models produce relatively similar results (Figure 2.4). Although in different magnitude levels, all models find that the probability for a household to select the solar cogeneration alternative increases relatively to an increase of thermal savings. The RF algorithm, contrary to the other models, shows that an increase in savings from 0 to 1.500 euros increases the probability of adopting solar cogeneration, but for savings above more than 1.500 euros, the effect is constant. The nonparametric models produce similar results concerning the effect of solar cogeneration thermal bill savings on other micro-generation alternatives, with the RF depicting more nonlinearities in this effect. The age of the head of the household seems to have an essential role in the prediction of household choice, and all models, produce similar results (Figure 2.5). Again, the RF algorithm depicts more nonlinearities in the predicted averaged effects. For instance, the probability of selecting the SQ alternative reduces for ages between 25 to 35, then it sharply increases for ages from 35 to 55 and is stabilized for older respondents. This means that households with decision-makers around 35 years old are more likely to adopt a micro-generation technology. On the other hand, we cannot argue something similar based on the predictions of the other models.

In Figure 2.6, we present the estimated effect of the family income level on choice probabilities. Both parametric and nonparametric results produce relatively similar results in terms of their causal effect. All models show that an increase in family income results in a higher probability of adopting a micro-generation RET. However, the nonparametric models address this effect in a nonlinear way, in contrast to the parametric ones, and show that there is an income level of 40.000 up to where the estimated probability of adoption is no longer increased. Once again, the parametric and nonparametric models produce different interpretations of the effect of residence size (Figure 2.7). The parametric logit models indicate that as the residence size increases, the probability of a household to select the SQ alternative always increases.

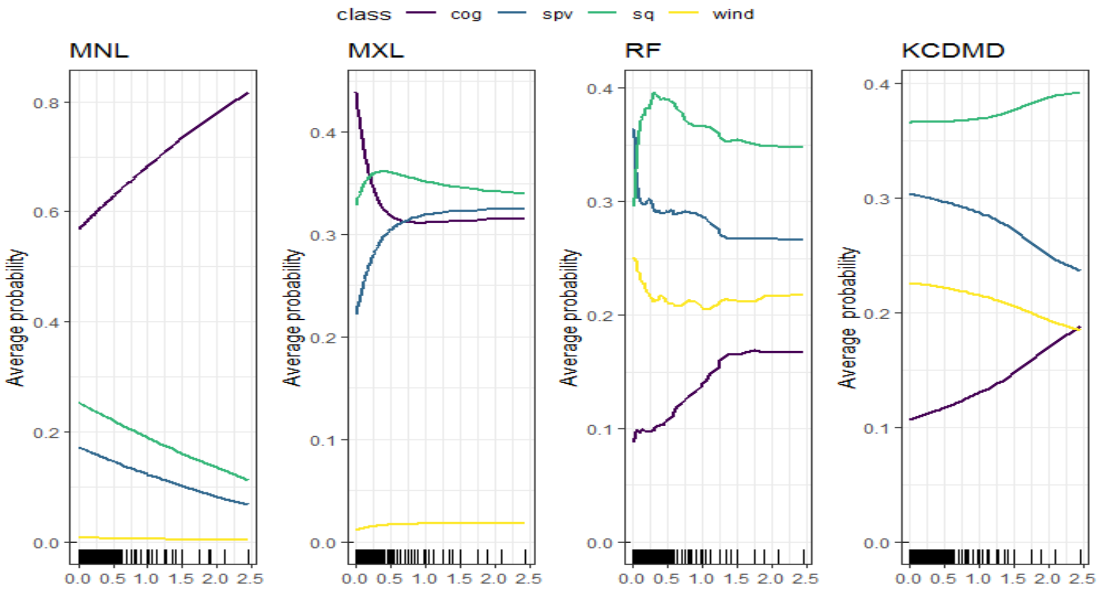

Figure 2.4: Partial Dependence Plots for Thermal Savings (thousands euro)

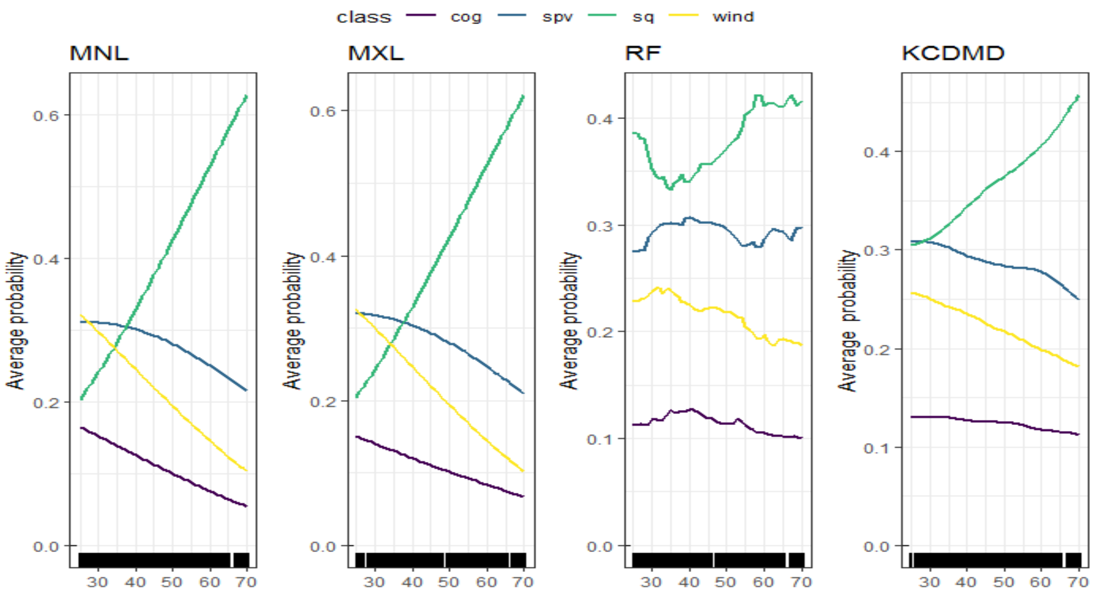

Figure 2.5: Partial Dependence Plots for Age

In contrast, the nonparametric models' findings indicate that the probability of selecting the SQ alternative reaches the maximum for a residence size of around 100 square meters, and decreases for the other values. The probability of selecting a particular micro-generation technology also has to do with the residence size. According to both nonparametric models, the probability of selecting an SPV micro-generation RET is at its maximum when the residence size is 100 to 150 square meters.

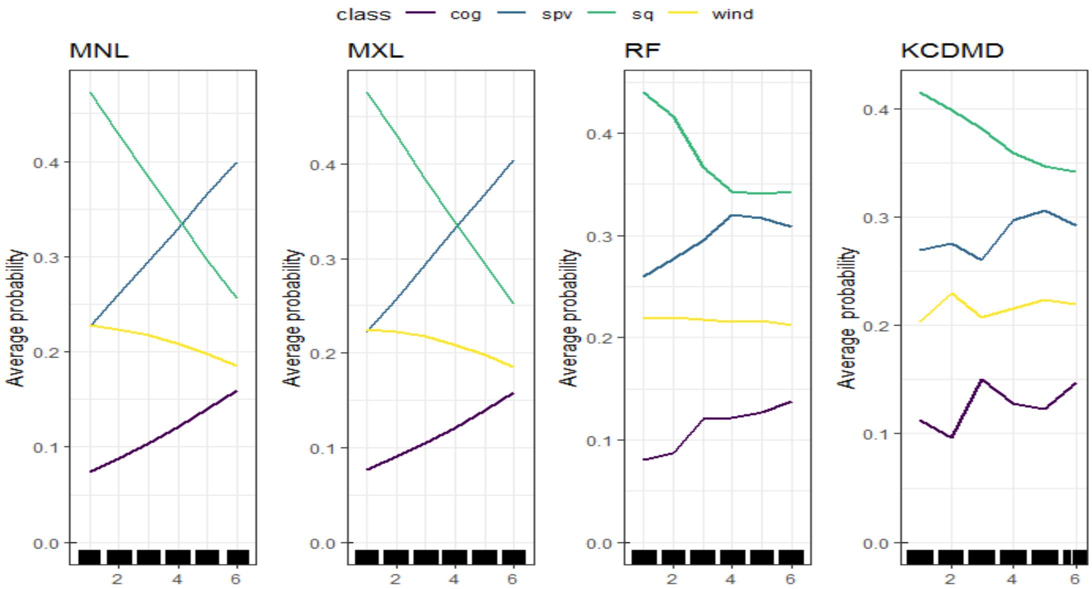

Figure 2.6: Partial Dependence Plots for Family income level

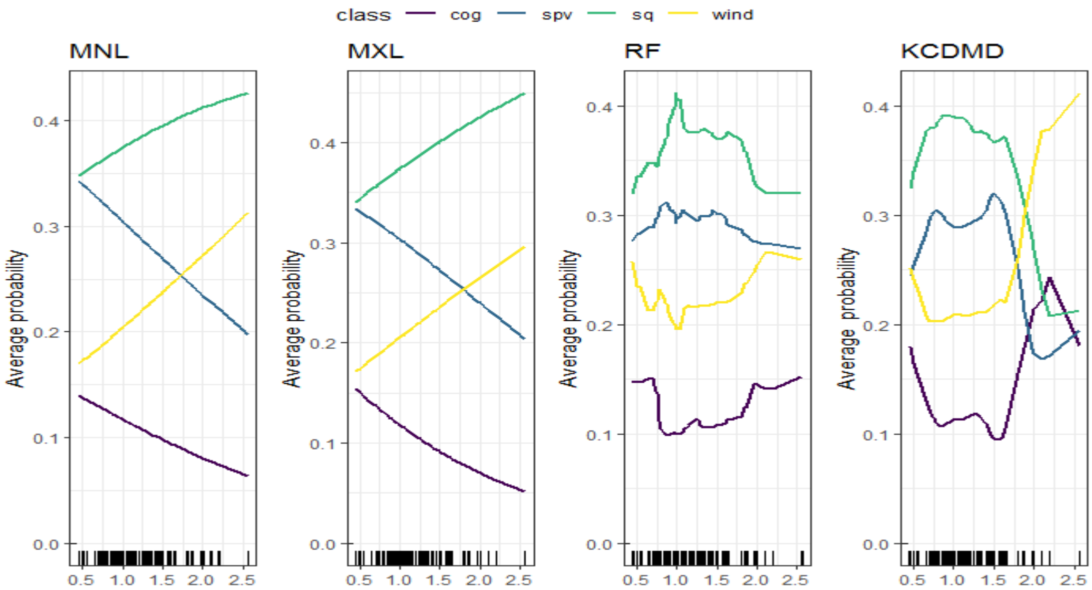

Figure 2.7: Partial Dependence Plots for Residence size (hundred sq meters)

Finally, in Figure 2.8, we show the partial effect of the number of children in a household on the choice for a micro-generation RET. Both parametric and the RF algorithm predict that the maximum probability for selecting the SPV alternative is for families with two kids. According to the KCDMD estimator, the probability of selecting the SPV alternative has a local maximum for two kids, and then the probability is further increases for more than four kids. Again the predictions of the RF algorithm and the KCDMD estimator results indicate that the probability of selecting the SQ alternative is stable for RF or increasing for KCDMD at the point between two and three kids and then starts to decrease again.

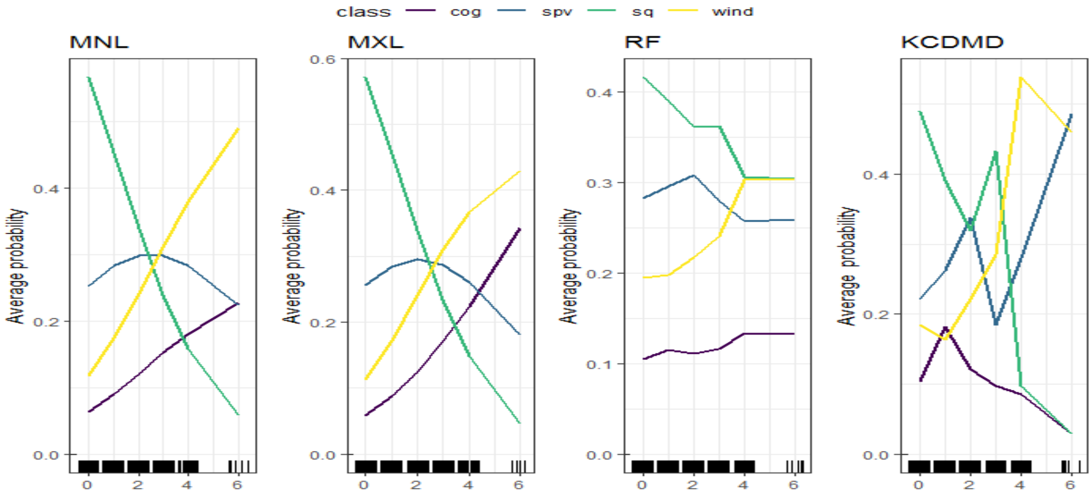

Figure 2.8: Partial Dependence Plots for the No of Kids in the family

6. Discussion and conclusions

The goal of this research is to perform a comparative study between parametric logit and nonparametric models in a discrete choice setting. We compare model development, evaluation of results, and behavioral interpretation. In particular, we examine two basic well-known logit models, namely the Standard Conditional Logit and the Mixed Logit and compare them with the state of the art machine learning algorithm of Random Forests and the nonparametric kernel multinomial model. We compare the models using data related to a survey on consumer choice over micro-generation technologies conducted in Crete, Greece.

In terms of accurately predicting the choice of micro-generation RETs, this study's results are partly in agreement with those of the study of Hensher and Ton (2000) that finds NN to be similar or, in some cases, worse than a Nested Logit model. The term "partly" is used here because our results depend on whether the choice of the training set is based on individuals or observations. If the choice is based on individuals, so that some randomly chosen individuals are not included in the training set, then all models used in the present study have an equal and low rate of choice prediction accuracy and fail to transfer their results for predicting new individual's behavior. Although the nonparametric models perform better for in-sample predictions, on the other hand, when the trained models are used to predict new choices of the same individuals, then the scales are tipped against the parametric logit models. This result is a logical consequence of the nature of the data-driven methodologies used in the present study. In particular, the RF algorithm is a “supervised” learning methodology where its outcome relies on the input data (Mohri et al. 2012; Athey and Imbens. 2019. Thus, missing data patterns cannot be capitalized, and “new” choices cannot be accurately predicted.

In contrast to the growing literature using ML as a means of predicting discrete choices claiming that they outperform traditional parametric logit models (Chen et al. 2019; Zhao et al. 2019; Lhéritier et al. 2018; Alwosheel et al. 2018; Brathwaite et al. 2017; Hagenauer and Helbich, 2017; Tribby et al. 2017; Sekhar et al. 2016; Wang et al. 2016) this study raises the issue of representability, especially in the case of small sample datasets, and shows that the accurate prediction of the models is similar. On the other hand, when the models are called to predict a new choice of an individual that the training model learned from her experience, then we find the RF algorithm and the nonparametric KCDMD model to outperform the parametric ones.

In the present study, we additionally compare the models according to the indicated variable importance of the exogenous variables used. We compute the X-standardized coefficients of the estimated beta parameters as a measure of relative importance (Menard 2004), and we find that the parametric logit models draw their attention to the installation cost, the number of kids, the residence size, the education level, and gender. In the case of the RF algorithm and the KCDMD estimator, we use the mean Decrease Impurity Index (Breiman, 2001a) and the upper-level distance of the kernel density estimated bandwidths (Hall et al. 2004), respectively. Although with small differences, the nonparametric models draw their attention to thermal bill savings, the age of the head of the household, residence size, the financial state of each family, the number of kids, and the investment revenues. The RF algorithm and the KCDMD estimator results indicate the significance of the installation cost but place it nearly in the middle of the importance rank. As far as the other alternative specific variables are concerned, the nonparametric models place them in the lower importance rank, giving more importance to socio-economic factors.

Through the use of partial dependence plots (Friedman, 2001), this study compares the causal effect of the most significant variables indicated by the estimated models. Drawing on the results of the nonparametric models, we identify nonlinear effects that would not otherwise appear, warranting thus their usefulness in the interpretation of partial effects when a linear specification might not hold. The KCDMD estimator is found to have similar results to the RF algorithm, both in terms of predictability and interpretation, indicating that both approaches can be an effective alternative methodology for discrete response models. Within the nonparametric models, the researcher does not have to enforce any restrictive assumptions about the distribution of the unobserved part of the utility and for the functional form of the observed part, exploiting informational patterns from the data.

A limitation of the present study is that none of the models discussed above takes into account the panel data nature of the SP data used, and it might be worthwhile investigating whether taking it into account improves the performance of the RF algorithm. Last but not least, all of the above methodologies could be combined in a given setting. For instance, RF and the KCDMD could be supportive or not about the choice of explanatory variables and functional form in a more heavily parametrized random utility model, although the former is not necessarily based on smooth preferences.

7. References

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Appendix I

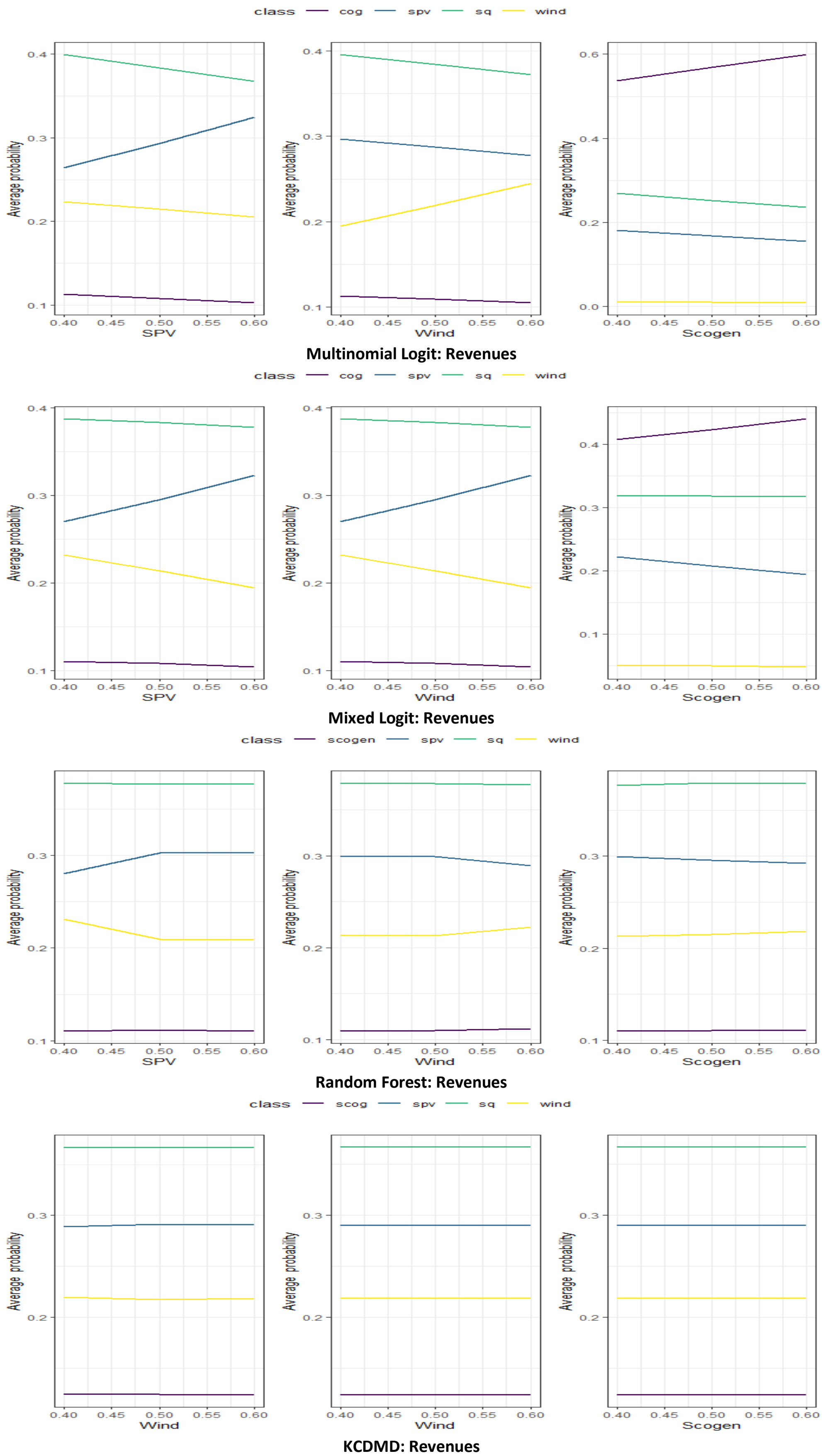


Figure 2.9: Partial Dependence Plots for the alternative specific Revenues variable

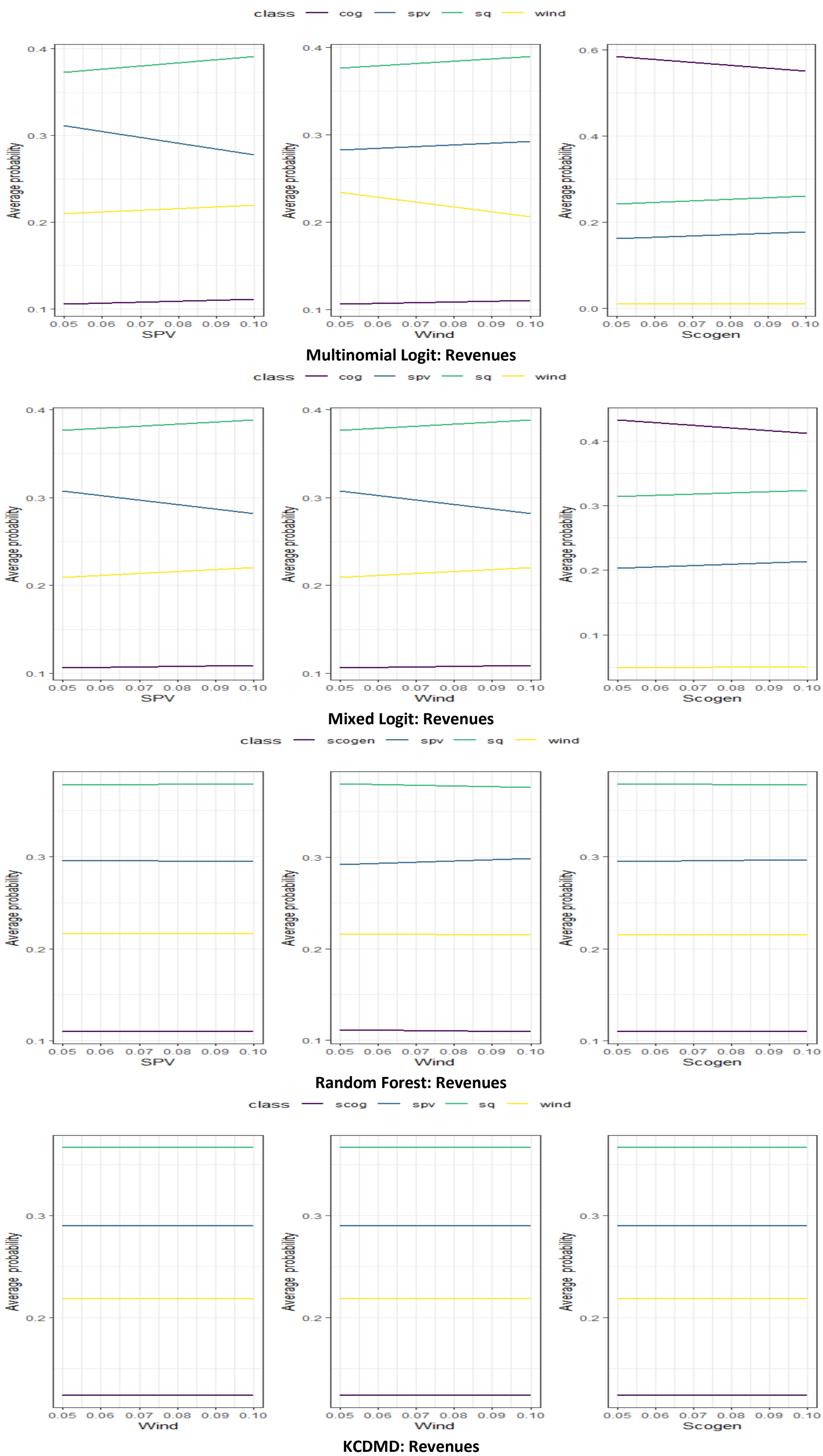


Figure 2.10: Partial Dependence Plots for the alternative specific Maintenance Cost variable

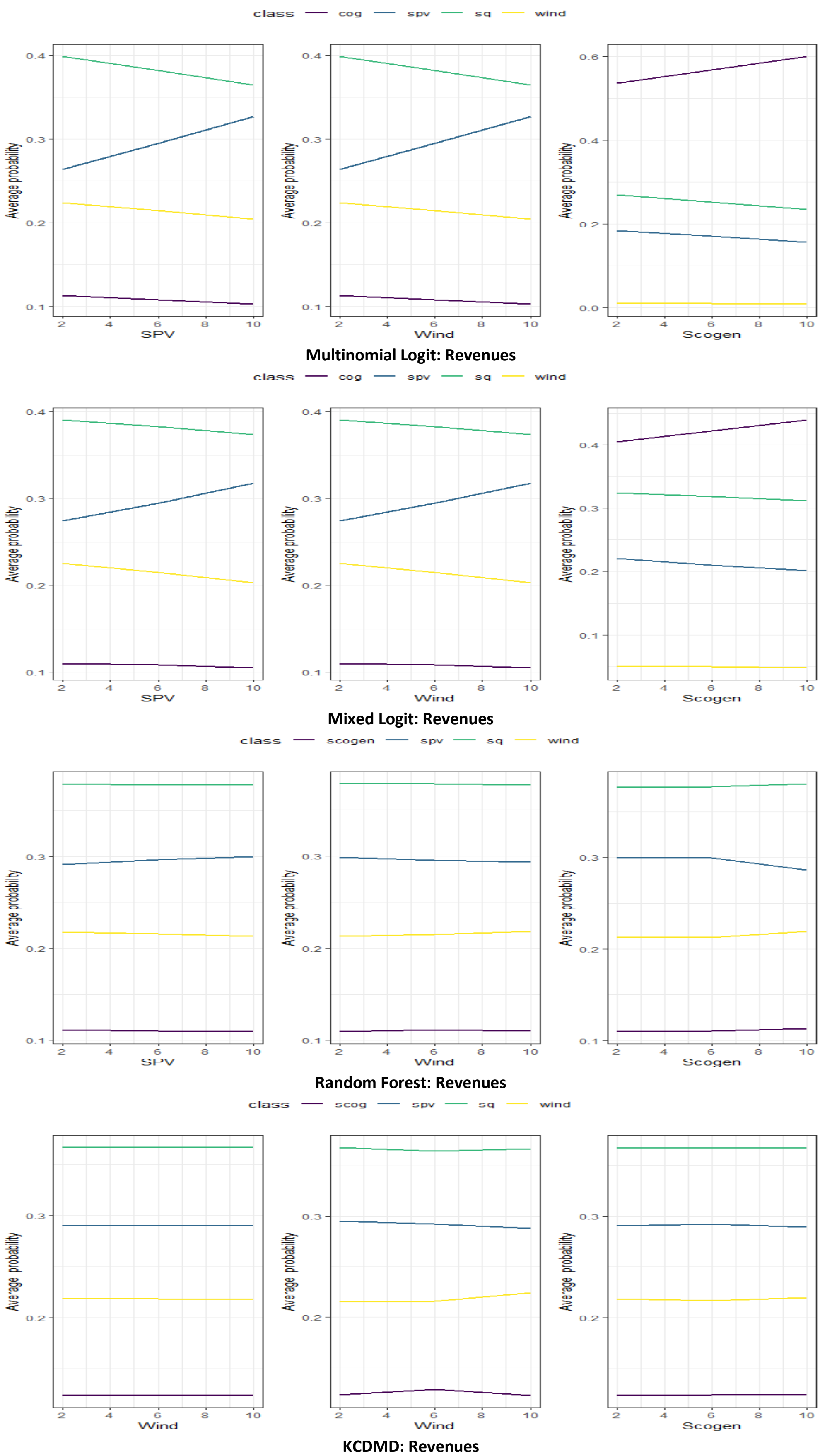
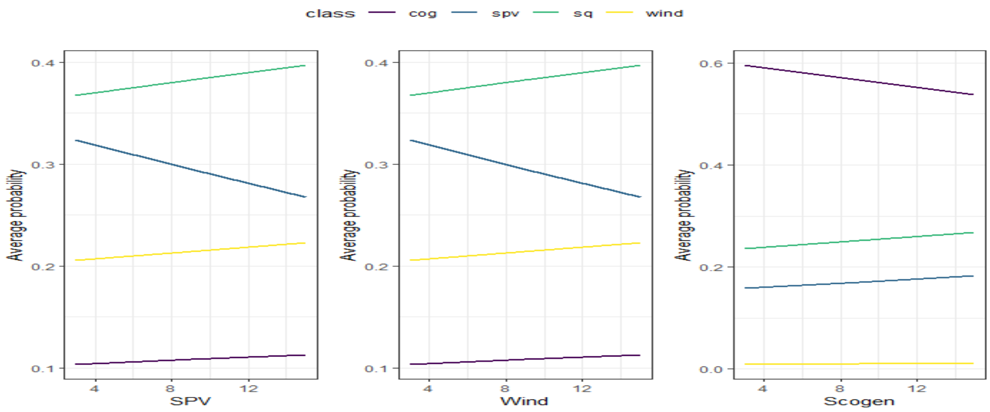
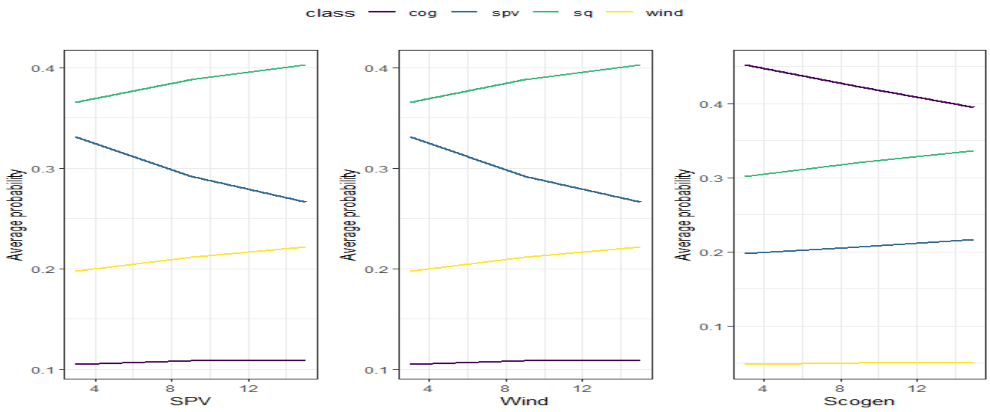


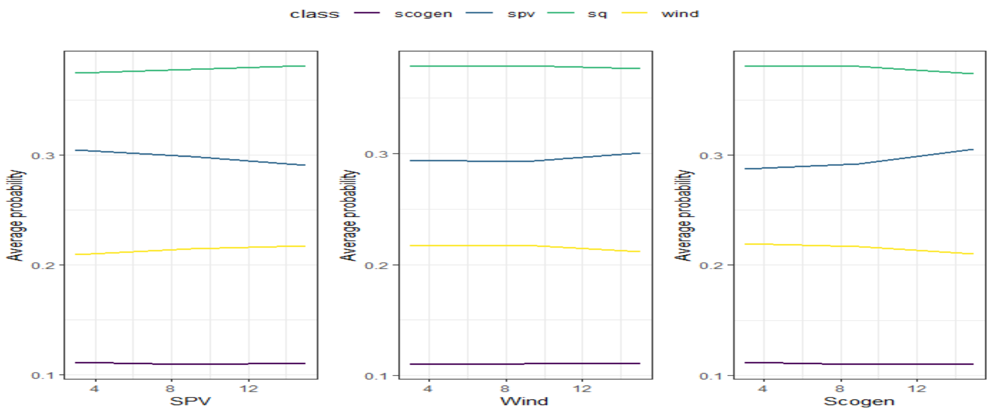
Figure 2.11: Partial Dependence Plots for the alternative specific Guaranty variable



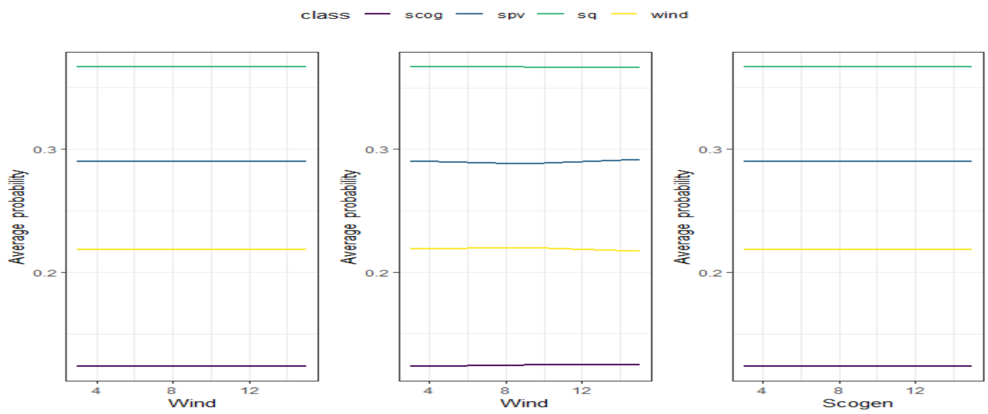
Multinomial Logit: Revenues



Mixed Logit: Revenues

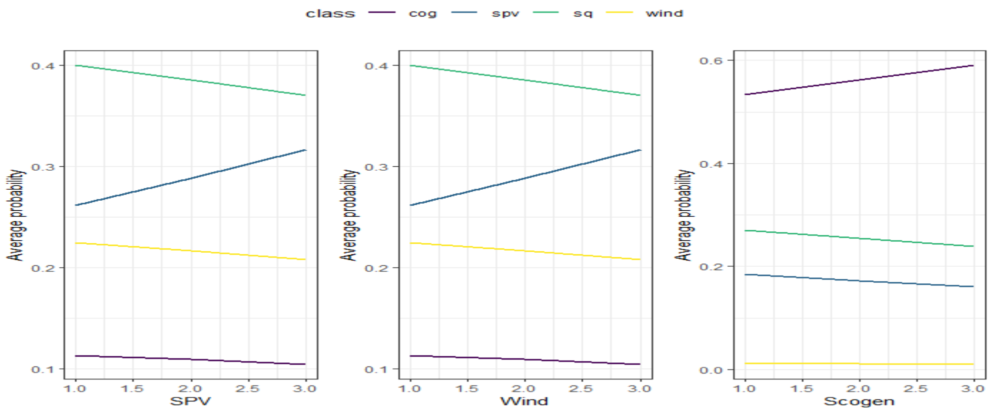


Random Forest: Revenues

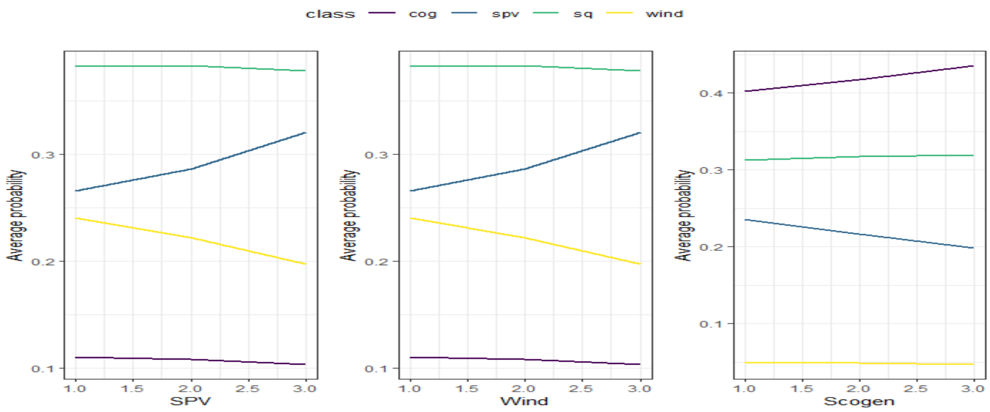


KCDMD: Revenues

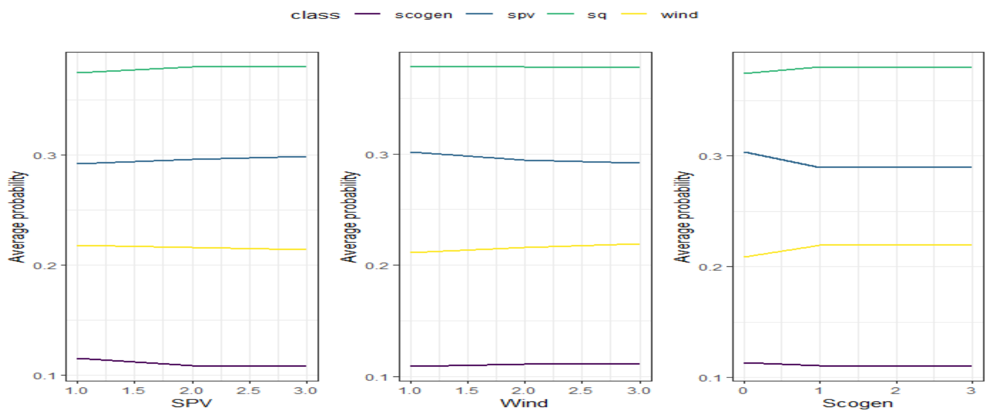
Figure 2.12: Partial Dependence Plots for the alternative specific Approval Time variable



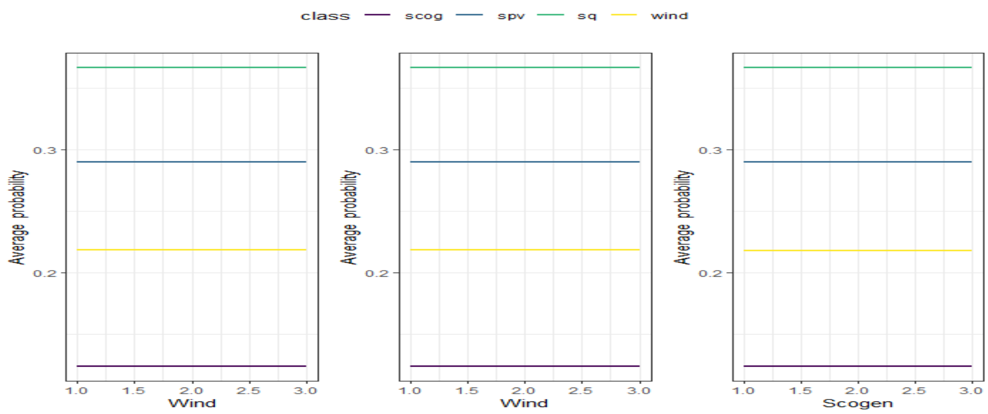
Multinomial Logit: Revenues



Mixed Logit: Revenues



Random Forest: Revenues



KCDMD: Revenues

Figure 2.13: Partial Dependence Plots for the alternative specific Aesthetics variable

CHAPTER 3: FEED-IN-TARIFFS AND GOVERNMENT CORRUPTION: ANOTHER LOOK AT THE DIFFUSION OF RENEWABLE ENERGY TECHNOLOGIES

1. Introduction

Investments in Renewable Energy (RE) have flourished in the past two decades, even though most economies worldwide were affected by the recent economic crisis that started in 2008. However, governments, in order to attract investment funds in the RE sector, continue to provide incentives to investors through differently implemented policy frameworks. As a result, in 2011, RE investments almost reached the level of investments on fossil fuel energy-producing technologies, with China and USA leading the race of investments reaching 51 billion US dollars in the case of the US (BNEF 2012). This rise in investments is also stemming from the cost competitiveness of RETs such as onshore wind and solar photovoltaics, compared to other fossil fuels technologies, where the former, in some cases, act as mainstream technologies (REN21 2016; BNEF 2016).

Although the RE sector is rapidly growing, it has a long way to cover until it can fully substitute the energy produced from fossil fuels. For instance, the proportion of power generated from clean sources in 2016 accounts for only 10% of the total energy power (BNEF 2016). Power plants from fossil fuels are still in operation, and not only more time but also more effort in terms of government intervention will be needed to gradually substitute them. On the other hand, the diffusion of mainstream Renewable Energy Technologies (RETs) is still ongoing, and its progress has been slower than expected. The reason behind this lies in the fact that RETs investors are confronted with high upfront costs and long term depreciation periods, which increase the risk of the undertaken investment. This risk may be influenced by several factors in each country, namely policy design and its sudden changes, electricity market and regulation, institutions, financing, and grid access. As a result, higher risk necessitates greater returns, thus more generous policy instruments for an investment to be selected. One could argue that the level of risk and the incentives faced by investors reflect the rate at which investments on RETs are being made.

This study's objective is to shed light on the effect of policy instruments introduced to support RETs investments. Several scholars claim that governments should create an effective and efficient policy framework providing stability security and predictability to investors of RETs (Jaccobson and Bergek, 2004; Ringel 2006; Angoluchi 2008). Risk reduction can be achieved through financial sustainability and the proper allocation of costs and benefits of a policy framework so as not to distort the energy sector. However, in several countries, sudden changes were made with respect to their RE supporting schemes. For instance, until 2008, Spain provided an overgenerous Feed-in-tariff (FIT) program for the new photovoltaic (PV) investments. The increasing national debt, along with the magnitude of the tariff, resulted in the suspension of the program for new PVs installations causing investments towards this technology to collapse (Mahalingam and Reiner, 2016). Likewise, during the sovereign debt crisis in 2010, Greece suddenly reduced the FIT levels for large-scale Photovoltaic installations for new and already existing projects causing investments to freeze (DEDDIE 2019). Thus, investors will hardly trust a policymaker that abruptly harms investment returns in the future.

In addition to policy instruments applied by each country, other factors can influence the diffusion process of RETs. Institutional factors and particularly government corruption, can negatively affect investment activities (Everhart et al. 2009; Mauro, 1995) and distort incentives provided by the policymaker (Fredriksson, List and Millimet, 2003; Fredriksson, Vollebergh and Dijkgraaf, 2004) thereby increasing investors' risk. In particular, corruption can distort RETs adoption by influencing various aspects of the investment process, such as decisions regarding the use of land and authorization of investments, among others (Tanzi, 1998; Jain 2001; Aidt, 2003) and creates a less appealing environment for investment activities since investors' incentives are distorted. However, some authors claim that corruption could be investment enhancing in the sense that red-tape can be bypassed through small side payments (Leff 1964) or increase investors' access to public funds (Tanzi and Davodi, 1997). Another strand of the industrial organization literature argues that the level of the organization networks of corruption and the time horizon of government officials can have a decisive role in the effect of corruption over investments and growth (Olson, 1993; Rock and Bonnett, 2004).

In an attempt to unravel the effect of government intervention through the implemented policy mechanisms and the effect of corruption on RE investments, this research employs an empirical panel data analysis for investments on windmills in 48 countries. Our contribution to the literature is that we handle Feed-in-tariffs, which is a price policy mechanism for RES producers compensation, as endogenous following the intuition proposed from the diffusion literature (Söderholm and Klaassen, 2007, Jaffe and Stavins, 1995; Maza and Winden, 2004). From an econometric point of view, if the endogeneity of policies is not appropriately taken into account, it can lead to erroneous conclusions and results for researchers. In addition, the present research tries to shed light on the possible directions in which corruption can affect investments over the deployment of Wind Technologies and further test whether this effect changes within different geographic regions. In order to analyze this effect, we use the Corruption Perceptions Index (TI 2005-2012), and we further assess our estimation results using a different measure of corruption, the World Bank Control of Corruption Index (WGI 2005-2012). Our empirical results indicate that the FITs policy scheme has a key role in the growth of large-scale wind investments and provides solid empirical evidence of the East Asian paradox where high perceived corruption levels result in investment development.

The remainder of the chapter is organized as follows: Section 2 provides a background review concerning the role of government intervention through the implementation of policy frameworks on RE investments while at the same time analyze the way in which corruption may distort these investments. Section 3 describes the variables used, while section 4 presents the empirical strategy followed, the estimation results and the robustness check of the results with an alternative measure of corruption. Sections 5 and 6 offer a discussion of the results and present the main conclusions and limitations of our methodology and data.

2. Diffusion of Renewable Energy Technologies

Scholars have identified several factors that can influence the diffusion process of RETs. Due to the fact that RET electricity market is highly capital intensive, government intervention is necessary to improve the efficiency of the market. The implementation of policy mechanisms provide incentives that would not otherwise exist in the market and can mitigate the financial and technological risk of RETs investments. Related literature identifies three channels through which governments can promote RE investments, namely s) through public R&D investments that gradually reduce the cost of the investment, b) through indirect environmental regulation increasing the competitiveness of RETs against conventional energy sources and c) through direct policy mechanisms increasing the profitability of the investment. When the applied policy mechanisms are not considered as reliable or sufficient, the risk of initiating a RET investment project increases, and the project may not be carried out (De Jager and Rathmann, 2008). However, investors' trust and confidence are affected not only by the existence of incentives but also by the institutional framework that sets up the rules for their implementation, defining the interaction between economic agents (North 1990). Thus, the interplay between the institutional framework, such as the political and legal system and the cultural structures and overall corruption, can distort the incentives provided by policymakers. In view of the above, in this section, we lead our discussion by focusing on the analysis of the literature on the two main RETs investments risk influencing factors, namely government intervention and the institutional factor of corruption.

2.1 Government Intervention

In the two past decades, countries all over the world implemented several policy mechanisms to strengthen investments on RETs and achieve their Renewable Energy targets. However, this progress has been slower than expected. The reason behind this lies in the fact that investors act in a highly capital intensive market and have not been presented with the right incentives (Pizer and Popp, 2008; Agnolucci, 2008). Without policy intervention, investors do not have incentives to allocate their funds towards RETs (Jaccobson and Bergek 2004), mainly due to the fact that substantial risks are involved in terms of both the technology and also the economic and social environment of the investment. In this sense, government intervention through policy mechanisms results in an increase in the profitability of an investment, or, in other words, reduces the undertaken investment risk, which is the determining factor that influences investors' decisions to adopt them (Söderholm and Klaassen, 2007). Therefore, for a RET investment to be worthwhile, the implemented policy mechanisms should focus on the fact that the expected return should exceed capital cost and, in the long run, should provide security for investors (Ayoub, 2012; Rodriguez et al. 2015).

The literature on the diffusion of environmentally friendly technologies argues that there are three main channels through which a government can enhance the competitiveness of new technologies. The first is through public R&D and innovation, where new technological advances result in cost reductions of new technologies (Söderholm and Klaassen, 2007; Pizer and Popp, 2008; Popp et al. 2011). Söderholm and Klaassen (2007) empirically find that investments in R&D translated into technological cost reductions, which promoted the diffusion process of windmills in Europe. Using patent data for a panel of 26 OECD countries, Popp et al. (2011) find evidence that technological innovation has a small but positive effect on RETs investments. Further analysis of the effects of technological change can be found in the review provided by Pizer and Popp (2008).

The second type of schemes includes the regulation imposed by governments to reduce greenhouse gas emissions produced from the existing technologies by simply raising their production cost (Jaffe and Stavins, 1995; Kemp, 1998; Gray and Shadbegian, 1998; Xepapadeas and Zeeuw, 1999; Kerr and Newell, 2003), making them thus less competitive. Examples of such environmental regulation are carbon tax emissions and technology standards, among others. For instance, Jaffe and Stavins (1995) analyze the effect of building codes and energy taxes on the adoption of thermal insulation by US households. The authors find no evidence that building codes had a significant effect on insulation adoption. In the same direction are the results of Snyder et al. (2003), who find that regulatory factors has no effect on the adoption of new technologies in their particular example of membrane-cell technology. The main disadvantage of imposing policy mechanisms to reduce the competitiveness of existing more polluting technologies is the downsizing of the profitability of the industry, which may have adverse effects and scare new investment funds (Xepapadeas and Zeeuw, 1999). On the other hand, Gray and Shadbegian (1998) and Kerr and Newell (2003) find evidence that stringent environmental regulation could raise the profitability of new, less polluting technologies with respect to the existing ones and thus enhance their diffusion process.

Finally, governments can promote the diffusion of new technologies by providing direct incentives for their deployment. A number of direct policy schemes enhancing the diffusion of RETs have been implemented, aiming at either the prompt increase of electricity production from renewable energy sources (RES) or at the long term viability of RES investments. Some of the main policy mechanisms implemented in countries worldwide are a) Feed-in Tariffs (FITs) where RES electricity producers are paid a fixed tariff larger than the electricity market price, b) Quotas/Renewable Portfolio Standards where a minimum share of renewable energy is imposed in the energy mix of consumers and retailers or producers and the benefit for RES electricity producers is subject to the level of quota obligation and the level of the penalty, c) Tradable Green Certificates[9] (TGC) upon which a parallel market of renewable energy certificates is established with producers benefiting from the sale of certificates, and d) Investment incentives where a proportion of the overall investment cost of RES electricity production projects is financially supported and e) Fiscal and tax relief incentives.

Each of the above types of instruments has attributes that should be taken into consideration when designing a policy scheme. For instance, FITs have a number of attributes such as the level of the tariff, the duration, and their possible digression for new installations. Similarly, quota's effectiveness is subject to the level of the imposed share, whether it is applied in a technology-specific way or following a general approach for the total RES electricity production, the level of the penalty, and the length of the contracts for electricity or green certificates. The implementation of the above instruments presents a different level of investment risk, which means that policy design should be made in an efficient, predictable, and consistent way aiming at reducing it.

The designed attributes of policy instruments influence the motivation provided to investors by the government. Inadequate design of policy schemes may originate from either the fact that policymakers make honest mistakes or that they are doubtful over the new technological advances, wherein any case resulting in preserving old, more polluting energy-producing technologies (Nilson 2004). Following this argument, policymakers who are not totally convinced that RETs can fully substitute conventional sources may devise and implement a mix of policy mechanisms to experiment over

[9] TGCs are in general applied along with Quotas/RPS. When the two policy instruments are applied together the value of the green certificate is determined from the level and duration of the quota obligation and the size of the penalty.

their efficiency and promote green innovation (Nesta, Vona, and Nicolli 2014). In this respect, inadequate or continuously changing policy mechanisms implemented towards reaching a low-target of RETs installed capacity may increase investments' risk and may act as an impediment to their diffusion process (Masini and Menichetti 2012). In the case where these actions result in abruptly harming investment funds, a government will hardly be trusted in the future. Besides, the main condition for a supporting scheme to be considered as efficient is the financial sustainability, and the proper allocation of costs and benefits so as not to create distortions to the energy sector (Agnolucci 2008). As a final point, the energy sector is enormous and involves several opposing coalitions to renewable energy (Jaccobson and Bergek, 2004; Marques, 2011), which may result in either inefficient design and implementation of policy instruments or to the lack of government intervention towards the deployment of renewables. Jaccobson and Bergek, (2004), analyze the effect of intense lobbying in the German energy market between wind and conventional energy sources actors, which resulted in the victory of the wind party and the enforcement of the feed-in-law of 1991 which assisted wind energy market to make a transition to a more developed stage.

Scholars also focus their interest on the effect of the direct government intervention policy instruments in enhancing RETs. In particular, there is an ongoing debate over the effectiveness of FITs and TGCs. Policy schemes must be constructed in compliance with both economic effectiveness and ecological efficiency (Ringel, 2006). The author raises doubts on how FITs can be compatible with a common European electricity market following these principles and acknowledge that FITs constitute the proper mechanism for a country seeking to adopt RETs rapidly. In that respect, Falconett and Nagasaka (2010) argue that FITs is the best instrument to support less mature RETs, while TGCs are more suitable for more mature technologies. In the same line, Wang (2006) claims that the TGCs supporting mechanism is unable to boost high capital cost technologies such as Windmill systems. EU countries using predominantly FITs instead of TGCs showed a substantial increase in electricity produced from Wind and Solar Photovoltaic technologies for the decade from 1996 to 2005 (Maza et al. 2010). Moreover, Mulder (2008) maintains that although relatively low Feed-in-Tariffs have been an effective policy scheme for Germany, Denmark, and Spain, their effectiveness relied on the early and consistent way in which they were implemented.

In this direction, several authors in an attempt to empirically examine the effect of policy instruments implemented to proliferate RETs use different approaches and, as a result, find different results. A positive effect of FITs on the expansion of wind capacity in four European countries, namely Denmark, Germany, Spain, and United Kingdom, is obtained in Söderholm and Klaassen (2007). Although these authors find that ceteris paribus FITs increase investment capacity, they also show that high FITs can discourage investments in innovation activities because there is no need to reduce the costs of new technology. In contrast, Popp et al. (2011) find that both FITs and other policies such as TGCs, investment incentives, have an insignificant effect on RE investments made in 26 OECD countries. Verdolini et al. (2018), extended the specification of Popp et al. (2011) by introducing other electricity generation sources capacity and find the same positive result of FITs on RE investment. Using a different approach, Jenner et al. (2013) include FITs as an index of the return of the investment on either wind or Solar Photovoltaic technologies and find this index to have a significant positive effect in 26 European countries.

In an attempt to test the effect of the existence of policy schemes in 108 developing countries, Pfeiffer and Mulder (2013) find to be positively correlated with non-hydro RE electricity generation. Furthermore, Rodriguez et al. (2015), when studying the effect of policy instruments, and in particular FITs, TGCs and tax relief, in 87 countries, argue that different implemented policy instruments are appropriate for each RET according to the technological and market characteristics. The authors find evidence that FITs boost investments on biomass and solar technologies, while TGCs are more efficient for small hydro. Also, they find that none of the above policy instruments has any significant effect over Wind investments. In the same line are the findings of Zhang (2013), who studies the effect of FITs on Wind deployment in 35 European countries and argues that characteristics of the FIT instrument such as longer periods contracts along with guaranteed grid access and not their amount are what prompted wind technology deployment. Finally, Smith and Urpelainen, 2014, study the causal effect of FITs on renewable electricity generation in 26 industrialized countries and find empirical evidence that their usage not only induces RETs proliferation but also enhances wind and solar electricity share.

All of the studies above use different econometric techniques in order to examine the effect of policy instruments on boosting RETs. As it has been argued in the technology diffusion and policymaking literature, policy instruments are endogenously defined by the policymakers along with the RE electricity targets (Söderholm and Klaassen, 2007, Jaffe and Stavins, 1995; Mazaa and Winden, 2004). Consequently, from an econometrics point of view, the endogeneity of policies may stem from either the simultaneity effect of the policy instruments and the related targets or other econometric inference problems such as omitted variables. In this direction, when using policy instruments as determinants of RETs investments or electricity production and endogeneity is not appropriately taken into account, one can be led to erroneous conclusions over their effect. Some studies attempted to examine the endogeneity of policy instruments and, in particular, of FITs but failed to reject the exogeneity assumption (Söderholm and Klaassen, 2007; Zhang, 2013; Rodriguez et al. 2015). On the contrary, only Smith, and Urpelainen, 2014, use an instrumental variables approach to point out the positive effect of FITs on the proliferation of wind and solar electricity percentage change in 26 industrialized countries. The present study, other than studying the effect of policy instruments on wind investments, further assess possible endogeneity issues of FITs to measure its effect.

2.2 Corruption as a factor affecting the diffusion process of RETs

Another important factor taken under consideration by RETs investors is the structure of institutions that determine the transaction setting for carrying out an investment. The public office defines the rules of the transactions, and the bureaucratic structure is strongly affected by social norms and behaviors established in a country. Thus, it is a tough task for someone to distinguish corruption from social norms and behaviors (Theobald, 1990) and consequently define them by drawing the line in the so-called corruptive behavior. In this direction, scholars use different definitions that cover different aspects of corruption. However, there is a broad consensus of scholars that corruption is a behavior that can be defined as the "abuse of public roles or resources for private gain (Jain, 2001; Johnston 2011; Tanzi, 1998).

Corruption can take different forms, including bribery, extortion, fraud, embezzlement, and can flourish under the coexistence of discretionary powers over the allocation of resources, economic rents, and low probability of detection and punishment (Tanzi, 1998; Jain 2001; Aidt, 2003; Transparency International). Corruption can be further classified according to the source of the public officers' misuse of powers. In this context, corruption can be classified as "petty," "grand," and "legislative" (Kaufmann, 1998; Jain, 2001). Petty or bureaucratic corruption can be thought of as acts from bureaucrats that deviate from their duties when interacting with citizens to favor access to public services in return to personal social or economic gains. On the other hand, grand corruption can be considered as acts taking place at the higher-level public office, such as political elites influencing policy-making and implementation to satisfy personal gains or special interest groups' agenda. This form of corruption is the most complex one since policymakers should also take into consideration the interests of the society if they want to remain in power. Finally, legislative corruption occurs when the legislative branch is susceptible to influences to promote certain rules and laws concerning personal or groups' gains. It is very hard to measure corruption and consequently analyze its impacts on social welfare and economic development, taking into consideration the various corruption forms occurring in different levels of the established rules and norms of a country.

It has not been until recently that the literature has examined corruption as a threat to economic growth, the level of investments, and the design or implementation of policy instruments. Investment activities can be negatively affected by the existence of corruption since it creates an environment where returns to investment are harder to predict (Everhart et al. 2009). Jain (2001) argues that corruption can act as a hurdle to resource allocation by influencing the evaluation of an investment project where, in turn, reduces the probability of undertaking the investment. In his seminal paper, Mauro (1995) finds evidence that corruption lowers private investment for a sample of 67 countries where several of them are included in our study.

In an attempt to further explain the effect of corruption on investments and growth, several authors have turned their attention to institutional and political characteristics of corruption and discovered different effects according to spatially grouped countries with similar institutional and political characteristics. For instance, when government corruption can take a predictable form or is organized in the sense that investors do get what they are aiming at through corruptive behavior, then it could result in more investments as it is empirically examined by Campos et al. (1999) in the case of Asian countries. Similarly, Blackburn and Forgues-Puccio (2009) make the claim that countries with organized corruption networks are likely to display higher rates of growth than countries with disorganized corruption arrangements. In addition, some authors claim that corruption could be investment enhancing in the sense that red-tape can be bypassed through small side payments (Leff 1964) or increase investors' access to public funds (Tanzi and Davodi, 1997). Egger and Winner (2005) find empirical evidence that corruption is a stimulus to foreign direct investments in less developed countries.

Using arguments from industrial organization theory, Olson, (1993), identifies that according to the level of the organization networks and the time horizon of government officials, which tends to be common in spatially grouped countries, investments and growth can be evasively affected. In particular, the prospect of a future profit from the monopolization of theft, through generating privileges for capitalists and entrepreneurs, may enable economic agents to generate even higher incomes and more wealth. In this line are the findings of Ventelou (2002), where the authors using a theoretical approach of an economic growth analysis concerning grand corruption, find that corrupted politicians balance their rent-seeking activities with effective policy-making to remain in power.

In particular, in the case of East Asian countries, scholars tried to analyze how increased corruption leads to increased growth rates. According to Rock and Bonnett (2004), East Asian countries fall into the category of governments monopolizing power with long time horizons of government officials and empirically support that corruption hinders investments in small developing countries but has the opposite effect in the large East Asian countries. Also, the authors argue that both the size of a country but also the organizational structures of corruption can justify the increased growth of East Asian countries concerning high corruption rates. In terms of manufacturing plant investments in Indonesia, Vial and Hanoteau (2010) empirically support that corruption in the form of bribes positively affects the investment benefits. In the same line, Wedeman (2002) identifies that East Asian countries' although they face high rates of corruption, this does not act as an impediment to their high growth rates.

Regarding other geographical areas, researchers find that corruption act as an impediment to investments and growth. For instance, Asiedu et al. (2009), using data from enterprises, find that corruption has no significant effect on Latin American and Sub Saharan Africa developmental growth. The authors also find that increased levels of corruption positively influence investments in transition countries. Also, in a firm-level survey, Gaviria, (2002), empirically finds that corruption and crime reduce the profitability of firms in Latin American countries. The different effects of corruption on economic growth and investments may be due to the institutional settings of each country (Vaal 2011), which may differ between different geographical regions.

Following the above discussion, corruption cannot be an absent factor when analyzing RE investment development. Government officials, politicians, and RE investors may have an incentive to perform corruptive activities when there are profits to be gained by excessive tariffs or tax reliefs, among others. Under a grand corruption setting, several authors argue that the level of corruption could negatively affect the stringency and the effectiveness of environmental laws and consequently may influence the allocation of resources (Fredriksson, List and Millimet 2003; Fredriksson, Vollebergh and Dijkgraaf, 2004; Leitão, 2010; Damania et al. 2003). Petty corruption can take place in the process of implementing a RE project such as discriminating information exchange, authorizing investments, rendering power to particular electricity producers, and decisions regarding the use of land. For instance, when governments have set up heavy bureaucratic licensing and regulatory requirements for issuing a RE production permit to connect to the grid, lower public office agents may abuse their role and assist investors to bypass red tape. In both cases, when the probability of being detected and punished is low because of the corruptibility of political and judiciary institutions along with less strict societal norms, corrupted activities can escalate.

Although there is abundant literature analyzing the effects of corruption on investments and growth, its relationship to the diffusion of RETs investments, to the best of our knowledge, has only been analyzed by Gennaioli and Tavoni (2016). The authors provide a simple model of bribery and criminal activity and empirically find that criminality is positively related to the growth of wind installations in regions of Italy, especially when higher economic gains can be exploited from public incentives. Their analysis consists of a bureaucratic environment where firms that are willing to invest in producing electricity from wind can bribe in order to obtain a permit more quickly. In the context of RE usage, other institutional factors have also been introduced, such as the quality of governance and democracy (Brunnschweiler, 2010; Pfeifer and Mulder, 2013). Brunnschweiler, (2010) analyze the effect of the quality of governance on the use of RE, in a sample of 119 none-OECD countries, and finds evidence that stable institutional regimes have a positive effect on RE development. In the same line are also the findings of Pfeifer and Mulder, (2013), where the authors find evidence that solid democratic regimes positively influence RE development.

However, the effect of corruption on RE investments to the best of our knowledge is not yet analyzed within different geographic regions. By summarizing the above discussion, corruption could be either investment deterring or enhancing. It may be considered as a tax and add more risk to RE investment decision if unorganized government officials act as independent monopolists asking bribes, or it may be the case that investors might be willing to undertake a corrupted behavior to bypass red-tape and gain access to public funding in a more organized and predictable environment.

3. Data and variables

The present study analyzes the effect of government intervention and corruption on wind investments, where the latter is measured as changes in the wind power installed capacity. The sample we use consists of 48 countries that cover more than 98% of the world's wind installed capacity, including countries from North Africa, South and East Asia, Latin America, and OECD countries not included in the previous groups. The data represent a balanced panel for the period 2005-2012. We have excluded from the analysis other sources of renewable energy such as solar photovoltaics, biomass, wave, and tidal, and cogeneration because of their most recent appearance in electricity production and the lack of data for the countries under study. Table 3.1 presents the description, definition, the measurement units, and the sources of the data used in the present study, while Table 3.5, in Appendix I, presents the descriptive statistics of all the variables used.

In order to depict the annual net investment in wind technologies, we followed the related literature (Marques et al. 2011; Zhang 2013), and we selected as dependent variable the country's wind capacity additions per capita (*DWCAPPC)*. We selected capacity installations to reflect wind energy investments, rather than electricity production, because the latter is subject to multiple factors that cannot be controlled or foreseen by investors, namely, weather conditions, technology efficiency, and possible damage to equipment, among others. Data on the capacity of wind installations were taken from the U.S. Energy Information Administration database (EIA), and are expressed in KW nominal power per capita. Table 3.6, in Appendix I, presents the wind net capacity additions per capita for each country. Sweden had the highest rate of net investments per capita, followed by Portugal, Ireland, and other EU countries. Although the United States has the highest value for installed wind capacity, still for its size, the net wind investment per capita is lower than other smaller EU countries for the period considered in this research. The negative values of the wind net capacity additions per capita represent that additions of new capacity installations in a particular year is less than the capacity loss from damages or technology's end of life-cycle. The greatest negative value is found in Spain in 2011, mainly due to the enormous increase of new installations in the previous year and also because investors were not sure whether new projects would receive FITs support (REVE 2012).

Table 3.1: Variables Definition, units, and source

	Definition	Description	Source
DWCAPPC	First difference of the of the cumulative capacity of Wind Installations divided by the population of each country	Net annual wind capacity additions	EIA - Total Electricity Installed Capacity (Million Kilowatts) / (Millions) persons
FIT	The unweight mean of applied Feed-in-Tariffs for Wind installations	€cents	IRENA – REN21,
QUO	Existence of quotas	Dummy: 1 if there a quota exists 0 otherwise	IRENA – REN21,
TAX	Existence of Tax reliefs for Wind investments	Dummy: 1 if a tax relief exists 0 otherwise	IRENA – REN21,
INVSUB	Existence of Investment Subsidies for wind investments	Dummy: 1 if investment subsidies exist 0 otherwise	IRENA – REN21,
NUCS	Share of Nuclear in the total electricity production	percentage	World bank
HYDROS	Share of Hydro in the total electricity production	percentage	World bank
COALS	Share of Coal in the total electricity production	percentage	World bank
OILS	Share of Oil in the total electricity production	percentage	World bank
GASS	Share of Gas in the total electricity production	percentage	World bank
COR	Country corruption perception index (index 0-10)	larger: better performance	Transparency International
IMDPEP	Electricity Import Dependency	percentage	EIA
CO2PC	Tones of CO2 emissions per Capita	(kg/Capita)	EIA

Following our discussion in section 2 concerning the direct government intervention, we include various policy instruments as explanatory variables, namely Feed-in-Tariffs ***(FIT)*,** tax reliefs *(TAX)*, Quota obligations (*QUO*) and Investment subsidies *(INVSUB)*.

The *FIT* variable was gathered from IRENA (2016), and the Renewable Energy Policy Network (REN21 2016) and measures the un-weighted[10] average of the Feed-in-Tariff level applied in a country on a given year. For the calculation of the *FIT* variable, we used the published data on FITs corresponding to the price producers of electricity from wind systems receive at the year of installation, without taking into account any possible future digression. For instance, Germany's and France's wind installation Feed-in-Tariff mechanism includes a 2% annual tariff reduction for existing installations. For the other policy mechanisms such as tax and fiscal reductions, tradable green certificates, and investment subsidies, we introduced dummy variables for their existence. We proceeded in this way because the IEA/IRENA database only provides information about whether these mechanisms are in place and not on their level.

Figure 3.1 presents the frequency of policy mechanisms implementation in the countries under study. The FITs is the most "popular" mechanism promoting wind investments followed by investment subsidies, tax reliefs, and quotas. While most of the countries under study implement a combination of policy schemes, they are switching them to meet their renewable energy targets. Countries from the EU and North America widely use Feed-in-tariffs and Quota Obligations as their primary policy mechanisms and supplement their policy strategy with other mechanisms such as investment subsidies, tax exemptions, and tenders towards enhancing wind investments. However, this is not the case for Latin American and Asian countries where most of them used investment subsidies and tax exemptions as their main policy mechanism. Besides, some countries use different supporting mechanisms for the promotion of small and large-scale wind investments. For instance, Italy used FITs to promote small-scale wind investments, while for large-scale wind investments, it used tradable green certificates. In the former case, a substantially high rate of investment was achieved, reaching the amount of $24.1 billion in 2011, while tradable green certificates mechanism led to the stagnation of the market due to the uncertain prices (REW 2013).

[10] Several countries have designed complex tariff schemes whereas the level of the tariff depends to the levels of installed capacity, thus higher nominal capacity installations end up receiving smaller tariffs due to economies of scale. Due to the fact that we do not have data on the number and the size of installation by country and year we proceeded in with calculating this variable as the un-weighted average of the tariffs for each level of capacity.

In order to test whether energy insecurity leads to higher investments towards wind, we introduce a variable measuring the electricity import dependency (*IMDEP*) (Marques, 2011). Import dependency can be considered as a measure of self-sufficiency of countries where higher imports of energy or electricity could either lead to more investments towards wind or other conventional or renewable energy sources, depending on their energy planning. The *IMDEP* variable is computed as the total electricity net imports of a country divided by the total electricity production of that country.

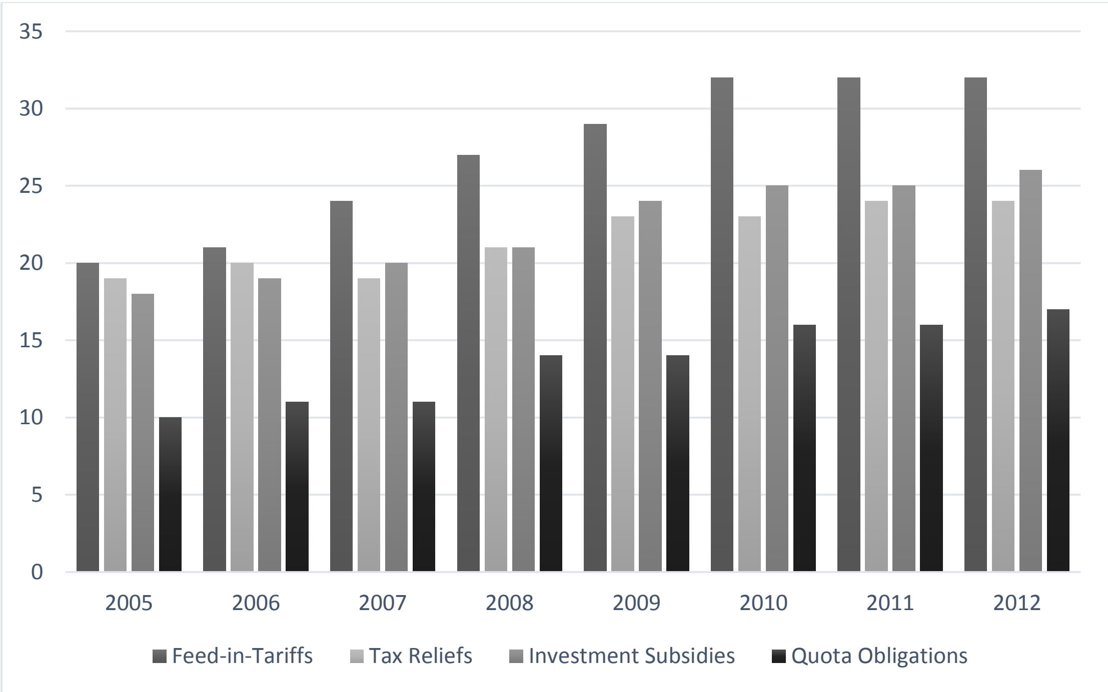


Figure 3.1: Policies schemes applied in the 48 countries

Following the literature of political theory, investments, and growth (see Fredriksson, Vollebergh and Dijkgraaf, 2004; Ederveen et al. 2006; Evrensel 2010; Asiedu et al. 2009), we use the Corruption Perception Index (*COR*) (TI 2005-2012), to account for government corruption. The *COR* index is an aggregate indicator that measures perceptions on corruption for the public sector using data from different surveys, scaling from 0 to 10, where a higher score denotes lower levels of perceived corruption. The COR index is a composite index using data sources from independent institutions surveys on governance. The annual *COR* index is based on data gathered in the past 24 months and measures perceptions of corruption in the public sector. Thus since lagged values of corruption may affect future economic activities and growth (Aghion et al. 2016), we use the lagged value of the *COR* index in our empirical setting.

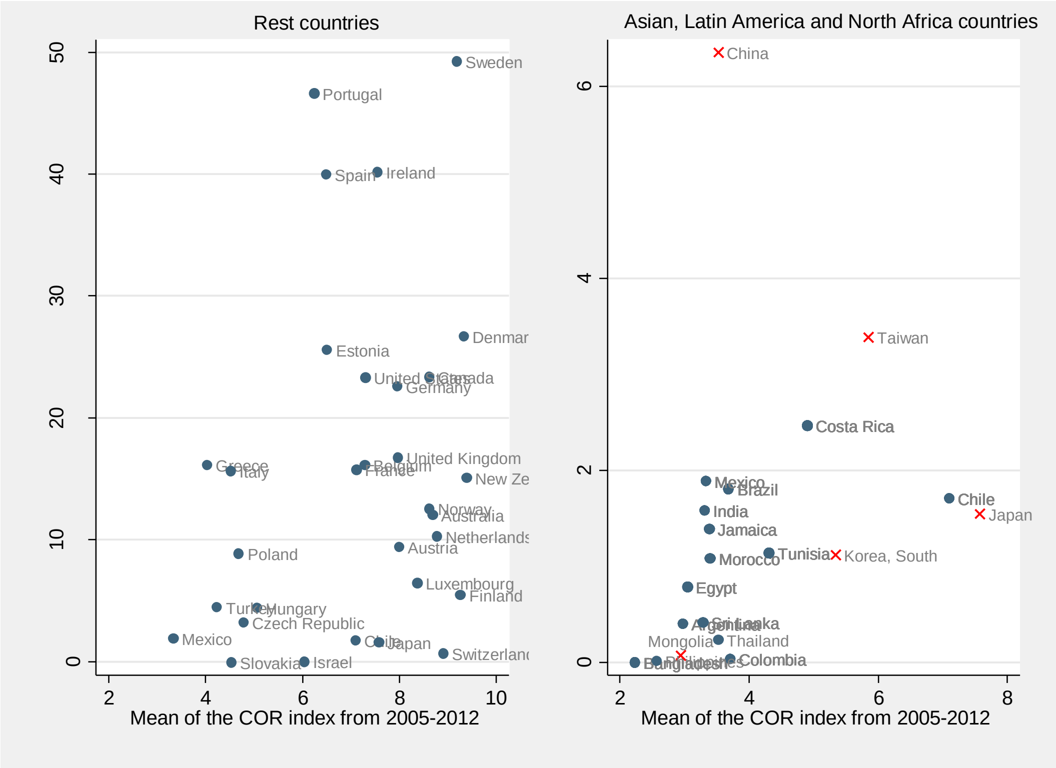


Figure 3.2 presents an illustration between the *COR* scores and the average capacity additions in the countries under study, where the Asian, Latin American, and North African countries are presented in the right, and the rest of the countries in the left. The former countries experience higher levels of perceived corruption compared to other countries in our sample. In particular, Asian and especially East Asian (marked with red) countries experience poor scores over their government corruption index or, in other words, higher perceived level of corruption. Nonetheless, their annual net wind capacity installations are comparable to countries with higher *COR* scores. On the other hand, European countries such as Denmark, Finland, and Sweden experience the highest rank in terms of the *COR* index. During the recent economic crisis, these countries had the lowest impact regarding the reductions in the perceived government corruption, and at the same time, they experience the highest wind net capacity installations per capita.

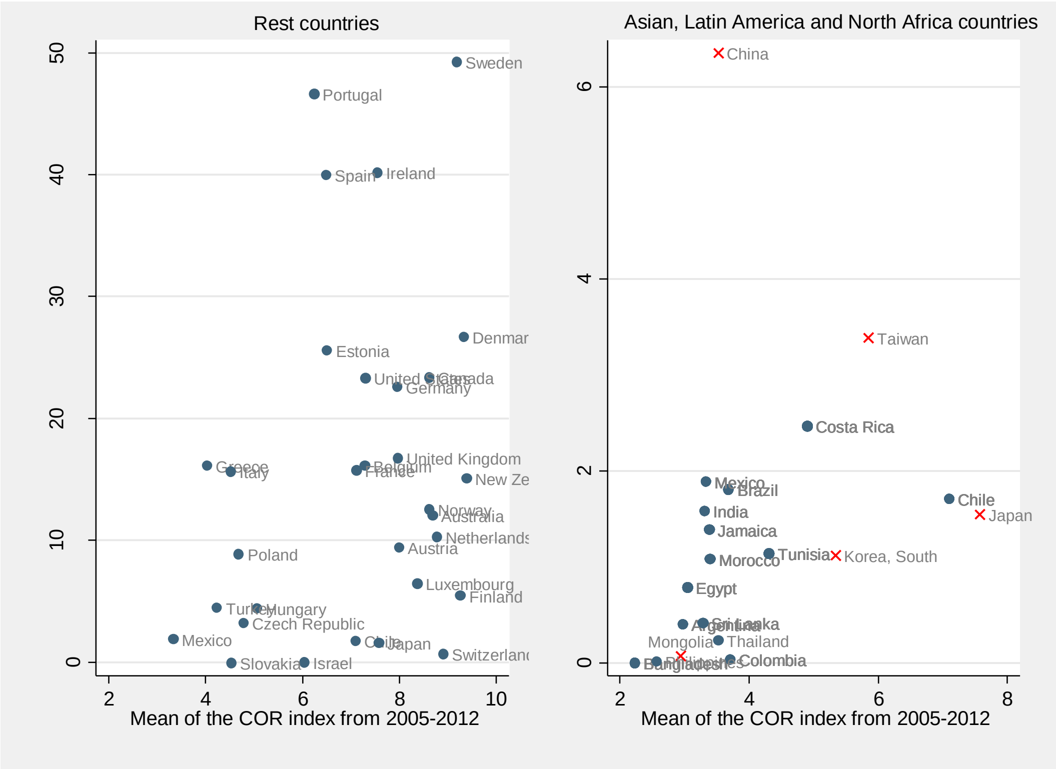


Figure 3.2: Corruption and Wind Investments in Latin America, Asian, North African and the rest of countries

In addition to the policy and the corruption variables described earlier, we introduce, the natural logarithm of the Carbon Dioxide emissions per capita (*LCO2PC)* and the share of coal in the total electricity production (*COALS)* to account for the level of a country's pollution (Marques, 2011). Also, in order to account for the lobbying effect that may exist between opposing coalitions and renewable energy, we control for the contribution of traditional energy sources of oil and gas, introducing their share in the total electricity production (*COALS*, *OILS*, *GASS*). We expect that the existence of traditional energy sources coalitions will influence the strategic goals of governments over the selection of future energy sources and therefore influencing government intervention and investments over renewable energy sources (Sovacool 2009; Marques 2011). We additionally introduce data on the level of CO_2 emissions per capita (U.S. Energy Information Administration) in order to control for the level of a country's level of pollution. Finally, in order to test if the availability of clean substitutes is correlated with lower investments in wind, our specification includes the nuclear and hydroelectric share (Popp et al.. 2011; Smith and Urpelainen, 2013) in the total electricity production (*NUCS*, *HYDROS*) (EIA).

4. Econometric modeling and Results

4.1 Estimation strategy

In order to uncover which of the factors $X_{\iota t}$ in Table 3.1, affect the diffusion of wind investments, we use the panel data specification given by Eq. (3.1) below,

$$DWCAPPC_{it} = \beta' X_{it} + a_i + \varepsilon_{it} \tag{3.1}$$

where $DWCAPPC_{it}$ is the first difference of the per capita cumulative wind capacity installed in the country i at time t, β is the vector of parameters to be estimated, a_i represents unobserved individual (country) heterogeneity, and ε_{it} is the usual idiosyncratic error. The unobserved individual effect is assumed to be fixed over time and captures factors that influence the diffusion of windmills that are country-specific such as geographic or weather conditions. This study's goal is to obtain consistent estimates from Eq. (3.1). A simple pooled OLS estimator would result in omitted variable problems since the unobserved individual effect will be added into the idiosyncratic errors. In particular, if the country-specific effects a_i are correlated with the other independent variables of Eq. (3.1), then a simple pooled OLS estimation will not yield consistent estimators.

In order to avoid this issue, the Fixed Effects (FE) or the Random Effects (RE) transformations can be used for the estimation of Eq. (3.1). As in the pooled OLS, the RE incorporates a_i into the idiosyncratic errors and make the hypothesis that it is not correlated within any of the strictly exogenous variables $\mathrm{X_{it}}$ introduced in Eq. (3.1). On the other hand, the FE transformation eliminates the country-specific time fixed effects by subtracting the within-group mean of each variable in Eq. (3.1). By averaging Eq. (3.1) over time t, we get

$$DWC\bar{A}PPC_{it} = \beta \bar{X}_i + a_i + \bar{\varepsilon}_t, \tag{3.2}$$

If we then subtract Eq. (3.2) from Eq. (3.1), the FE transformed equation is as follows:

$$DWC\hat{A}PPC_{it} = \beta \hat{X}_{it} + \hat{\varepsilon}_{it}, \tag{3.3}$$

where $\hat{X}_{\mathrm{it}} = \mathrm{X_{it}} - \bar{X}_{\mathrm{i}}$, $\hat{\varepsilon}_{\mathrm{it}} = \varepsilon_{\mathrm{it}} - \bar{\varepsilon}_{\mathrm{i}}$, and $DWC\hat{A}PPC_{it} = DWCAPPC_{it} - DWC\bar{A}PPC_i$.

The possible correlation of the unobserved effect and the other exogenous variables led us to decide over the Fixed Effects transformation. This is the case for the present study since a country's geographical or weather conditions influence the produced hydroelectric energy share or the country's level of pollution. In order to test this hypothesis, the robust Hausman specification test (Wooldridge, p288, 2002), which accounts for serial correlation across time, as well as general heteroskedasticity, leads to the rejection of the null hypothesis of uncorrelated unobserved heterogeneity with the regressors with a p-value of 0.01 favoring thus a fixed-effects specification for our model.

The estimation of the FE transformed Eq. (3.3) is made by pooled OLS. However, in order for the estimators to be consistent and efficient, the following assumptions must hold:

$$E(X_{is}\varepsilon_{it}) = 0, \forall\, s, t = 1,2, \dots, T, \tag{3.4}$$

representing the strict exogeneity assumption and

$$E\left(\varepsilon_{i,}\varepsilon'_{i}|X_i, \alpha_i\right) = \sigma_u^2 I_T, \tag{3.5}$$

implying that the idiosyncratic errors ε_{it} have constant variance given by $\sigma_u^2 I_T$ and are not serially correlated.

In order to check for possible autocorrelation of the error term in Eq. (3.1), we follow Wooldridge (2002, p. 282) and estimate the first difference (FD) transformation. The estimated first-order correlation coefficient of the FD residuals is $\hat{\rho} = -15.71$ with a standard error of 0.4948, and therefore the Wald test rejects the null hypothesis that the corresponding population parameter is equal to -0.5. In order to account for the autocorrelation of the errors, we estimate Eq. (3.3) by pooled OLS using the clustered sandwich estimator, which is robust to both autocorrelation and heteroscedasticity[11].

Another issue that is of great importance for the validity of the estimation results is whether there are some issues of endogeneity in our model. According to the diffusion literature discussed in section 2, government intervention through policy mechanisms should be treated as endogenous (Söderholm and Klaassen, 2007; Jaffe and Stavins, 1995). To this extent, both simultaneity and omitted variables problems can arise. For instance, support mechanisms such as FITs could be adjusted downward as the wind installed capacity increases because investment costs are lower and not included in our

[11] The clustered sandwich standard error estimator relaxes the assumption of independence of the observations and requires only that the observations be independent across clusters but not necessarily within groups.

specification or adjusted upward whenever the capacity targets are not met. In view of the above, the assumption in Eq. (3.4) will fail. Endogeneity may also stem from the measurement error of the *FIT* variable. In this study, the *FIT* variable is calculated as the unweighted mean of the different level prices. However, new windmill installations are supported with different levels of FIT price levels according to the magnitude of their capacity. We test for the endogeneity of FIT, using the Hausman (1978) specification test for endogeneity using the clustered robust standard errors from the auxiliary regressions.

The strictly exogenous instruments used to conduct this test are a) a dummy variable that indicates whether a FIT scheme is in place for other RETs different from Wind (*OTHFIT*) and b) the mean of FITs for the countries that are close in terms of real GDP per capita level (*FITGDP*). For the latter instrument computation, we divided our sample into five groups of countries based on the percentiles of real GDP per capita and computed *FITGDP* for country i at time t as the mean of the applied level of FITs of all other countries in the same group as i. The descriptive statistics of the two exogenous instruments are presented in Table 3.5, in Appendix I. The results of the testing procedure indicate that the level of FITs is endogenous at the 5% level, with the value of the test statistic to be 4.468 distributed as a chi-squared with one degree of freedom.

The regression of FIT_{it} as a dependent variable on all strictly exogenous variables of Eq. (3.1), and on all of the exogenous instruments shows that all of them are highly significant (see Table 3.7 in Appendix II). The Sargan (1975) test (OIR in the table) fails to reject the null hypothesis that the instruments are uncorrelated with the idiosyncratic error term since the value of the statistic is 0.024, and the p-value is 0.88. One can further argue that *OTHFIT* is exogenous since it is intended to support alternative RETs rather than wind. Thus the existence of a FIT mechanism for solar photovoltaic investments will not affect wind capacity additions. Also, it is the case that countries supporting different energy strategies rely, mostly but not all of the time, on the same policy instruments. For instance, a policymaker that decides to promote small hydro along with windmills will more likely use the same instrument unless the targets set for the technology define otherwise, which means that the correlation of FITs and *OTHFIT* is high. The use of the second instrument, *FITGDP*, is based on the idea that the average level of FITs of similar income per capita countries could be a good predictor of a country's FIT while the country's investments in wind technologies do not influence it nor does it affect those investments directly. In the same context, Smith and Urpelainen (2014) treat FITs as an endogenous factor and uses as instrument the mean of FIT prices applied in the adjacent countries[12].

4.2 Estimation results

The first column of Table 3.2 presents the estimation results of the FE estimator (FE-1) for Eq. (3.1) where the variables from Table 3.1 are used as exogenous variables. In order to account for the endogeneity of FITs, the second column of Table 3.2, reports the results of the Fixed Effects two-stage least squares (FE 2SLS) methods (FE-IV-2). Also, in order to assess whether the effect of corruption has a regional or spatial dimension, the different countries were grouped into five major groups. The first group includes countries from East Asia, while the other four includes countries from South Asia, Latin America, North Africa, and the rest OECD countries not included in the previous four groups. The regional dummies interacted with the lagged corruption index, namely EA_COR for East Asia, SA_COR for South Asia, LA_COR for Latin America, and NA_COR for North Africa were then used as new regressors. The results of the FE 2SLS estimation of the model that includes the variables mentioned above are presented in the third column of Table 3.2 (FE–IV-3).

Table 3.2: Estimation Results: Fixed Effects and 2SLS Fixed Effects with CPI index

	FE-1 (b/se)	FE-IV-2 (b/se)	FE–IV-3 (b/se)
FIT	0.0436 (0.13)	0.5100** (0.24)	0.5419** (0.26)
COR(t-1)	2.0142 (1.85)	2.2030* (1.38)	3.8581** (1.73)
QUO	2.5297 (9.97)	2.5773 (4.23)	2.5796 (4.26)
TAX	4.9141 (6.37)	4.5747 (6.54)	5.5305 (6.61)
INVSUB	2.7850 (1.94)	2.6933 (1.94)	2.9963 (2.12)
NUCS	-1.428 (1.07)	-1.1270 (1.09)	-1.4599 (1.13)
HYDROS	-0.2521 (0.52)	-0.2007 (0.48)	-0.2030 (0.49)
GASS	-0.6356 (0.44)	-0.6242 (0.41)	-0.6909* (0.42)
OILS	-0.3365 (0.45)	-0.1762 (0.42)	-0.1952 (0.43)
COALS	0.1131	0.1787	0.1613

[12] The authors constructed this instrument as the mean *FIT* values for all neighboring countries for a given year. If a country does not have any neighbors then the authors use the global mean of FITs.

	(0.60)	(0.57)	(0.56)
LCO2PC	-20.7264** (10.34)	-18.6314* (9.53)	-17.730* (10.45)
IMDEP	-0.0492 (0.36)	-0.0373 (0.36)	-0.0428 (0.36)
EA_COR			-23.0813* (14.08)
LA_COR			-2.3328 (2.59)
SA_COR			-2.6899 (3.83)
NA_COR			-4.0690 (3.47)
Constant	66.5407 (41.88)		
Cross Sections	48	48	48
Time periods	7	7	7
OIR	-	0.024	0.046
(p-value OIR)	-	0.8774	0.8306
Under-ID test	-	11.471	11.283
p-value	-	0.0032	0.0035

standard errors in parentheses

*p<0.10, ** p<0.05, *** p<0.01

The Underidentification test, developed by Kleibergen and Paap (2006), is an LM test of whether the equation is identified, or in other words, that the excluded instruments are correlated with the endogenous regressors. A rejection of the null hypothesis indicates that the model is identified.

The results of the FE-1 model show that only the CO_2 emissions per capita are significant at the 5% level, with a negative coefficient. The FE-1 specification findings show that both the variables of *FIT* and *COR* are insignificant, indicating no effect on wind investments. Also, this is the case for the other variables used in Eq. (3.1). However, one should take into account that the endogeneity of FITs may cause the FE estimators to be inconsistent (Wooldridge, 2002), and if not controlled for, to lead to an underestimation of the model parameters. Turning now to the parameter estimates of the FE-IV-2 and FE-IV-3 specifications, we note that correcting for endogeneity has mostly affected the parameter estimates for the FITs and COR variables. The differences between the robust standard errors of the two estimated models are reasonable, as expected, but they are higher in the case of IV estimation. The results indicate that increases in the Feed-in-tariff level have a positive effect on the growth rate of Wind installed capacity. This result comes in accordance with the empirical results of the relevant literature, arguing that FITs indeed spur RETs investments (Jenner et al. 2013; Smith and Urpelainen, 2014).

Furthermore, the existence of a policy mechanism such as Investment subsidies, Tax reliefs, and Tradable Green certificates continue to have an insignificant effect on Wind Energy investments. This indicates that without data on the level of the implemented policy instrument, we cannot argue on its efficiency. This result is in line with the findings of Popp et al. (2011) and Verdolini et al. (2018) that control for the effect of the existence of another policy mechanism, except for FITs and TGCs, on the RE investments uptake in 26 OECD countries and find it to have an insignificant effect. As far as a country's level of pollution is concerned, all models show that an increase in the CO_2 emissions levels negatively affects, at the 5% level of significance, the diffusion of wind technologies, which means that still, the increasing levels of CO2 emissions are not capable of invoking a transition towards wind investments (Marques et al. 2011). However, such an argument must be further analyzed by considering the economic situation of the country to support such a transition. For instance, in the G7 countries, Sadorsky (2009) argues that an increase of the real GDP and the level of pollution, are major drivers towards the increase of RE consumption. It also may be the case that a country selected another RE technology other than wind, as primary towards the fight against pollution. In this direction, the findings of FE-IV-3 specification results indicate that Gas may act as a competitor to wind energy investments.

Furthermore, both the FE-IV-2 and FE-IV-3 specification results show that improvements in the perceived level of government corruption positively affect net investments on windmills. In other words, an increase in the corruption level (i.e., reduction in the corruption index) negatively affects wind investments for all countries except East Asina countries. Also, we find that improvements in the perceived level of government corruption can have both negative and positive effects on the diffusion of wind systems. In general, this empirical study findings show that an increase in the institutional factor of the corruption level (i.e., reduction in the corruption index) harms Wind investments. However, this is not the case for East Asian countries that benefit in terms of wind investments from the existence of government corruption. In this respect, this study results provide solid empirical evidence of the East Asian Paradox for wind investments. This might be the case since East Asian countries' governments acting within long time horizons and through strong monopolized, and organized corruption networks may provide incentives to economic agents to generate higher incomes and more wealth, thus attracting more investments (Olson, 1993; Rock and Bonnett, 2004). As far as the other regions are concerned, confirming the literature findings over the effect negative effect of corruption on investments and growth in these geographic regions (Asiedu et al. 2009; Gaviria, 2002; Vaal 2011), we find that corruption negatively affects wind investments and that this effect is similar between all the countries under study, as the respective dummy coefficient estimates are not significant even at the 10% level.

4.3 Robustness test

In order to assess whether the differential spatial effect of corruption on wind energy investments is robust to different measures of corruption, we also use the Control of Corruption Index (WCC) WGI (2005-2012), which measures perceptions of corruption in both the private and the public sector. Both the COR and the WCC indices combine data from different sources and rank countries with lower levels of perceived corruption with a higher score. The WCC index scales from -2.5 to 2.5, and we rescale it to a 0-10 scale in order to be able to compare its effect with the COR variable.

At this point, we should note that the WCC index is computed using data from the current and the two previous years, while the COR index uses data from the past 24 months. Consequently, in order for the two measures to capture the same periods, we use the current level of the WCC index. Table 3.3 shows the descriptive statistics of the two indices both between and within-group variation. Notably, as it is expected for the two indices, there is more considerable variation between countries than within time, and the COR index variance is greater than the WCC index.

We additionally also test whether FIT variable is endogenous when WCC is used. The results indicate that the FITs mechanism is endogenous at the 5% level, with the value of the test statistic to be 4.351 distributed as a chi-squared with one degree of freedom. We used the same instruments as discussed previously, and the regression of FIT_{it} as a dependent variable on all strictly exogenous variables with the use WCC instead of COR and on all of the exogenous instruments shows that all of them are highly significant (see Table 3.7 in Appendix II).

Table 3.3: Descriptive Statistics of the COR and WCC indices

	Mean	SD	Min	Max	N
COR	5.8164	2.2904	1.7	9.6	336
Between		2.2958			
Within		0.26415			
WCC	6.4980	2.0804	2.1541	10	336
Between		2.0896			
Within		0.1994			

In this direction, we re-estimated Eq. (3.1) using FE 2SLS methods with the WCC index (FE-IV-4), and the results are presented in Table 3.4. We also interacted the regional dummies with the WCC index, namely *EA_WCC* for East Asia, *SA_WCC* for South Asia, *LA_WCC* for Latin America, and *NA_WCC* for North Africa and inserted it in our specification (FE-IV-5). For comparison purposes, we also include the FE-IV 2 and FE-IV-3 in which the *COR* variable is used. Our results provide empirical support to the East Asian paradox, even if another measure of corruption is used. Higher levels of corruption negatively affect the deployment of wind technologies, but this is not the case for East Asian countries. Note that when the *WCC* measure is used (see Model FE-IV-5), the magnitude of the negative effect of an increase in the corruption index (or a decrease in the level of the perceived corruption) for the East Asian countries is again negative and similar in magnitude as with the results when the *COR* index is used (see FE-IV-3 model). Also, the results of the rest coefficients remain the same except one of FITs, which increases in magnitude. Within the FE-IV-4, and FE-IV-5 specification results, the existence of investment subsidy has a positive effect (significant at the 10%) on wind investments, denoting that countries introducing policy mechanisms that reduce the installation cost of a windmill may attract new investment funds.

Table 3.4: Estimation Results for the per capita First Difference of Wind capacity

	FE-IV-2 (b/se)	FE–IV-3 (b/se)	FE-IV-4 (b/se)	FE–IV-5 (b/se)
FIT	0.5100** (0.24)	0.5419** (0.26)	0.5048** (0.26)	0.8124*** (0.31)
COR(t-1)	2.1859* (1.37)	3.8581** (1.73)		
WCC			4.7508 (3.47)	11.5711* (7.11)
QUO	2.5773 (4.23)	2.5796 (4.26)	2.4195 (4.13)	2.3757 (4.51)
TAX	4.5747 (6.54)	5.5305 (6.61)	4.9324 (6.52)	5.6835 (6.67)
INVSUB	2.6933 (1.94)	2.9963 (2.12)	3.0440* (1.88)	3.6332* (1.96)
NUCS	-1.1270 (1.09)	-1.4599 (1.13)	-1.0589 (1.08)	-1.1338 (1.10)
HYDROS	-20.0670 (48.17)	-0.2030 (0.49)	-0.1711 (0.49)	-0.1637 (0.49)
GASS	-0.6242 (0.41)	-0.6909* (0.42)	-0.5944 (0.41)	-0.6425 (0.42)
OILS	-0.1762 (0.42)	-0.1952 (0.43)	-0.1653 (0.41)	-0.2222 (0.45)
COALS	0.1787 (0.57)	0.1613 (0.56)	0.2019 (0.60)	0.2349 (0.62)
LCO2PC	-18.6314* (9.53)	-17.730* (10.45)	-20.2747** (10.07)	-19.8053** (9.99)
IMDEP	-0.0373 (0.36)	-0.0428 (0.36)	-0.0389 (0.36)	-0.0273 (0.36)
EA_COR		-23.0813*		

		(14.08)		
EA_WCC				-30.1428** (13.85)
LA_COR		-2.3328 (2.59)		
LA_WCC				-11.2610 (9.34)
SA_COR		-2.6899 (3.83)		
SA_WCC				-6.8651 (7.09)
NA_COR		-4.0690 (3.47)		
NA_WCC				-7.1561 (6.79)
Cross Sections	48	48	48	48
Time periods	7	7	7	7
OIR	0.024	0.054	0.011	0.004
(p-value OIR)	0.8774	0.8165	0.9179	0.8424
Under-ID test	11.471	11.283	10.301	10.115
p-value	0.0032	0.0035	0.0042	0.0067

standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.01
The Underidentification test, developed by Kleibergen and Paap (2006), is an LM test of whether the equation is identified, or in other words, that the excluded instruments are correlated with the endogenous regressors. A rejection of the null hypothesis indicates that the model is identified.

5. Discussion and conclusions

The literature dealing with the diffusion of environmentally friendly technologies argues that government intervention through direct policy instruments can create incentives to promote the substitution of more polluting energy technologies. On the other hand, the institutional factor of corruption may have a complex effect on the investor’s decision strategy. In the present study, we capture the positive effect of a widely applied policy instrument, namely Feed-in-Tariffs, and try to unravel the complex dynamics that government corruption has on the diffusion of wind investments.

In the struggle to reduce the risks and impacts of climate change, countries all over the world have widely used FITs as a mechanism to support renewable energy deployment. However, there is an on-going debate in the literature concerning the FITs policy effectiveness. The effectiveness of FITs can be measured by using a country-based cost-benefit analysis or by examining the extent to which the targets set by governments have been reached. This study’s empirical findings contribute to this debate, showing that increased FIT compensation levels spur investments towards windmills installations. Although not empirically studied by the present research, the effectiveness of the FIT policy instrument is also influenced by other important characteristics that should be taken into account by a policymaker. The first is consistency in its implementation. For instance, the FIT scheme's effectiveness in Germany and

Denmark was mainly due to its early and consistent implementation (Mulder, 2008). Another important characteristic is the contract periods of compensation and the security guaranteed grid access, which, according to Zhang (2013), prompted wind installations in 26 EU countries. Even more importantly, policymakers should also focus on the financial sustainability of the scheme in order to maintain its effectiveness. With this in mind, the proper allocation of costs and benefits from a FIT scheme will prevent opposing coalitions from harming renewable energy strategy and thus the deployment of renewable energy technologies (Agnolucci, 2008) such as windmills.

In addition, the present research findings indicate that the existence of investment subsidies positively affects the diffusion of Wind technologies. This outcome could be easily explained in the sense that wind investment projects are highly capital intensive, and even a small reduction on the initial capital cost results in an investment risk reduction. On the other hand, other policy mechanisms such as Tax Exemption and Tradable Green certificates have an insignificant effect on increasing investments in Wind Energy. Once again, we should note that the policy mechanisms mentioned above are introduced as dummy variables to our specification. Thus, countries should focus on the efficiency of the already applied policy mechanisms rather than just introduce new instruments for the sake of political gains (Agnolucci, 2008).

However, investors' decisions are not only affected by the existence of incentives but also by the institutional framework defining the interaction between economic agents (North 1990). Thus, as in any other investment, government corruption can also influence the risks undertaken by investors. In particular, this study's results indicate that improvements in the perceived level of corruption can have both negative and positive effects on the diffusion of wind systems. In general, an increase in the corruption level (i.e., reduction in the corruption index) harms wind power investments, but this is not the case for East Asian countries. Our results provide empirical evidence that the East Asian Paradox is present in wind investments as well. One explanation for this can be found in the industrial organization literature (Olson, 1993; Rock and Bonnett, 2004) where it is claimed that East Asian countries' through the political structure of corruption, namely long time horizons of government officials and strong monopolized corruption networks, can jointly create incentives to new investment funds. While, these incentives are translated from the literature studying corruption as bypassing red-tape through small side payments (Leff 1964) or increase investors' access to public funds (Tanzi and Davodi, 1997). Both of them can be the case in investments regarding the installation of windmills.

On the other hand, our results indicate that for the rest of the countries in other geographical regions, increased perceptions of corruption negatively affect wind investments. According to Parker et al. (2004), in the past decade, Latin American countries suffered from weak political parties that did not represent the public but instead their self-interest. Although there has been a significant amount of effort from governments in the Latin American region to tackle this problem, the solution is still some distance ahead (Miller&Chevalier, 2012). In this direction, according to Olson (1993) and Rock and Bonnett (2004), we would expect that politicians with either short time horizons or inefficient control of other corruption networks and opportunistic behavior will try to extract as much profit as they can in the period they will stay in power. Consequently, they will harm investment funds in general and, therefore, wind investments also.

Likewise, South Asian countries suffer from political parties that are not willing to serve the public interest (TI, 2014). The main difference between East and South Asia regions, as it is stated by Rock and Bonnett (2004), is that in East Asian countries, government officials possess strong power over their corruption networks. According to Khan et al. (2013), South Asian countries still work within complex patron-client corruption networks where patrons are identified as local bureaucrats favoring citizens, which may offer them bribes. Concerning RE investments, more side payments may be required from government officials, which act independently from politicians, so as to approve a new permit for a windmill installation. In the same line, North African countries have also established a patron-client network for bureaucratic procedures, increasing investment risks (TI 2015). A possible explanation is that the lack of predictability in terms of regulation and bureaucratic procedures increases the risk of undertaking an investment in North African countries (Komendatova et al. 2012), which might also be the case for RET investments.

However, our results do not answer to the question “at which cost” do investments in windmills increase in East Asian countries, and this is where future research should point its interest. A possible explanation is from the inefficient allocation of funds directed to other social or economic sectors. However, this has an impact on the overall social welfare, which is identified either as the opportunity cost of giving a less competitive firm a permit, or an inefficient waste of public funds in terms of bribe paying, time consumed, and resource allocation (Jain 2001). The overall cost of corruption in terms of social welfare is a question left to be answered for future research. Although, as it is stated above, corruption certainly acts as a deterrent to investments generally, it also might be the case that a sector of a country may be developed at the expense of other economic areas.

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Appendix I

Table 3.5: Descriptive Statistics for all countries

Variable	Obs	mean	sd	min	max
DWCAPPC	336	10.3745	22.6019	-182.1872	231.8555
FIT	336	6.0750	6.7045	0	40.8343
QUO	336	0.2946	0.4566	0	1
TAX	336	0.4583	0.4990	0	1
INVSUB	336	0.4762	0.5002	0	1
COR(t-1)	336	5.8164	2.2904	1.7000	9.6000
WCC	336	6.4980	2.0804	2.1541	10.0000
NUCS	336	11.2061	18.4828	0	79.6700
HYDROS	336	0.2026	0.2564	0	0.9888
OILS	336	7.4124	15.5161	0	96.0525
COALS	336	25.1506	26.2572	0	96.7833
GASS	336	25.7977	26.0590	0	97.6965
LCO2PC	336	1.6659	0.9114	-1.1605	3.2706
IMDEP	336	7.2802	5.1947	0.3133	26.3263
OTHFIT	336	0.6042	0.4876	0	1
FITGDP	336	0.0647	0.0275	0.0147	0.1226

Table 3.6: Descriptive Statistics of wind capacity additions per capita by Country

Country	mean	sd	min	max
Argentina	0.4012	0.5772	0	1.5529
Australia	12.0124	6.2182	3.8297	20.4606
Austria	9.3681	13.3326	-1.5498	35.1996
Bangladesh	0.0010	0.0027	0	0.0071
Belgium	16.1072	11.5666	4.2812	29.2023
Brazil	1.8039	1.7643	0.0528	5.4055
Canada	23.3556	8.8127	11.5684	37.8393
Chile	1.7080	3.0289	0	8.4470
China	6.3575	4.6152	1.0187	11.8165
Colombia	0.0312	0.0687	0	0.1843
Costa Rica	2.4691	4.1121	0	11.1882
Czech Republic	3.1835	2.2587	0	6.8266
Denmark	26.6439	25.5695	-2.0195	57.8842
Egypt	0.7849	0.6607	0	1.5424
Estonia	25.5483	25.4239	0.7402	67.1698
Finland	5.4717	5.8604	0.3703	16.3995
France	15.7288	4.4617	10.8610	22.4966
Germany	22.5853	3.7879	18.2014	28.0041
Greece	16.1255	8.0622	8.7042	30.7471
Hungary	4.3864	3.4827	-0.6041	9.2870
India	1.5801	0.6112	0.7965	2.4930
Ireland	40.1645	14.6292	24.9086	59.5323
Israel	-0.0207	0.0547	-0.1448	0
Italy	15.6589	5.9241	4.5984	22.9488
Jamaica	1.3886	2.5608	0	6.5336
Japan	1.5491	1.9903	-2.1722	4.5209
Korea South	1.1167	0.6248	0.3704	2.2064
Luxembourg	6.4650	10.0636	0	25
Mexico	1.8843	2.9288	0	7.9962
Mongolia	0.0693	0.3351	-0.3690	0.7484
Morocco	1.0786	1.4600	0	3.9665
Netherlands	10.2896	8.9291	0.9209	24.3828
New Zealand	15.0508	18.0629	0.1802	40.4624
Norway	12.5656	12.7152	0.4075	37.9119
Philippines	0.0126	0.0332	0	0.0879
Poland	8.8423	6.8459	1.3366	18.0601
Portugal	46.6405	11.7451	25.8058	61.7586
Slovakia	-0.0528	0.1398	-0.3698	0
Spain	39.9591	120.7045	-182.1872	231.8555
Sri Lanka	0.4149	1.0978	0	2.9044
Sweden	49.2469	37.8466	2.5239	102.2394
Switzerland	0.6965	1.0772	0	3.0825
Taiwan	3.3869	1.5785	0.3002	5.3633
Thailand	0.2354	0.5732	0	1.5318
Tunisia	1.1412	1.8874	0	4.6399
Turkey	4.4774	2.8782	0.5476	7.7853
United Kingdom	16.7365	10.2012	6.4373	37.8777
United States	23.3247	11.2852	8.7726	42.6511
Total	10.3745	22.6019	-182.1870	231.8555

Appendix II

Table 3.7: Auxiliary regression of FIT on all exogenous instruments and the rest of regressors

Variable	b/(se) *COR*	b/(se) *WCC*
OTHFIT	7.103 (1.269)***	10.55 (1.977)***
FITGDP	19.698 (9.163)**	14.062 (7.543)**
COR(t-1)	-.2614 (1.668)	-.2614 (1.668)
WCC		-0.547 (.379)
QUO	-1.351 (2.991)	-0.905 (2.369)
TAX	0.240 (1.384)	0.0240 (0.957)
INVSUB	-0.304 (-0.716)	-0.5 (-0.62)
NUCS	-0.590 (0.316)*	-0.686 (0.307)*
HYDROS	0.020 (0.149)	0.021 (0.151)
GASS	0.064 (0.207)	0.062 (0.1843)
OILS	-0.152 (0.233)	-0.215 (0.211)
COALS	0.039 (0.165)	-0.021 (0.51)
IMDEP	-0.035 (0.058)	0.052 (0.074)
LCO2PC	-6.769 (3.514)**	-2.341 (4.085)**
Constant Term	18.749 (18.046)	16.828 (13.501)
Cross Sections	48	48
Time periods	7	7

standard errors in parentheses
*p<0.10, ** p<0.05, *** p<0.01