ΠΑΝΕΠΙΣΤΗΜΙΟ ΚΡΗΤΗΣ
ΣΧΟΛΗ ΚΟΙΝΩΝΙΚΩΝ ΕΠΙΣΤΗΜΩΝ
ΤΜΗΜΑ ΟΙΚΟΝΟΜΙΚΩΝ ΕΠΙΣΤΗΜΩΝ

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«Μικροοικονομική Ανάλυση των Επιδράσεων της Χρήσης Χημικών Εισροών στην Προσφορά Αγροτικών Προϊόντων: Η Περίπτωση των Θερμοκηπιακών Καλλιεργειών στην Ιεράπετρα Κρήτης»

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ΕΥΧΑΡΙΣΤΙΕΣ

Η παρούσα διδακτορική διατριβή ξεκίνησε τον Δεκέμβριο του 2005 και ολοκληρώθηκε επιτυχώς τον Δεκέμβριο του 2009. Η εκπόνηση της διδακτορικής διατριβής πραγματοποιήθηκε από τον υποψήφιο Διδάκτορα του Τμήματος Οικονομικών Επιστημών του Πανεπιστημίου Κρήτης, Χατζημιχαήλ Κωνσταντίνο. Ο βασικός επόπτης της διατριβής ήταν ο Αναπληρωτής Καθηγητής Οικονομικών Επιστημών του Πανεπιστημίου Κρήτης, **Τζουβελέκας Βαγγέλης**. Τα άλλα δύο μέλη της τριμελούς επιτροπής ήταν ο καθηγητής Οικονομικών Επιστημών, **Αναστάσιος Ξεπαπαδέας** και ο καθηγητής Οικονομικών επιστημών, **Σπύρος Στεφάνου**.

Η παρούσα διατριβή συγχρηματοδοτήθηκε κατά:

- 75% της Δημόσιας Δαπάνης από την Ευρωπαϊκή Ένωση – Ευρωπαϊκό Κοινωνικό Ταμείο
- 25% της Δημόσιας Δαπάνης από το Ελληνικό Δημόσιο – Υπουργείο Ανάπτυξης – Γενική Γραμματεία Έρευνας και Τεχνολογίας
- και από τον Ιδιωτικό Τομέα

στο πλαίσιο του Μέτρου 8.3 του Ε.Π. Ανταγωνιστικότητα – Γ΄ Κοινοτικό Πλαίσιο Στήριξης.

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ΠΕΡΙΕΧΟΜΕΝΑ

ΠΕΡΙΛΗΨΗ ΔΙΔΑΚΤΟΡΙΚΗΣ ΔΙΑΤΡΙΒΗΣ

1. ΕΙΣΑΓΩΓΗ

Η παρούσα διδακτορική διατριβή έχει ως στόχο την ανάπτυξη ενός συνεπούς θεωρητικού πλαισίου για την μέτρηση των αποτελεσμάτων της χρήσης χημικών εισροών στην παραγωγικότητα των γεωργών. Η χρήση χημικών εισροών εκτός από τις άμεσες θετικές συνέπειες που έχει στην αγροτική παραγωγή, μπορεί να προκαλέσει σοβαρά προβλήματα υγείας στους εργαζόμενους, τα οποία εκτός από κοινωνικές επιπτώσεις έχουν και σημαντικές οικονομικές συνέπειες λόγω της μείωσης της παραγωγικότητας της εργασίας, η οποία προκαλείτε από μειώσεις στο ανθρώπινο κεφάλαιο. Ως ανθρώπινο κεφάλαιο ορίζουμε το σύνολο των ικανοτήτων των εργαζομένων που αποκτούνται μέσα από την εργασία, την εκπαίδευση και την εμπειρία, αλλά και τα χαρακτηριστικά εκείνα που μπορούν εν δυνάμει να μεταβάλουν την αξία της εργασιακής προσπάθειας, όπως η υγεία.

Στο πλαίσιο αυτό, η εν λόγω διδακτορική διατριβή διερευνά τον ρόλο του ανθρώπινου κεφαλαίου στην παραγωγική διαδικασία, εστιάζοντας στα δύο σημαντικότερα συστατικά του ανθρώπινου κεφαλαίου όπως αυτά επισημαίνονται στην υπάρχουσα οικονομική βιβλιογραφία: την εκπαίδευση και την υγεία. Αρχικά, αναλύεται ο ρόλος της εκπαίδευσης σε επίπεδο χωρών, παρέχοντας μια εικόνα για την σχέση ανθρώπινου κεφαλαίου και παραγωγικότητας σε διεθνές επίπεδο και έπειτα διερευνάτε ο ρόλος της υγείας στην παραγωγικότητα του αγροτικού τομέα, όπου έχουν παρατηρηθεί σημαντικές μειώσεις στο ανθρώπινο κεφάλαιο και συγκεκριμένα στην υγεία των γεωργών, λόγω των δύσκολων συνθηκών εργασίας και της επαφής με επικίνδυνες χημικές εισροές, όπως εντομοκτόνα και ζιζανιοκτόνα.

Πιο συγκεκριμένα, η παρούσα διατριβή εστιάζει στην ανάπτυξη κατάλληλων θεωρητικών υποδειγμάτων για τον εντοπισμό των αποτελεσμάτων του ανθρώπινου κεφαλαίου στην παραγωγικότητα τόσο σε εθνικό όσο και σε αγροτικό επίπεδο. Η παρούσα διδακτορική διατριβή αποτελείτε από τρία μέρη. Ο στόχος του πρώτου μέρους είναι η ανάπτυξη ενός ολοκληρωμένου θεωρητικού και εμπειρικού μοντέλου για την ανάλυση των άμεσων αποτελεσμάτων της εκπαίδευσης και της τεχνικής αποτελεσματικότητας στην παγκόσμια παραγωγικότητα της εργασίας και η ποσοτικοποίηση των διάφορων παραγόντων που την συνθέτουν. Το δεύτερο μέρος της διατριβής έχει ως στόχο την παροχή ενός θεωρητικά συνεπούς πλαισίου αποσύνθεσης

(decomposition framework) με σκοπό την εμπειρική αξιολόγηση των ποιοτικών και ποσοτικών αποτελεσμάτων της εκπαίδευσης και της υγείας των γεωργών στην συνολική παραγωγικότητα τους (TFP-Total Factor Productivity). Τέλος, το τρίτο μέρος της διατριβής έχει ως στόχο την ανάλυση των αποτελεσμάτων της χρήσης εντομοκτόνων στην υγεία των γεωργών και στην παραγωγικότητα τους μέσω της ανάπτυξης ενός κατάλληλου θεωρητικού και εμπειρικού υποδείγματος.

Στο πρώτο μέρος της διατριβής αναλύουμε τον ρόλο του ανθρώπινου κεφαλαίου στην παγκόσμια παραγωγικότητα της εργασίας, λαμβάνοντας υπόψη την ύπαρξη τεχνικής αναποτελεσματικότητας της εργασίας (labor technical inefficiency). Παρέχουμε ένα θεωρητικό πλαίσιο αποσύνθεσης της παραγωγικότητας της εργασίας σε ποικίλους παράγοντες, κάποιοι από τους οποίους αναφέρονται στις μεταβολές της εκπαίδευσης και της τεχνικής αποτελεσματικότητας. Το υπόδειγμα αυτό εφαρμόζεται εμπειρικά σε 52 εθνικές οικονομίες ανά τον κόσμο καλύπτοντας μια χρονική περίοδο από το 1965 έως το 1990. Το δεύτερο μέρος της διατριβής διερευνά τα ποσοτικά και ποιοτικά αποτελέσματα της υγείας και της εκπαίδευσης στην παραγωγικότητα των γεωργών. Παρέχει ένα ολοκληρωμένο θεωρητικό πλαίσιο για την αποσύνθεση της συνολικής παραγωγικότητας των γεωργών, το οποίο χρησιμοποιείτε εμπειρικά σε δεδομένα που προήλθαν από πρωτογενή έρευνα στην Ιεράπετρα της Κρήτης. Τέλος, το τρίτο μέρος της διατριβής αναλύει τα αποτελέσματα από την χρήση χημικών εισροών στην παραγωγικότητα των γεωργών, λαμβάνοντας υπόψη και τις βλαβερές συνέπειες που έχουν στην υγεία τους. Αναπτύσσει ένα κατάλληλο πλαίσιο αποσύνθεσης της συνολικής παραγωγικότητας σε διάφορες πηγές, κάποιες από τις οποίες σχετίζονται με επιδεινώσεις στην υγεία των γεωργών λόγω της χρήσης χημικών εισροών. Το θεωρητικό μοντέλο χρησιμοποιείτε στα ίδια δεδομένα με αυτά που χρησιμοποιήθηκαν στο δεύτερο μέρος και αφορούν 50 θερμοκηπιακούς καλλιεργητές, οι οποίοι παρατηρήθηκαν από το 2003-07.

1.1. ΣΥΝΕΙΣΦΟΡΑ ΣΤΗΝ ΒΙΒΛΙΟΓΡΑΦΙΑ

Όπως αναφέρθηκε στην προηγούμενη ενότητα, η παρούσα διδακτορική διατριβή αποτελείτε από τρία κεφάλαια. Το θεωρητικό υπόδειγμα που αναπτύσσεται κατά σειρά σε κάθε κεφάλαιο αποτελεί την βάση για την ανάπτυξη του επόμενου υποδείγματος,

ούτως ώστε να επιτευχθεί τελικά η ορθή μέτρηση των επιπτώσεων της χρήσης εντομοκτόνων στην παραγωγικότητα των γεωργών. Παρόλο που όλα τα υποδείγματα που αναπτύσσονται συνδέονται μεταξύ τους, έχοντας ως κοινό παρανομαστή την σχέση μεταξύ ανθρώπινου κεφαλαίου και παραγωγικότητας, κάθε κεφάλαιο αποτελεί συγχρόνως και μια αυτοτελή προσέγγιση συνεισφέροντας με διάφορους τρόπους στην υπάρχουσα βιβλιογραφία.

Το πρώτο μέρος της διδακτορικής διατριβής διερευνά τα αποτελέσματα της τεχνικής αποτελεσματικότητας της εργασίας και τα αποτελέσματα του ανθρώπινου κεφαλαίου στις μεταβολές της παγκόσμιας παραγωγικότητας της εργασίας, χρησιμοποιώντας δεδομένα από 52 αναπτυσσόμενες και αναπτυγμένες χώρες. Τα δεδομένα εξάχθηκαν από την διαδικτυακή πηγή δεδομένων Penn World Tables και καλύπτουν την χρονική περίοδο από το 1965 έως το 1990. Ξεκινώντας από την δυική προσέγγιση του Kuroda (1995) για την μέτρηση της μερικής παραγωγικότητας, ενσωματώσαμε το ανθρώπινο κεφάλαιο στην ανάλυση, επιτρέποντας συγχρόνως την ύπαρξη τεχνικής αναποτελεσματικότητας στην εργασία. Στην συνέχεια αναπτύξαμε ένα συνεπές θεωρητικό μοντέλο αποσύνθεσης της παραγωγικότητας της εργασίας σε έξι αποτελέσματα: 1. μεταβολές στην τεχνική αποτελεσματικότητα της εργασίας, 2. οικονομίες κλίμακας, 3. αποτέλεσμα υποκατάστασης, 4. μεταβολές στο ανθρώπινο κεφάλαιο, 5. αποτέλεσμα μεταβολών στην τεχνολογία και 6. αποτέλεσμα μεροληπτικών τεχνολογικών μεταβολών.

Το εμπειρικό μοντέλο βασίστηκε στην γενικευμένη Cobb-Douglas συνάρτηση παραγωγής (Fan, 1991), επεκταμένη όμως σε μία πολύπλευρη δομή παραγωγής ("*multilateral*" production structure) στα πλαίσια της προσέγγισης των Jorgenson και Nishimizu (1978). Με αυτόν τον τρόπο, οι τεχνολογικές διαφορές μεταξύ των χωρών στο δείγμα λήφθηκαν υπόψη. Η μέτρηση της τεχνικής αποτελεσματικότητας της εργασίας βασίστηκε στον ορθογώνιο μη-ακτινικό δείκτη (orthogonal non-radial index) του Kopp (1981) τροποποιημένο σε παραμετρικό πλαίσιο. Τέλος, το ανθρώπινο κεφάλαιο εισήχθη στην ανάλυση ως πολλαπλασιαστικός παράγοντας της εργασίας (Griliches, 1963), χρησιμοποιώντας την προσέγγιση των Hall και Jones (1999). Το συγκεκριμένο υπόδειγμα συνεισφέρει στην βιβλιογραφία με τους παρακάτω τρόπους:

- Πρώτον, παρέχει ένα ολοκληρωμένο και θεωρητικά συνεπές παραμετρικό πλαίσιο αποσύνθεσης των μεταβολών της μερικής παραγωγικότητας, λαμβάνοντας υπόψη την παρουσία τεχνικής αναποτελεσματικότητας συγκεκριμένης εισροής (input specific technical inefficiency). Η πλειοψηφία των ερευνητικών και επιστημονικών εργασιών σε αυτό το πεδίο εστιάζει στην μέτρηση της συνολικής παραγωγικότητας. Υπάρχει μόνο ένας πολύ περιορισμένος αριθμός εργασιών που μελετά την μέτρηση της μερικής παραγωγικότητας, οι οποίες όμως είτε χρησιμοποιούν μη-παραμετρικές μεθόδους, είτε αγνοούν την ύπαρξη τεχνικών αναποτελεσματικοτήτων.
- Δεύτερον, παρέχει ένα συνεπές δυικό παραμετρικό πλαίσιο για την ταυτοποίηση των άμεσων αποτελεσμάτων του ανθρώπινου κεφαλαίου στις μεταβολές της παραγωγικότητας της εργασίας. Η υπάρχουσα εμπειρική έρευνα αναλύει κυρίως είτε τον ρόλο των σχολικών ετών στην διαδικασία οικονομικής ανάπτυξης, είτε τις αποδόσεις της εκπαίδευσης (returns to education). Υπάρχουν πολύ λίγες έρευνες που επικεντρώνονται στην ανάλυση των αποτελεσμάτων της εκπαίδευσης στην παραγωγικότητα της εργασίας, οι οποίες όμως στηρίζονται σε μη-παραμετρικές προσεγγίσεις.
- Τρίτον, επεκτείνει την δίπλευρη δομή παραγωγής ("*bilateral*" production structure) των Jorgenson και Nishimizu (1978), χρησιμοποιώντας την γενικευμένη Cobb-Douglas συνάρτηση παραγωγής. Αυτή η μετατροπή μειώνει πιθανά λάθη στην προσέγγιση της παγκόσμιας τεχνολογίας παραγωγής και επιτρέπει συγχρόνως την ύπαρξη πιο ευέλικτων χαρακτηριστικών της τεχνολογίας ανάμεσα στις διάφορες χώρες. Με αυτόν τον τρόπο, ξεπερνά πιθανά λάθη που σχετίζονται με την κατασκευή της παγκόσμιας τεχνολογίας, τα οποία εντοπίζονται στις περισσότερες εμπειρικές έρευνες.

Το δεύτερο μέρος της διατριβής εστιάζει στην ανάλυση των ποιοτικών και ποσοτικών αποτελεσμάτων του ανθρώπινου κεφαλαίου στην παραγωγικότητα του αγροτικού τομέα, μελετώντας τους δύο σημαντικότερους τύπους ανθρώπινου κεφαλαίου: την εκπαίδευση και την υγεία. Βασιζόμενοι στις ιδέες των Welch (1970) και Schultz (1961), χρησιμοποιήσαμε την εκπαίδευση και την υγεία ως ξεχωριστούς συντελεστές

παραγωγής, επιτρέποντας τους επίσης να επηρεάζουν την διάχυση νέων γεωργικών τεχνολογιών (Nelson και Phelps, 1966). Επιπλέον, επιτρέψαμε και στα δύο προαναφερθέντα είδη ανθρώπινου κεφαλαίου να επηρεάζουν ποιοτικά την παραγωγικότητα των γεωργών μέσω ποιοτικών προσαρμογών της εισροής της εργασίας., δεδομένου ότι τα ποιοτικά χαρακτηριστικά του ανθρώπου συνδέονται άρρηκτα με τις δυνατότητες του και άρα και με την αξία της εργασιακής προσπάθειας (Schultz, 1961; 1980).

Πιο συγκεκριμένα, υιοθετήσαμε σε αυτό το υπόδειγμα τα μεθοδολογικά εργαλεία των Griliches (1963) και Deolalikar (1988) για να εκφράσουμε την αποτελεσματική εργασία ως το γινόμενο της φυσικής εργασίας και των συστατικών του ανθρώπινου κεφαλαίου, εγκαθιδρύοντας όμως μια μη αναλογική σχέση μεταξύ εκπαίδευσης, υγείας και εργασίας. Στην συνέχεια, χρησιμοποιήσαμε τα ευρήματα της έρευνας των Chan και Mountain (1983), για να ταυτοποιήσουμε τόσο τα ποσοτικά όσο και τα ποιοτικά αποτελέσματα της εκπαίδευσης και της υγείας στις μεταβολές της συνολικής παραγωγικότητας των γεωργών. Το εμπειρικό μοντέλο βασίστηκε στην γενικευμένη Cobb Douglas συνάρτηση παραγωγής (Fan, 1991) και εφαρμόστηκε σε διαχρονικά και διαστρωματικά δεδομένα που προήλθαν από πρωτογενή έρευνα. Τα δεδομένα αφορούν 50 θερμοκηπιακούς καλλιεργητές στην Ιεράπετρα της Κρήτης που παρατηρήθηκαν κατά την χρονική περίοδο από το 2003 έως το 2007. Η συνεισφορά αυτού του υποδείγματος στην βιβλιογραφία έγκειται στο ότι:

- Πρώτον, συνδυάζει και ολοκληρώνει τις εργασίες των Griliches (1963) και Welch (1970), χρησιμοποιώντας καταλλήλως τις ιδέες των Nelson and Phelps (1966) ώστε να παρέχει ένα θεωρητικό πλαίσιο για την μέτρηση των ποσοτικών και ποιοτικών αποτελεσμάτων του ανθρώπινου κεφαλαίου στην συνολική παραγωγικότητα των γεωργών και στην διάχυση νέων τεχνολογιών. Οι υπάρχουσες μελέτες σε αυτό το πεδίο περιορίζονται στο να διερευνούν μονοδιάστατα τα αποτελέσματα του ανθρώπινου κεφαλαίου, αγνοώντας την πολυδιάστατη φύση του. Έτσι αποτυγχάνουν να μετρήσουν συγχρόνως τις ποσοτικές και τις ποιοτικές επιπτώσεις του ανθρώπινου κεφαλαίου στην παραγωγικότητα αλλά και στην διάχυση νέων γεωργικών καινοτομιών.

- Δεύτερον, βασιζόμενο στις ιδέες των Schultz (1961) και Griliches (1963), παρέχει μία ολοκληρωμένη μέτρηση των επιπτώσεων όλων των σημαντικών συστατικών του ανθρώπινου κεφαλαίου στην γεωργική παραγωγή, λαμβάνοντας υπόψη όχι μόνο την εκπαίδευση αλλά και την υγεία. Οι σχετικές υπάρχουσες έρευνες περιορίζονται στην διερεύνηση μόνο του ενός από τα δύο σημαντικά είδη ανθρώπινου κεφαλαίου. Το γεγονός αυτό δίνει μία μη ολοκληρωμένη εικόνα σχετικά με το πραγματικό μέγεθος των επιπτώσεων του ανθρώπινου κεφαλαίου στην γεωργική παραγωγικότητα και οδηγεί σε μεροληπτικά και πολλές φορές αντιφατικά συμπεράσματα.
- Τρίτον, βασιζόμενο στα μεθοδολογικά εργαλεία της έρευνας του Deolalikar (1988), επεκτείνει την προσέγγιση του Griliches (1963), εγκαθιδρύοντας μία μη αναλογική σχέση μεταξύ εκπαίδευσης, υγείας και εργασίας. Με αυτόν τον τρόπο, επιτρέπει στην εκπαίδευση και την υγεία να επιδρούν με διαφορετικό τρόπο στα ποιοτικά χαρακτηριστικά της εργασίας.

Το τρίτο μέρος της διατριβής αναλύει τις επιπτώσεις της χρήσης εντομοκτόνων στην παραγωγικότητα των γεωργών. Σύμφωνα με τους Ram and Schultz (1979) και Schultz (1961, 1980), το ανθρώπινο κεφάλαιο είναι μία σημαντική πηγή της παραγωγικότητας του αγροτικού τομέα, επηρεάζοντας την αποτελεσματικότητα των γεωργών με ποικίλους τρόπους: 1. Έχει άμεση επίπτωση στην φυσική ικανότητα τους να απασχολούνται σε εργασίες, και 2. παρέχει ένα επιπρόσθετο κίνητρο για σχολική εκπαίδευση ως μία επένδυση για μελλοντικά κέρδη τα οποία διαρκούν για εκτενέστερη περίοδο εξαιτίας της βελτίωσης της διαχειριστικής ικανότητας τους ή για την υιοθέτηση νέων περισσότερο κερδοφόρων τεχνολογιών.

Από την άλλη πλευρά, οι αποφάσεις των γεωργών για την χρήση ορισμένων εισροών μπορεί να επηρεάσει την ποιότητα του ανθρώπινου κεφαλαίου. Ένα αξιοσημείωτο παράδειγμα στον αγροτικό τομέα είναι η χρήση χημικών εισροών όπως εντομοκτόνα, τα οποία παρόλο που ενθαρρύνουν την παραγωγή, την ίδια στιγμή μειώνουν το ανθρώπινο κεφάλαιο των γεωργών μέσω των επιβλαβών επιπτώσεων που αυτά έχουν στην υγεία τους.

Το υπόδειγμα αυτό αναλύει τα αποτελέσματα του ανθρώπινου κεφαλαίου στην συνολική παραγωγικότητα των γεωργών λαμβάνοντας υπόψη και τις αρνητικές

συνέπειες των εντομοκτόνων στην υγεία των παραγωγών. Βασιζόμενοι, στο έργο του Griliches (1963), το ανθρώπινο κεφάλαιο ενσωματώθηκε στην ανάλυση, χρησιμοποιώντας την εκπαίδευση και την υγεία ως πολλαπλασιαστικούς παράγοντες της εργασίας, ενώ οι αρνητικές επιπτώσεις των χημικών εισροών στην υγεία εισήλθαν στην ανάλυση μέσω της κατασκευής ενός δείκτη επιδείνωσης της υγείας (Antle και Pingali, 1994). Ο δείκτης αυτός αναπτύχθηκε περαιτέρω ώστε να λαμβάνει υπόψη τα αποτελέσματα των χημικών εισροών που σχετίζονται με μακροχρόνια έκθεση σε αυτά, καθώς επίσης και αλληλεπιδράσεις μεταξύ εκπαίδευσης και υγείας.

Το εμπειρικό μοντέλο βασίστηκε σε μια translog συνάρτηση παραγωγής και εφαρμόστηκε σε διαχρονικά και διαστρωματικά δεδομένα που προήλθαν από πρωτογενή έρευνα. Τα δεδομένα αφορούν 50 θερμοκηπιακούς καλλιεργητές στην Ιεράπετρα της Κρήτης που παρατηρήθηκαν κατά την χρονική περίοδο από το 2003 έως το 2007 και αποτελούν το ίδιο δείγμα με αυτό που χρησιμοποιήθηκε στο δεύτερο υπόδειγμα. Η συνεισφορά αυτού του υποδείγματος στην βιβλιογραφία έγκειται στο ότι:

- Πρώτον, παρέχει ένα ολοκληρωμένο πλαίσιο αποσύνθεσης της παραγωγικότητας που καθιστά δυνατό τον εντοπισμό τόσο των άμεσων θετικών επιδράσεων της χρήσης εντομοκτόνων στην παραγωγή όσο και των αρνητικών αποτελεσμάτων που έχουν λόγω της επιδείνωσης της υγείας των γεωργών. Από την μια πλευρά, τα εντομοκτόνα και οι άλλες χημικές εισροές δρουν ως κλασικοί συντελεστές παραγωγής που μειώνουν τους ζημιογόνους παράγοντες από τα έντομα και τα ζιζάνια, ενώ από την άλλη προκαλούν την ίδια στιγμή σοβαρά προβλήματα υγείας στους γεωργούς μειώνοντας την παραγωγικότητα τους. Το γεγονός αυτό υπονοεί ότι τα οικονομικά πλεονεκτήματα από την χρήση χημικών ουσιών στην γεωργία μπορεί να αντισταθμίζονται από μειώσεις της παραγωγικότητας που προκαλούνται από επιδεινώσεις στην υγεία των παραγωγών. Παρόλο που αρκετές έρευνες έχουν προσπαθήσει να εντοπίσουν και να μετρήσουν αυτές τις αλληλεπιδράσεις, οι περισσότερες εστιάζουν κυρίως σε αναλύσεις συναρτήσεων κόστους, αγνοώντας να διερευνήσουν τον μηχανισμό με τον οποίο οι χημικές εισροές επηρεάζουν την αποτελεσματική εργασία άλλα και την παραγωγικότητα των γεωργών.

- Δεύτερον, παρέχει ένα συνεπές τρόπο μοντελοποίησης της κατάστασης της υγείας των γεωργών που επιτρέπει σε αυτήν να καθορίζεται ενδογενώς κατά την παραγωγική διαδικασία, αφού οι προσωπικές αποφάσεις των παραγωγών για την χρήση χημικών εισροών είναι αυτές που καθορίζουν το μέγεθος των δύο αντίθετων αποτελεσμάτων που έχουν στην παραγωγή.
- Τρίτον, παρέχει ένα θεωρητικό πλαίσιο που επιτρέπει στην εκπαίδευση να έχει μια διπλή επιρροή στην αποτελεσματική εργασία: 1. μία άμεση λόγω της αύξησης του ανθρώπινου κεφαλαίου και μια έμμεση μέσω βελτιώσεων στην υγεία των γεωργών. Παρόλο που η πλειοψηφία των υπαρχουσών μελετών λαμβάνει υπόψη τα άμεσα αποτελέσματα της εκπαίδευσης, αγνοεί τις έμμεσες επιπτώσεις της. Το γενικό επίπεδο εκπαίδευσης καθώς και η εκπαίδευση που σχετίζεται με την γνώση και την ασφαλή χρήση χημικών εισροών μπορεί να παρέχει επιπλέον πληροφόρηση στους γεωργούς σχετικά με τις βλαβερές συνέπειες στην υγεία τους και σχετικά με την κατάλληλη χρήση τους.

1.2. ΣΥΝΤΟΜΗ ΠΑΡΟΥΣΙΑΣΗ ΑΠΟΤΕΛΕΣΜΑΤΩΝ

Τα εμπειρικά αποτελέσματα που προέκυψαν από τα τρία υποδείγματα της παρούσας διδακτορικής διατριβής αναδεικνύουν τον πολύ σημαντικό ρόλο του ανθρώπινου κεφαλαίου στην παραγωγική διαδικασία τόσο σε εθνικό επίπεδο όσο και στον αγροτικό τομέα. Οι μεταβολές στο ανθρώπινο κεφάλαιο βρέθηκαν να εξηγούν ένα πολύ σημαντικό μέρος των μεταβολών της παραγωγικότητας, γεγονός που ενισχύει την άποψη ότι η απουσία του ανθρώπινου κεφαλαίου από την ανάλυση οδηγεί σε μεροληπτικά και λανθασμένα αποτελέσματα.

Πιο συγκεκριμένα, τα εμπειρικά αποτελέσματα από την εφαρμογή του πρώτου υποδείγματος έδειξαν ότι ο μέσος ετήσιος ρυθμός αύξησης της παγκόσμιας παραγωγικότητας της εργασίας ήταν 1.4018 % για την χρονική περίοδο 1965-90. Η τεχνολογική μεταβολή βρέθηκε να αποτελεί την κινητήριο δύναμη της παραγωγικότητας της εργασίας εξηγώντας τις μεταβολές της κατά 40.98 %, την στιγμή που το αντίστοιχο ποσοστό για τα αποτελέσματα των οικονομιών κλίμακας ήταν 13.79%. Από την άλλη πλευρά οι βελτιώσεις στην τεχνική αποτελεσματικότητα της εργασίας και στο ανθρώπινο κεφάλαιο βρέθηκαν να ευθύνονται για το 20% των μεταβολών στην παραγωγικότητα της

εργασίας. Επιπλέον, οι Ασιατικές Τίγρεις βρέθηκαν να έχουν βιώσει την μεγαλύτερη αύξηση στην παραγωγικότητα της εργασίας (2.7546%) κατά την χρονική περίοδο που αναλύθηκε, η οποία ήταν δύο φορές μεγαλύτερη από τις επόμενες δύο ομάδες χωρών, την Β. Αμερική και Ωκεανία και την Ευρώπη, και τρείς φορές μεγαλύτερη από τις Αφρικάνικές και Ασιατικές χώρες.

Τα εμπειρικά αποτελέσματα από την εφαρμογή του δεύτερου υποδείγματος κατέδειξαν την σημαντική συνεισφορά της εκπαίδευσης και της υγείας στην συνολική παραγωγικότητα των θερμοκηπιακών καλλιεργητών, η οποία βρέθηκε να είναι 1.0704% για την περίοδο 2003-07. Συγκεκριμένα, τα εμπειρικά ευρήματα έδειξαν ότι η απουσία του ανθρώπινου κεφαλαίου από την ανάλυση θα είχε ως αποτέλεσμα την υποεκτίμηση κατά 28% της πραγματικής παραγωγικότητας των γεωργών. Επιπλέον, βρέθηκε ότι αγνοώντας τις επιπτώσεις της υγείας των γεωργών, θα είχαμε υπερεκτιμήσει την παραγωγικότητα κατά 6%.

Τέλος, τα αποτελέσματα από την εμπειρική εξειδίκευση του τρίτου υποδείγματος έδειξαν ότι η συνολική παραγωγικότητα των θερμοκηπιακών καλλιεργητών στην Ιεράπετρα Κρήτης αυξήθηκε ετησίως κατά 1.2826% από το 2003-07. Η κύρια πηγή της αύξησης αυτής ήταν βελτιώσεις στην τεχνολογία (53,24%), ενώ οι μεταβολές στην ποιότητα του ανθρώπινου κεφαλαίου βρέθηκαν να εξηγούν το 38.5% της συνολικής παραγωγικότητας. Επιπλέον, η χρήση εντομοκτόνων βρέθηκε να επηρεάζει θετικά 5.49% την παραγωγικότητα. Το αποτέλεσμα των εντομοκτόνων στην υγεία των γεωργών βρέθηκε να είναι αδύναμο αλλά θετικό στην παραγωγικότητα (0.86%) εξαιτίας της ύπαρξης φθινουσών αποδόσεων κλίμακας.

University Of Crete
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Phd Dissertation:

Microeconomic Analysis of the Impacts of Pesticides Use on the Supply of Agricultural Products: The Case of Greenhouse Farms in Ierapetra of Crete

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CONTENTS

1. INTRODUCTION

The present dissertation aims at developing a consistent theoretical and empirical framework for the measurement of the effects of pesticides use on farmer's productivity. Beside the direct positive effect of pesticides use on agricultural production, pesticides may cause serious health problems to farmers that have important economic implications since they related with reductions in labor productivity, which in turn are caused by reductions in human capital levels. Human capital is defined as the set of skills which an employee acquires on the job, through training and experience, together with those features which can potentially change the productive value of labor effort, e.g. health.

Along these lines, this dissertation investigates the role played by human capital in the production process, focusing on the two most important aspects of human capital as they appeared in the relevant economic literature: education and health. Initially, we analyze the role played by education in country level, providing a picture about the relation between human capital and national productivity, and then we explore the effects of health changes on agricultural productivity, where significant human capital reductions have been observed due to the hard working conditions and the inappropriate use of dangerous chemical inputs, e.g. pesticides and herbicides.

More specifically, this dissertation focuses on the development of different theoretical frameworks for the identification of the impact of human capital on productivity growth in national and agricultural level. It aims at: (a) developing a complete theoretical and empirical model in order to analyze the direct effects of education on worldwide labor productivity in the presence of labor technical inefficiency and to identify quantitatively the various sources that compose it, (b) providing an integrated decomposition framework for the theoretical and empirical assessment of the qualitatively and quantitatively effects of two elements of human capital, namely, education an health on farm productivity and (c) analyzing the effects of pesticides use on farmers' health and on their productivity performance through the development of an appropriate theoretical and empirical model.

The first part analyzes the role of human capital in worldwide labor productivity growth in the presence of labor technical inefficiency. A decomposition analysis is provided to identify the various sources of labor productivity growth, some of which

capture the effects of changes in education and labor technical efficiency. The empirical model is applied to a panel data set consisted by 52 national economies around the world covering a time period from 1965-90 drawn from Penn World Tables. The second part of the present dissertation investigates the quantitatively and qualitatively effects of two aspects of human capital, namely, education and health on agricultural productivity. It modulates an integrated theoretical framework for the decomposition of farmers' total factor productivity growth that is applied empirically to a panel data set of 50 farmers in Ierapetra region in Crete for the period from 2003-07 obtained from a primary survey. Finally, the third part analyzes the productivity effects of pesticides use, taking into account the associated effects on farmers' health status due to exposure to pesticides along with educational effects. An appropriate decomposition framework is developed to identify the various sources of TFP changes, some of which capture the effects of changes in farmers' education and health. The total effects of pesticides use are also identified. The theoretical model is further applied to the same data set used in the second paper.

1.2. CONTRIBUTION TO THE LITERATURE

As it was above-mentioned, the present dissertation is consisted by three parts. The theoretical and empirical framework that is developed in turn in each part constitute the basis for the development of the next part, so that we end up with a consistent measurement of the effects of pesticides use on farmer's total factor productivity growth. Although all parts of the dissertation are connected having as a common factor the relation between human capital and productivity, each chapter constitutes an independent paper that contributes differently to the literature.

The first part of the present dissertation investigates the effects of labor technical efficiency and human capital on worldwide labor productivity growth, studying a sample of 52 developed and developing countries from 1965-90 drawn from Penn World Tables. A decomposition analysis is used for the identification of the various sources of labor productivity growth. In particular, Kuroda's (1995) dual approach of partial factor productivity measurement is extended, incorporating human capital into the analysis, and

relaxing at the same time the restrictive assumption of labor-specific technical efficiency. A theoretically consistent parametric decomposition of labor productivity growth is provided into six components: a. changes in labor technical efficiency, b. scale economies, c. substitution effect, d. changes in human capital, e. changes in production technology and f. extended labor biased technological change effect. The generalized Cobb-Douglas functional specification suggested by Fan (1991) is adopted for the empirical estimation of the aggregate production frontier model, extended though into a "*multilateral*" production structure, using Jorgenson and Nishimizu (1978) context of bilateral production functions. Thus, differences in technological structures among countries in the sample are taken into account. The measurement of labor technical efficiency is based on Kopp's (1981) orthogonal non-radial index of factor-specific technical efficiency modified in a parametric frontier framework. Finally, following Griliches (1963), human capital is proxied using Hall and Jones (1999) construction which is introduced into the analysis as an augmenting factor of labor input. The approach described briefly above contributes to the relative literature with various ways:

- First, it provides a complete and theoretically consistent parametric decomposition framework to analyze partial factor productivity growth in the presence of input specific technical inefficiency. The majority of the existent work in this field focuses mainly on total factor productivity (TFP) measurement. There are only a few studies investigating partial factor productivity (PFP) measures, which are though based either on a non parametric framework, or simply neglect the impact of technical inefficiency on PFP growth.
- Second, it provides a consistent dual parametric framework to capture the direct effect of human capital on worldwide labor productivity change. The existent empirical research focuses mainly either on assessing the role of years of schooling in the growth process or on the investigation of the returns to education. There are only few studies investigating the direct impact of education on measured labor productivity growth, which are based on non parametric techniques.
- Third, it extents Jorgenson and Nishimizu (1978) "*bilateral*" production structure into a "*multilateral*" context within the generalized Cobb-Douglas production

frontier model. This formulation reduces possible bias in approximating the worldwide production technology and it allows for more flexible patterns for technological features among countries. Hence, it overcomes measurement error problems related with the construction of the worldwide technology that are identified in most empirical studies.

The second part of this dissertation focuses on the quantitative and qualitative impacts of the two most important aspects of human capital in agriculture, namely, education and health, on farm productivity. Based on the seminal papers of Welch (1970) and Schultz (1961), education and health are treated as separate factors of production, allowing them also to affect the diffusion of new farm technologies following the ideas of Nelson and Phelps (1966). Both aspects of human capital are further allowed to affect qualitatively farmers' productivity through quality adjustments in labor input, since human quality components affect human capabilities and increase the value productivity of labor effort (Schultz, 1961; 1980). Specifically, Griliches (1963) and Deolalikar (1988) specifications are adopted to express effective labor as a multiplicative augmentation of physical labor and human capital elements, establishing at the same time a not proportional link between education, health and effective labor. Then, using Chan and Mountain (1983) findings, quantitative and qualitative effects of human capital on farmers total factor productivity growth are captured. Moreover, different assumptions are examined regarding the specification of human capital effects on TFP growth. The empirical model is based on a generalized Cobb Douglas production frontier suggested by Fan (1991) which is applied to a panel data set of 50 greenhouse farms observed during the 2003-07 period that is obtained from a primary survey in the region of Ierapetra in Crete. The paper contributes to the relative literature as follows:

- First, it combines and integrates the works of Griliches (1963) and Welch (1970), within Nelson and Phelps (1966) providing a consistent theoretical framework for the identification of the quantitative and qualitative effects of human capital on farmers' productivity within a TFP decomposition analysis. The existent studies in this area are limited in investigating only a one-dimensional impact of human capital on production, neglecting thus its multi-dimensional productive value.

- Second, based on the early ideas of Schultz (1961) and Griliches (1963), it provides an integrated measurement of the overall human capital effect on farm production, taking into account the two most important aspects of human capital in agriculture, namely, health and education. Studies in this field are limited in considering only the role played by only one of these two elements of human capital neglecting the other. This provides an incomplete picture about the real magnitude of human capital and leads in biased and controversial conclusions regarding its impact on farmers' productivity.
- Third, based on the methodological developments of Deolalikar (1988), it extends Griliches (1963) approach establishing a not proportional relation between education, health and labor input. Hence, relaxing Griliches (1963) assumption, the impact of education and health on labor quality is allowed to vary.

The third part of the present dissertation analyzes the impacts of pesticides use on farmers' productivity. According to Ram and Schultz (1979) and Schultz (1961, 1980) human capital is an important source of farmers' productivity affecting the effectiveness of laborers in a variety of ways: i) there is a clear implication of an increase in the physical ability to engage in work that increase the amount of effective work, ii) there is an additional incentive to acquire schooling as investment in future earnings which accrue over a longer period due either to improvements in managerial ability or to adopt new more profitable technologies. On the other hand, individual decisions on the use of certain variable inputs affect the quality of human capital engaged in production process. A notable example in agricultural sector is the use of damage control inputs, i.e., pesticides, that although enhance farm yields at the same time deteriorates farmer's human capital through the adverse effects on their health status. Along these lines, this paper analyzes the effect of human capital on individual total factor productivity growth taking into account the adverse effects of pesticide use. Following Griliches (1963), human capital is incorporated into the analysis using education and farmer's health as multiplicative augmentations of labor input, while the adverse effects of pesticides use on farmers' health are captured through the development of a health impairment index suggested by Antle and Pingali (1994). The health impairment index is extended though

to capture pesticides effects related with long exposure and interactions between education and health. The empirical model is based on a translog production frontier which is applied to a panel data set of 50 greenhouse farms observed during the 2003-07 period obtained from a primary survey in the region of Ierapetra, Greece. This paper contributes to the relative literature in the following ways:

- First, it provides an integrated decomposition framework for the identification of both the direct effects of pesticides on farm production and the adverse effects of pesticides on farmers' productivity due to impairments in farmers' health. On the one hand pesticides act as a productive factor that controls damage from pests, enhancing thus farmers' production, while on the other hand pesticides cause serious health problems to farmers, reducing their productivity performance. This implies that the economic benefits from the pesticides use could be offset by productivity losses from impaired health. Although many studies have attempted to capture these trade-offs, they focus mainly on cost functions, ignoring to analyze the mechanism underlines the impact of pesticides on effective labor and farmers' productivity.
- Second, it permits farmers' health status to be determined endogenously in the production process, since it is the own decision of farmers regarding pesticides use that determines the magnitude of the two opposite effects on production.
- Third, it allows for education to have a two-way impact on effective labor, one direct impact as a direct augmentation of labor input and an indirect impact through improvements in farmers' health. Although many studies acknowledge the impact of educational improvements on effective labor, they implicitly ignore the accompanied improvements in farmers' health. The general level of education together with education related with safe use of pesticides may provide additional information to farmers about the health consequences of pesticides and be important for their safe use during applications, especially, in developing countries.

1.3. BRIEF PRESENTATION OF THE RESULTS

The results that came up from the empirical application of the three theoretical models emerge the important role played by human capital in the production process in both national level and in agricultural sector. Improvements in human capital were identified in all models to explain a significant part of productivity growth, confirming the suspicion that its absence from the analysis is possible to lead in biased and sometimes controversial results.

In particular, the results came up from the empirical application of the first model indicated that the average annual rate of labor productivity growth was 1.4018 per cent over the period analyzed. Technical change was found to be the driving force of labor productivity contributing 40.98 per cent to changes in labor productivity growth, followed by scale effect with 13.79 percentage contribution. Furthermore, improvements in labor technical efficiency and human capital were found to explain about 20 per cent of labor productivity growth. Furthermore, we found Asian Tigers (2.7546) to have experienced the higher labor productivity growth during 1965-90 time period that was almost two times higher than the next two groups, namely North America and Oceana (1.2920 per cent) and Europe (1.1782 per cent) and approximately three times higher than the two lower groups namely, Asia (0.9344 per cent) and Africa (0.9344 per cent). In addition, South and Central America was found to have on average a 1.1432 per cent rate of labor productivity growth.

The empirical results from the second model indicated an important contribution of both education and health to farmers' total factor productivity (TFP) growth. Specifically, Considering the full model case, the annual TFP growth was found to have increased 1.0704 per cent on average during the period from 2003-07. The absence of human capital from the analysis would result in about 28 per cent underestimation of farmers' TFP growth. Furthermore, ignoring the role of health as an important aspect of human capital would result in an upward bias of 6 per cent on the measured productivity growth Finally, the empirical evidence do not support the existence of an important human capital impact on technical change.

The results from the third model indicated that greenhouse farm productivity increased 1.2826 per cent over the period analyzed. The main source of productivity

growth was found to be technical change contributing (53.24 per cent) to TFP changes. Changes in labor quality due to human capital improvements were found to account for about 38.5 per cent of TFP growth, indicating the important role of human capital in Greenhouse production. Furthermore, the pesticides effect on TFP growth was 5.49 per cent, driven mainly by the biased technical change of pesticides. Finally, the health effect of pesticides on productivity was found to be weak but positive (0.86 per cent) due to the existence of decreasing returns to scale.

PART I: Labor Productivity Growth and the Role of Human Capital

2. INTRODUCTION

The productivity fall observed in many industrialized countries during the 60's and early 70's initiated an intense public debate regarding the internal mechanism of economic growth. This heated public debate resulted into two controversial strands of the relevant economic literature. On the one hand, growth theorists, building upon the pioneering work of Solow (1956), consider technological progress as the main driving force of observed productivity changes supporting at the same time that decreasing returns to accumulated factors have a negative effect on growth and *vice-versa*. On the other hand, endogenous growth theorists, following the theoretical contributions of Romer (1986) and Lucas (1988), pointed to human capital as the main sources that generate economic growth. Despite their differences, the two approaches seem to share a common belief: they both identify productivity variations as the main source of growth changes, since differences among economies cannot be attributed to the factors accumulation alone. This general acceptance of productivity as the major source of economic growth renders it's understanding extremely interesting not only to economics but also to policy-makers.

As a consequence, the methodological developments related with the appropriate measurement and decomposition of productivity growth constituted for many years an area of great controversial for the economists, resulting in an enormous literature. Initially, the changes in productivity were sought as a synonym of the change in technology or to put it differently of the time derivative of the production or cost function. Needless to say this was very restrictive, since it presumes cost efficiency and constant returns-to-scale aggregate production technology. Overcoming these restrictions, Ohta (1974) and Nishimizu and Page (1982), based on a parametric framework, show that both scale economies and efficiency changes can be important dimensions of the measured rate of productivity growth. At the same time Caves, Christensen and Diewert (1982) and Färe et al., (1994) reached the same conclusion utilizing a non-parametric Malmquist index to decompose productivity changes. Even since both approaches constitute the bedrock for the empirical measurement of total factor productivity growth and many studies emerged worldwide trying to evaluate the bias of scale economies and efficiency changes in measured productivity changes.

However, most of these empirical studies are dealing almost exclusively with the decomposition of total factor productivity (TFP) growth, neglecting partial factor productivity (PFP) measures. This bias may be partly justified by the fact that PFP measures may over- or under-estimate measured productivity growth by not taking into account explicitly substitution possibilities among factors of production (Capalbo and Vo, 1988). However, still PFP measures may be useful providing detailed information about each factor of production separately, which is quite important from a policy point of view, given the diverse and complex nature of the modern economies. Further, as Hayami and Ruttan (1970) suggested, partial factor productivity indices represent significant measures of productivity growth when they refer to the scarce factor of production (*i.e.* labor and land).

Nevertheless among factors of production the measurement of labor productivity growth is important and useful from a welfare perspective as it is directly linked with income distribution in both developed and developing countries (Jones, 1997). The rapid economic growth observed in many countries around the globe has been accompanied with a continuous migration of labor force from agricultural activities to non-farm business and at the same time with significant technological advances in information technologies that are directly linked with labor productivity. Kuroda (1995) found that, besides the sizable transfer of labor from agriculture to the non-agricultural sectors, the productivity of labor in Japanese agriculture follows a decreasing trend over the 1956-90 time period. On the other hand, Black and Lynch (1996) revealed that investments in human capital and workplace practices such as the use of computers and high performance work systems considerably enhance labor productivity in both manufacturing and non-manufacturing sectors. Both studies underline the importance of labor productivity measures as an important policy mechanism in the modern complex and diverse national economies.

Besides the fact that endogenous growth theorists recognize the importance of human capital enhancements on measured productivity the majority of empirical research is focused either on assessing the role of years of schooling in the growth process or on the investigation of the returns to education and there is a little direct analysis of the impact of education on measured labor productivity. Investments in education and the

skills development of workers are a way to ensure higher labor productivity levels and therefore economic growth without igniting wage inflation. Black and Lynch (1996) using a simple accounting approach found that increasing the average educational level of workers within manufacturing sector by only one year results in an 8% increase in labor productivity *ceteris paribus*. This number besides being high and probably biased from not accounting for scale economies and substitution effects still underlines the significance and the need to measure consistently the impact of human capital investments on measured labor productivity growth.

Recognizing these, Kumar and Russell (2002) recently following the contribution of Farrell (1957) on efficiency measurement, analyzed labor productivity growth for 57 developed and developing countries. Specifically, they employed a non parametric analysis to break down labor productivity into components attributable to shifts in the world production frontier (technical change), movement towards or away from the production frontier (technological catch up) and movements along the frontier (changes in the capital-labor ratio) or changes in capital accumulation. Three years later, by constructing a worldwide technology that precludes the possibility of an implosion of the frontier, Henderson and Russell (2005) extended the idea of Kumar and Russell (2002), incorporating changes in human capital among the terms that affect labor productivity growth. Their results are quite different from those of Kumar and Russell (2002), indicating, however, that neglecting human capital in the productivity analysis leads to biased results.

Motivated by the work of Henderson and Russell (2005), we attempt in this paper to contribute in the relevant literature providing a theoretically consistent parametric decomposition of labor productivity growth. Using Kuroda's (1995) approach of partial factor productivity measurement, incorporating human capital in our decomposition analysis and relaxing the restrictive assumption of labor-specific technical efficiency we provide a complete decomposition analysis of labor productivity growth in a sample of 52 developed and developing countries from 1965-90. Our empirical aggregate production frontier model is based on the generalized Cobb-Douglas functional specification suggested by Fan (1991) and Karagiannis and Tzouvelekas (2001) extended into a "*multilateral*" production structure in order to take into account differences in

technological structures among countries in the sample using Jorgenson and Nishimizu (1978) context of bilateral production functions. Measurement of labor technical efficiency is based on Kopp's (1981) orthogonal non-radial index of factor-specific technical efficiency modified in a parametric frontier framework. Finally, following Griliches (1963) human capital proxied using Hall and Jones (1999) construction is introduced as an augmenting factor of labor input enabling the identification of its direct impact on measured labor productivity.

The remaining paper is organized as follows. In the next section, we present the theoretical framework for measuring labor productivity growth in a parametric context. Next section 3 presents data description and describes the empirical model and estimating procedures. Section 4 discusses the empirical results while, the last section provides the main conclusions, followed by the tables.

2.1. THEORETICAL FRAMEWORK

Let assume that countries in period t utilize labor, physical and human capital to produce a single aggregate output $y \in \Re_+$ through a well-behaved technology described by the following non-empty, closed set:

$$T = \{(k,l,\varepsilon,y) : y \leq f(k,l,\varepsilon,t)\} \tag{1}$$

where $k \in \Re_+$ denotes physical capital, $l \in \Re_+$ labor, $\varepsilon \in \Re_+$ human capital and, $f(k,l,\varepsilon,t) : \Re_+^3 \to \Re_+$ is a continuous and, strictly increasing, differentiable concave production function, representing the maximal output from physical capital and labor use given human capital and technological constraints. Using (1) we can define the input correspondence set as all the input combinations capable of producing $y \in \Re_+$ as: $L(y) = \{(k,l,\varepsilon) \in \Re_+^3 : (k,l,\varepsilon,y) \in T^t\}$. The input correspondence set is assumed to be a closed convex set satisfying strong disposability of labor and physical capital inputs.

Alternatively, production technology may be also defined by the dual cost function $C(\mathbf{w}, y, \varepsilon, t): R(y) \times \Re^2_{++} \rightarrow \Re^1_{++}$ for all $y \in \Re_+$ such that $L(y) \neq \varnothing$ as:

$$C(\mathbf{w}, y, \varepsilon, t) = \min_{k,l} \{ w_l l + w_k k : y \leq f(k, l, \varepsilon, t) \} \tag{2}$$

where $\mathbf{w} = \{w_l, w_k\} \in \Re^2_{++}$ are the strictly positive effective labor and capital prices. The cost function is assumed to be continuous differentiable in all its arguments, non-decreasing in **w** and y, non-increasing in ε and homogeneous of degree one in **w**.

Since production technology allows for free disposability of labor and physical capital inputs, the production of aggregate output may not be technical efficient, *i.e.*, countries are not able to minimize input use in the production of a given aggregate output.[1] Concentrating in labor input it should hold that $y = f(k, \theta_l \cdot l, \varepsilon, t)$ where θ_l is an input-oriented measure of labor technical efficiency indicating how much labor should be reduced still being able to produce the same level of aggregate output. Formally, θ_l may be defined according to Kopp's (1981) orthogonal non-radial index of input-specific technical efficiency that satisfies normalization, monotonicity, homogeneity and invariance properties as:[2]

$$LTE^{KP} = \min_{\theta_l} \{ \theta_l : \theta_l > 0,\ y \leq f(k, \theta_l \cdot l, \varepsilon, t) \} \tag{3}$$

If allocative efficiency at the labor-specific technically efficient point is assumed, then a simple index of labor-specific technical efficiency may be defined as the ratio of optimal over observed labor input use, *i.e.*,

$$LTE^{KP} = \frac{\theta_l \cdot l}{l} = \frac{l^*(\mathbf{w}, y, \varepsilon, t)}{l} \tag{4}$$

where $l^*(\mathbf{w}, y, \varepsilon, t)$ is the derived demand for labor obtained from (2) through Shephard's lemma which is assumed to be non-decreasing in y and non-increasing in ε.[3] Using the

above definition we can derive a detailed decomposition formula for labor productivity growth. Taking the logarithms on both sides of (4) and totally differentiating with respect to time we get:

$$\begin{aligned} \dot{LTE}^{KP} = & \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial ln\, y}\dot{y} + e_{ll}^d(\mathbf{w}, y, \varepsilon, t)\dot{w}_l + e_{lk}^d(\mathbf{w}, y, \varepsilon, t)\dot{w}_k \\ & + e_{l\varepsilon}^d(\mathbf{w}, y, \varepsilon, t)\dot{\varepsilon} + \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial t} - \dot{l} \end{aligned} \tag{5}$$

where a dot over a function or a variable indicates its time rate of change, $e_{ll}^d(\mathbf{w}, y, \varepsilon, t) = \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial ln\, w_l}$ and $e_{lk}^d(\mathbf{w}, y, \varepsilon, t) = \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial ln\, w_k}$ are the compensated own- and cross-price elasticities of labor demand, respectively and, $e_{l\varepsilon}^d(\mathbf{w}, y, \varepsilon, t) = \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial ln\, \varepsilon}$ is the compensated labor demand elasticity with respect to human capital. Then using the conventional *divisia* index of labor productivity, *i.e.*, $\dot{LP} = \frac{d\, ln(y/l)}{dt} = \dot{y} - \dot{l} = \dot{TFP} - S_k\dot{k} - (S_l - 1)\dot{l}$ and substituting it into (5), we obtain:

$$\begin{aligned} \dot{LP} = \dot{LTE}^{KP} & + \left[1 - \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial ln\, y}\right]\dot{y} - e_{ll}^d(\mathbf{w}, y, \varepsilon, t)\dot{w}_l \\ & - e_{lk}^d(\mathbf{w}, y, \varepsilon, t)\dot{w}_k - e_{l\varepsilon}^d(\mathbf{w}, y, \varepsilon, t)\dot{\varepsilon} - \frac{\partial ln\, l^*(\mathbf{w}, y, \varepsilon, t)}{\partial t} \end{aligned} \tag{6}$$

decomposing, thus, labor productivity growth into a labor-specific technical inefficiency effect (first term), an output effect (second term), a substitution effect (third and fourth terms), a human capital effect (fifth term) and, a technological change effect (last term). Using the cost share equation of labor input, *i.e.*, $\frac{\partial ln\, C(\mathbf{w}, y, \varepsilon, t)}{\partial ln\, w_l} = S_l(\mathbf{w}, y, \varepsilon, t) = \frac{w_l l^*(\mathbf{w}, y, \varepsilon, t)}{C(\mathbf{w}, y, \varepsilon, t)}$, taking logarithms and slightly rearranging terms we obtain:

$$ln\,l^*(\mathbf{w},y,\varepsilon,t) = ln\,S_l\,(\mathbf{w},y,\varepsilon,t) + ln\,C(\mathbf{w},y,\varepsilon,t) - ln\,w_l \tag{7}$$

Then using (7) we can further decompose the scale and technological change effect as (Kuroda, 1995):

$$\begin{aligned}\frac{\partial ln\,l^*(\mathbf{w},y,\varepsilon,t)}{\partial ln\,y} &= \frac{\partial ln\,S_l(\mathbf{w},y,\varepsilon,t)}{\partial ln\,y} + \frac{\partial ln\,C(\mathbf{w},y,\varepsilon,t)}{\partial ln\,y} \\ &= \frac{1}{S_l(\mathbf{w},y,\varepsilon,t)}\frac{\partial S_l(\mathbf{w},y,\varepsilon,t)}{\partial ln\,y} + \varepsilon_y^C(\mathbf{w},y,\varepsilon,t)\end{aligned} \tag{8}$$

and

$$\begin{aligned}\frac{\partial ln\,l^*(\mathbf{w},y,\varepsilon,t)}{\partial t} &= \frac{\partial ln\,S_l(\mathbf{w},y,\varepsilon,t)}{\partial t} + \frac{\partial ln\,C(\mathbf{w},y,\varepsilon,t)}{\partial t} \\ &= \frac{1}{S_l(\mathbf{w},y,\varepsilon,t)}\frac{\partial S_l(\mathbf{w},y,\varepsilon,t)}{\partial t} + C^t(\mathbf{w},y,\varepsilon,t)\end{aligned} \tag{9}$$

where $\varepsilon_y^C(\mathbf{w},y,\varepsilon,t) = \dfrac{\partial ln\,C(\mathbf{w},y,\varepsilon,t)}{\partial ln\,y}$ is the output cost elasticity and, $-C^t(\mathbf{w},y,\varepsilon,t) = \dfrac{\partial ln\,C(\mathbf{w},y,\varepsilon,t)}{\partial t}$ is the rate of cost diminution (*i.e.*, dual rate of technical change). Substituting equations (8) and (9) into (6) results in

$$\begin{aligned}\dot{LP} = &\underbrace{\dot{LTE}^{KP}}_{Efficiency\ effect} + \underbrace{\left[1-\varepsilon_y^C(\mathbf{w},y,\varepsilon,t)\right]\dot{y}}_{Scale\ effect} - \underbrace{e_{ll}^d(\mathbf{w},y,\varepsilon,t)\dot{w}_l - e_{lk}^d(\mathbf{w},y,\varepsilon,t)\dot{w}_k}_{Substitution\ effect} \\ &- \underbrace{e_{l\varepsilon}^d(\mathbf{w},y,\varepsilon,t)\dot{\varepsilon}}_{Human\ capital\ effect} - \underbrace{C^t(\mathbf{w},y,\varepsilon,t)}_{\substack{Technological\\ change\ effect}} - \underbrace{\frac{1}{S_l(\mathbf{w},y,\varepsilon,t)}\left[\frac{\partial S_l(\mathbf{w},y,\varepsilon,t)}{\partial t} + \frac{\partial S_l(\mathbf{w},y,\varepsilon,t)}{\partial ln\,y}\dot{y}\right]}_{Extended\ labor\ biased\ techological\ change\ effect}\end{aligned} \tag{10}$$

which is the final decomposition formula of labor productivity growth. Specifically, equation (10) attributes labor productivity growth into six sources. The first component of the right hand side of (10) indicates changes in labor-specific technical inefficiency

over time. It measures autonomous movements toward or away from the production frontier and it is positive (negative) as labor technical efficiency increases (decreases) over time. The second term measures the relative contribution of scale economies to labor productivity growth. This term vanishes under constant returns-to-scale as $\varepsilon_y^C(\mathbf{w}, y, \varepsilon, t) = 1$, while it is positive (negative) under increasing (decreasing) returns-to-scale as long as aggregate output increases and *vice versa*. The third term is the substitution effect of the labor demand due to changes in labor and capital prices. If the technology satisfies all neoclassical properties the own effect is positive (negative) as long as the price of labor increases (decreases) over time whereas the cross demand effect is negative (positive) if capital prices increases (decreases). The substitution effect is zero when both labor and physical capital prices remain constant over time. The fourth term is the effect of human capital on labor productivity. It is positive as an increase (decrease) in human capital affects negatively (positively) the optimal use of labor and it is zero if human capital remains constant over time.[4] The fifth term refers to the dual rate of technical change, which is positive (negative) under progressive (regressive) technical change which can be further decomposed into a neutral and factor biased effect depending on the maintained assumption of the aggregate production technology. The last term is the extended labor biased technical change effect (Blackorby, Lovell and Thursby, 1976; Antle and Capalbo, 1988). Changes in relative prices of capital and labor induces changes in the individual factor cost shares as production is moved along the expansion path (first term). Further if the assumption of input homotheticity is not maintained an additional output effect is induced altering further factor proportions relative to their initial values (second term). If the technology is labor-saving the extended labor biased technical change effect is positive, whereas it is zero when technical change is extended *Hicks* neutral or if the production technology is linear homogeneous. In homothetic technologies the second term of the extended labor biased technical change effect vanishes as $\frac{\partial S_l(\mathbf{w}, y, \varepsilon, t)}{\partial \ln y} = 0$.

2.2. DATA AND EMPIRICAL MODEL

For the quantitative measurement and decomposition of labor productivity growth we utilized a balanced data set of 52 developed and developing countries covering the period from 1965 to 1990.[5] For aggregate output, physical capital and labor input we make use of the Penn World Table Data (ver. 5.6).[6] Data on labor prices were obtained from Groningen Growth and Development Centre, while those for capital input were estimated using Jorgenson and Griliches (1967) approach. Human capital was proxied using Barro and Lee (1993; 1996; 2001) educational data that are available for the same group of countries and for the same time period.[7] Following Henderson and Russell (2005), we adopt Hall and Jones (1999) construction where education appears as an augmentation factor for labor using an exponential specification, *i.e.*, $h(\varepsilon) = e^{\varphi(\varepsilon)}$ with $\varphi(\varepsilon)$ being a piecewise linear function with zero intercept and slope that varies according to the time span.[8] Following Psacharopoulos (1994) survey on the evaluation of the returns to education, those parameters were defined as being 0.134 for the first four years, 0.101 for the next four years and 0.068 for education beyond the eight year.

Our empirical model for providing measurement of labor productivity growth is based on a simple Cobb-Douglas type of aggregate production frontier. Specifically, minimizing the cost on the flexibility of the functional specification, we adopt a generalized Cobb-Douglas (or quasi-translog) production frontier, proposed by Fan (1991) and Karagiannis and Tzouvelekas (2001). This functional specification, although not enough flexible like the translog, it allows for variable returns to scale, input-biased technical change, and time varying output and demand elasticities, but it restricts the latter to be unchanged over countries. It permits statistical testing for various features of the aggregate production technology, providing at the same time an analytical closed form solution for the corresponding dual cost frontier necessary to identify appropriately all terms in (10) (Fan and Pardey, 1997).

Since both developed and developing countries are included, it may be possible that some of those to introduce significant measurement errors in approximating the worldwide production technology (Heston and Summers, 1996). To overcome this problem we extent Jorgenson and Nishimizu (1978) "*bilateral*" production structure into

a "*multilateral*" context within the generalized Cobb-Douglas production frontier model. Specifically, we distinguish six different groups of countries (*i.e.*, South and Central America, North America and Oceana, Europe, Asia, Africa and Asian Tigers) assuming that each one of those groups exhibit it's "own" technological structure. In that way on the one hand it is possible to identify differences in all terms appearing in (10) between group of countries while on the other we allow for more flexible patterns for technological features (*i.e.*, returns to scale, technological change, production and demand elasticities) between groups of countries lessened further the cost of choosing a less flexible functional specification for the approximation of the worldwide production technology.

In particular, the multilateral generalized Cobb-Douglas production frontier model expressed in natural logarithms has the following form:

$$\begin{aligned} ln\, y_{it} = \beta_{it}^{0} + \beta^{t} t + 0.5\beta^{tt} t^{2} + \beta_{j}^{l}\, ln\left(l_{it} \cdot e^{\varphi(\varepsilon_{it})}\right) \\ + \beta_{j}^{k}\, ln\, k_{it} + \beta_{j}^{lt}\, ln\left(l_{jit} \cdot e^{\varphi(\varepsilon_{it})}\right) t + \beta_{j}^{kt}\, ln\, k_{it} t + v_{it} \end{aligned} \tag{11}$$

where $i = 1,\ldots,N$ are the countries in the sample, $t = 1,\ldots,T$ are the time periods, $j = 1,\ldots,J$ are the group of countries defined in the "multilateral" structure of the production technology, v_{it} depicts a symmetric and normally distributed error term, $v_{it} \sim N\left(0, \sigma_{v}^{2}\right)$, (*i.e.*, statistical noise), which represents left-out explanatory variables and measurement errors in the dependent variable and, $\beta_{j}^{l} = \beta^{l} D_{j}$, $\beta_{j}^{k} = \beta^{k} D_{j}$, $\beta_{j}^{lt} = \beta^{lt} D_{j}$ and, $\beta_{j}^{kt} = \beta^{kt} D_{j}$ with D being a dummy variable indicating the groups of countries, *i.e.*, $D_{j} = 1$ for country belonging in group j and $D_{j} = 0$ for every other country belonging to other groups. The above specification considers the data on inputs and aggregate output for each one of the countries in the sample belonging into different groups as a separate set of observations which are assumed to be generated by "*multilateral*" models of production. Hence, the presence of D_{j} as an argument in the production function above

allows for different production technologies to be assigned into the different groups of countries.

Finally, $\beta_{it}^{0} = \beta_{t}^{0} - \xi_{it}$ are country- and period-specific intercepts introduced into (11) in order to capture temporal variations in output technical efficiency following Cornwell, Schmidt and Sickles (1990) fixed effects specification. According to this formulation output technical inefficiency is assumed to follow a quadratic pattern over time, *i.e.*,

$$\xi_{it} = \zeta_{i0} + \zeta_{i1} t + \zeta_{i2} t^{2} \tag{12}$$

where, ζ_{i0}, ζ_{i1} and ζ_{i2} are the $(N \times 3)$ unknown parameters to be estimated. If $\zeta_{i1} = \zeta_{i2} = 0 \;\; \forall i$, then output technical efficiency is time-invariant, while when $\zeta_{i1} = \zeta_{1}$ and $\zeta_{i2} = \zeta_{2} \; \forall i$ then output technical efficiency is time-varying following, however, the same pattern for all countries in the sample.[9]

The model in (11) and (12) can be estimated following either an one or a two step procedure by single-equation methods under the assumption of expected profit maximization. When N/T is relatively small, one can adopt an one-step procedure where ξ_{it} is included directly in (11) using dummy variables. However, in this case it is not possible to distinguish between technical change and time-varying technical efficiency if both are modeled via a simple time-trend (as in our case). In the two-step procedure, OLS estimates on the within group deviations are obtained for *β's* and then the residuals for each producer in the panel are regressed against time and time-squared as in (12) to obtain estimates of *ζ*'s for each country in the sample. In both cases time-varying output technical inefficiency is obtained following the normalization suggested by Schmidt and Sickles (1984). Specifically, define $\beta_{t}^{0} = \max_{i}\{\xi_{it}\}$ as the estimated intercept of the production frontier in period *t*. Then output technical efficiency of each country in period *t* is estimated as $TE_{it}^{O} = exp(-\xi_{it})$, where $\xi_{it} = \left(\hat{\beta}_{t}^{0} - \hat{\beta}_{it}\right)$.[10] The advantages of this specification are its parsimonious parameterization regardless of functional form, its straightforward estimation, its independence of distributional

assumptions, and that it allows output technical inefficiency to vary across countries and time. Moreover, since the expression in (12) is linear to its parameters, the statistical properties of individual country-effects are not affected.

Under price uncertainty, expected profit maximization implies cost minimization allowing us to go back and forth between the production and cost functions in a theoretically consistent way (Batra and Ullah, 1974). Thus, the dual to (11) cost function has the following logarithmic form:

$$\begin{aligned} ln\, C_{it} &= \delta_t^0 + \delta_j^t t + \delta_j^{tt} t^2 + \delta_j^y\, ln\, y + \delta_j^l\, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) \\ &\quad + \delta_j^k\, ln\, w_{kit} + \delta_j^{lt}\, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) t + \delta_j^{kt}\, ln\, w_{kit} t \end{aligned} \tag{13}$$

where

$$\begin{aligned} &\delta_t^0 = ln\left(\frac{E_j}{\beta_j^l + \beta_j^{lt} t}\right) - \frac{1}{E_j}\left[\left(\beta_j^k + \beta_j^{kt} t\right) ln\left(\frac{\beta_j^k + \beta_j^{kt} t}{\beta_j^l + \beta_j^{lt} t}\right) + \beta_t^0\right], \\ &E_j = \beta_j^l + \beta_j^k + \beta_j^{lt} t + \beta_j^{kt} t\,,\ \delta_j^t = \beta^t \delta_j^y\,,\ \delta_j^{tt} = \beta^{tt} \delta_j^y\,, \\ &\delta_j^l = \beta_j^l \delta_j^y\,,\ \delta_j^k = \beta_j^k \delta_j^y\,,\ \delta_j^{lt} = \beta_j^{lt} \delta_j^y\,,\ \delta^{kt} = \beta_j^{kt} \delta_j^y\,,\ \delta_j^y = 1/E_j \end{aligned} \tag{14}$$

Then, through Shephard's lemma, we can derive the optimal demand function for labor input using (13) as:

$$\begin{aligned} ln\, l_{it}^* &= ln\left(\frac{\delta_j^l + \delta_j^{lt} t}{w_{lit}}\right) + \delta_{it}^0 + \delta_j^t t + \delta_j^{tt} t^2 + \delta_j^y\, ln\, y + \delta_j^k\, ln\, w_{kit} \\ &\quad + \delta_j^l\, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) + \delta_j^{lt}\, ln\left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}}\right) t + \delta_j^{kt}\, ln\, w_{kit} t \end{aligned} \tag{15}$$

From (15) we can derive the compensated own- and cross-price elasticities of labor demand, *i.e.*,

$$e_{ll}^{d} = \frac{\partial \, ln \, l_{it}^{*}}{\partial \, ln \, w_{lit}} = \delta_j^{l} + \delta_j^{lt} t - 1 \tag{16}$$

and

$$e_{lk}^{d} = \frac{\partial \, ln \, l_{it}^{*}}{\partial \, ln \, w_{kit}} = \delta_j^{k} + \delta_j^{kt} t \tag{17}$$

which are necessary for the estimation of the third term in (10). These demand elasticities are both group and time-specific. Similarly the labor demand elasticity with respect to human capital is obtained from:

$$e_{l\varepsilon}^{d} = \frac{\partial \, ln \, l_{it}^{*}}{\partial \, ln \, \varepsilon_{lit}} = -\left(\delta_j^{l} + \delta_j^{lt} t\right) \frac{\partial \varphi\left(\varepsilon_{it}\right)}{\partial \varepsilon_{it}} \varepsilon_{it} \tag{18}$$

that provides estimates of the fourth term in (10). The output cost elasticity necessary for the estimation of the scale effect is obtained from:

$$\varepsilon_{y}^{C} = \frac{\partial \, ln \, C_{it}}{\partial \, ln \, y_{it}} = \delta_j^{y} \tag{19}$$

The hypothesis of constant returns-to-scale can be statistically tested by imposing the restriction that $\delta_j^{y} = 1, \; \forall j$ which is equivalent with imposing linear homogeneity in the aggregate production frontier given the restrictions in (14), *i.e.*, $\beta_j^{l} + \beta_j^{k} = 1$ and $\beta_j^{lt} + \beta_j^{kt} = 0 \; \forall j$. If this hypothesis cannot be rejected then the underlying technology exhibits constant returns-to-scale and the second term in (10) vanishes.

For the estimation the technological change effects (last two terms in (10)) we need to compute the rate of cost diminution and the labor share equation. The former under the multilateral generalized Cobb-Douglas specification in (13) is obtained,

$$-C_{it}^{t} = \frac{\partial \, ln \, C_{it}}{\partial t} = \delta_j^{t} + \delta_j^{tt} t + \delta_j^{lt} \, ln \left(\frac{w_{lit}}{e^{\varphi(\varepsilon_{it})}} \right) + \delta_j^{kt} \, ln \, w_{kit} \tag{20}$$

The hypothesis of *Hicks*-neutral and zero technical change involves the following parameter restrictions in (20): $\delta_j^{lt} = \delta_j^{kt} = 0$ and $\delta_j^{t} = \delta_j^{tt} = \delta_j^{lt} = \delta_j^{kt} = 0 \quad \forall j$, respectively.[11] Accordingly, using the labor share equation, *i.e.*,

$$S_{lit} = \frac{\partial \ln C_{it}}{\partial \ln w_{lit}} = \delta_j^{l} + \delta_j^{lt} t \tag{21}$$

we can compute the extended labor biased technical change effect as:

$$\frac{1}{S_{lit}} \frac{\partial S_{lit}}{\partial t} = \frac{\delta_j^{lt}}{\delta_j^{l} + \delta_j^{lt} t} \tag{22}$$

Since the multilateral generalized Cobb-Douglas aggregate production model is homothetic the second term in the extended labor biased technological change effect is zero and therefore it does not contribute in labor productivity growth. If the underlying aggregate production technology exhibits zero technical change then the last two terms in (10) are zero and labor productivity growth is affected only from the first four terms. If, however, technical progress is Hicks-neutral then only the extended labor biased technical change effect vanishes. Finally, if the underlying technology is neutral with respect to labor use, *i.e.*, $\delta_j^{lt} = 0 \ \forall j$, then again the final term in labor productivity decomposition formula vanishes[12].

Finally, for the estimation of the first term in (10) we need to compute labor specific technical efficiency. For doing so we use Reinhard, Lovell and Thijssen (1999) approach in the context of the multilateral generalized Cobb-Douglas production frontier.[13] Conceptually, measurement of LTE_{it}^{KP} requires an estimate for the quantity $l_{it}^{*} = \theta_l \cdot l_{it}$ which is not observed. Nevertheless substituting relation (4) into the aggregate production function model in (11) and by noticing that the labor-specific technical efficient point lies on the frontier, *i.e.*, $\xi_{it} = 0$, relation (11) may be rewritten as:

$$
\begin{aligned}
ln\, y_{it} = \beta_t^0 + \beta^t t + 0.5\beta^{tt} t^2 + \beta_j^l\, ln\left(l_{it}^* \cdot e^{\varphi(\varepsilon_{it})}\right) \\
+ \beta_j^k\, ln\, k_{it} + \beta_j^{lt}\, ln\left(l_{it}^* \cdot e^{\varphi(\varepsilon_{it})}\right) t + \beta_j^{kt}\, ln\, k_{it} t + v_{it}
\end{aligned}
\tag{23}
$$

Since under weak monotonicity, output technical efficiency should imply and must be implied by labor-specific technical efficiency, we can set the input specification in (23) equal to the output-oriented specification in (11). Then using the parameter estimates obtained from the econometric estimation of the multilateral generalized Cobb-Douglas production model and solving for l_{it}^*, we can derive a measure of Kopp's (1981) non-radial labor-specific technical efficiency from the following relation (Reinhard Lovell and Thijssen):[14]

$$
LTE_{it}^{KP} = exp\left(-\frac{\xi_{it}}{\beta_j^l + \beta_j^{lt} t}\right) \tag{24}
$$

which is always different than zero as long as farms are technically inefficient from an output-oriented perspective, *i.e.*, $\xi_{it} > 0$ and labor is an essential input in production, *i.e.*, $\beta_j^l \neq 0 \wedge \beta_j^{lt} \neq 0$. It is time-invariant if both output technical efficiency is also time-invariant and biased technical change is labor neutral. In the context of our model this implies the following restrictions $\zeta_{i1} = \zeta_{i2} = 0 \;\; \forall i$ and $\beta_j^{lt} = 0$.

2.3. EMPIRICAL RESULTS

The fixed effects parameter estimates of the multilateral aggregate Cobb-Douglas production frontier model in (11) are presented in Table 1 along with their corresponding standard errors. All parameter estimates (except of two) were found to be statistically significant at the 1 or 5 percent level having the anticipated positive sign, while their magnitudes are bounded between 0 and 1 indicating that the bordered Hessian matrix of first- and second-order partial derivatives is negative semi-definite. This implies that all regularity conditions hold at the point of approximation, *i.e.*, positive and diminishing

marginal productivities. In the lower panel of Table 1 are also reported the country and time specific parameters of Cornwell, Schmidt and Sickles (1990) inefficiency effects model for the country with the maximum efficiency score in each one of the six groups. For the vast majority of the countries in the sample all parameters were found to be positive implying improvements in output technical efficiency over time (this finding is statistically examined next).[15]

Several hypotheses concerning the multilateral structure of the aggregate production frontier model were tested using the generalized likelihood-ratio test statistic[16] and the results are presented in the upper panel of Table 2. First, the hypothesis that the imposed multilateral structure of the model in (11) is not valid is rejected at the 5 per cent significance level (first hypothesis in table 2). Hence, indeed data on inputs and aggregate output in the sample are generated by multilateral models of production supporting our initial hypothesis of approximating production technology. Further, the assumption that biases of technical change are similar across countries in the sample was also rejected (second hypothesis in table 2), while the same is true for the marginal productivities of physical capital and labor inputs (third hypothesis in table 2). Statistical testing results in the same conclusion when each one of the estimated coefficients is tested separately (last four hypothesis).

The next set of hypotheses testing, using again generalized likelihood ratio test, concerns the structure of technology and the results are presented in the middle panel of Table 2. Statistical testing implies that the worldwide production technology is not characterized by constant returns-to-scale as the relevant hypothesis was rejected at the 1 per cent level, *i.e.*, $\beta_j^l + \beta_j^k = 1$ and $\beta_j^{lt} + \beta_j^{kt} = 0$. This implies that the scale effect is present constituting an important source of labor productivity growth. Average country and time estimates of scale coefficients were found to be increasing for South and Central American countries (1.0925), North America and Oceana (1.0412), Asian Tigers (1.2080) and European Countries (1.0141). On the other hand, African and Asian countries exhibit decreasing returns as the relevant point estimates were 0.9572 and 0.9573, respectively.

The hypotheses of zero technical change *i.e.*, $\beta_T = \beta_{TT} = \beta_j^{lt} = \beta_j^{kt} = 0$ and Hicks-neutral technical change *i.e.*, $\beta_j^{lt} = \beta_j^{kt} = 0, \forall j$ were also rejected at the 5 per cent significance level. On the average technical change was found progressive in all country groups with the highest value being for Asian Tigers, 1.0014 per cent. For North America and Oceania the corresponding figure was 0.6076, for European countries 0.6909, for South and Central American countries 0.5979, for African countries 0.6138 and for Asian countries 0.7559. The parameters related with the neutral technical change, *i.e.*, β^t and β^{tt}, were found to be positive and statistically significant at the 1 per cent level, implying that technical change was constantly progressive for the time period under consideration. The second order parameters related with the biased part of technological change, *i.e.*, β_j^{lt} and β_j^{kt} were found to vary among the different groups of countries. Specifically, technical change was found to be labor using for North America and Oceana and Europe and labor saving for South and Central America, Africa, Asia and Asian Tigers. On the other hand, technical change was capital using for South and Central America, Africa, Asia and Asian Tigers and capital saving for Europe. We have further examined the hypothesis of labor-neutral technical change using the LR-test that resulted in rejection of the relevant hypothesis. Thus, the labor biased technical change effect, *i.e.*, first term in the last parenthesis in relation (10) is present and it should be taken into consideration in the decomposition analysis o labor productivity growth.

The final set of statistical testing refers to the specification of technical efficiency and it's temporal pattern. First, output technical efficiency is present indicating that it should be taken into account when labor productivity growth is to be analyzed. Specifically the hypothesis that all ζ parameters are jointly equal to zero is rejected at the 5 per cent level of significance (first hypothesis in the lower panel of table 2). Technical efficiency was also found to be time varying during the 1965-90 period as the hypothesis that $\zeta_{i1} = \zeta_{i2} = 0$ is also rejected at the same significance level. The temporal pattern of output technical efficiency is not common across countries in the sample. Specifically the hypothesis that $\zeta_{i1} = \zeta_1$ and $\zeta_{i2} = \zeta_2 \ \forall i$ is rejected from the generalized LR-test. Finally, the same is true for labor specific technical efficiency which is not time invariant

following a different pattern between countries (last hypothesis in the lower panel of table 2).

Estimates of both output and labor technical efficiency levels in the form of frequency distribution within a decile range are reported in Table 3. Estimated mean output technical efficiency for the period 1965-90 is 71.58 per cent implying that aggregate output could have increased on the average for all countries almost by 18 per cent if technical inefficiency was eliminated. The most output technically efficient group was found to be North America and Oceania (86.52 per cent) , followed by Europe (85.12 per cent) and Asian Tigers (80.53 per cent), while the less output efficient groups were South and Central America (71.80 per cent), Asia (66.00 per cent) and Africa (57.00 per cent). There is a significant difference between group of countries with less developed continents exhibit quite low mean efficiency values. There is a notable difference in mean output technical efficiency scores between North America and Oceana and African countries that approximately reaches 30 per cent. The same high difference is observed also for Asian countries underlying the important gap between developed and developing countries in the efficient use of their own technology. On the other hand, mean labor technical efficiency was found to be lower (64.89 per cent) than that of output technical efficiency, ranging from a minimum of 40.91 to a maximum of 90.15 per cent. The estimated mean labor technical efficiency scores were lower than the corresponding values of output technical efficiency also at the mean values of each group, while the ranking of the most labor efficient groups remained the same in comparison with the corresponding ranking of the most output efficient groups. However the spread of individual labor technical efficiency scores is lower compared with that of output technical efficiency. Still, however, there is a big gap in efficient utilization of labor input between developed and developing countries as it was also stressed from output technical efficiency measures.

Figures 1 and 2 presents the temporal pattern of mean output and labor technical efficiency for each group of countries. In both figures, the three less efficient groups (South and Central America, Asia and Africa) were found to follow a similar temporal pattern, while the variations of labor technical efficiency over the period analyzed is greater compared with corresponding output technical efficiency scores. North America

and Europe were found to follow approximately a common path until 1982 as far as labor technical efficiency score, followed by a sharp increase for North America and Oceana after this year. The results for the two groups are similar, regarding output technical efficiency. The evolution of output technical efficiency was found to be closely parallel for the two groups during the first years, followed by a sharp increase for North America after 1988. Finally, Asian Tigers were found to experience a tremendous increase in both labor and output technical efficiency, especially, until the late 70's. Although output and labor efficiency scores for Asian Tigers were approximately 15 per cent lower than those of North America and Oceana and Europe in the beginning of the period, the picture changed in the middle 70's when Asian Tigers' efficiency score overcame the corresponding scores of North America and Oceana and Europe.

Table 4 next, presents the average values of labor productivity growth and it's decomposition over both countries and time periods. In the first column are the unweighted figures obtained by taking the simple average across countries and time-periods. In the second column are presented the weighted averages computed following Olley and Pakes (1996) aggregation scheme. This is actually a weighted average measure of worldwide labor productivity growth, using countries' output shares as weights. During the 1965-1990 time period, the weighted average labor productivity growth was 1.4018 per cent annually whereas the unweighted figure is lower, 1.3038 per cent. The greatest share of that growth (49.84 per cent) was due to the rate of technical change driven mainly by the autonomous part (45.98 per cent), while the smallest share was due to the extended labor biased technological change effect (7.48 per cent). The effect of scale economies on labor productivity growth was found to be the second most important source of labor productivity growth accounting for the 13.79 per cent of it. Improvements in labor technical efficiency and human capital were also found to be important sources of labor productivity growth contributing by 11.62 and 8.97 per cent to total growth, respectively. Finally, the substitution effect was found to have a positive impact on labor productivity growth (8.29 per cent) of which a greater portion was caused by labor input (5.78 per cent) and a smaller one by capital input (2.51 per cent).

Comparison of the two columns of Table 4 provides some useful insights about the ranking of the countries in the sample. The results indicate that the measurement of labor

productivity is greater in the case of the weighted average, implying that the more developed countries experienced a higher productivity growth during the period analyzed in comparison with the smaller ones. Furthermore, the substitution effect and the extended labor biased technological change effect were found to be lower when the calculation of the worldwide labor productivity growth is based on the weighted average, indicating that the two effects contributed relatively more to labor productivity growth for the smaller countries. On the other hand, the improvements in labor technical efficiency and human capital, the scale effect and the technical change effect were found to be more vigorous for the greater countries.

Tables 5a and 5b present the decomposition of the average measured labor productivity growth for each one of the countries in the sample country for the 1965-90 time period. Asian Tigers were found to have experienced the higher growth in labor productivity with Korea Republic (3.3022 per cent) to be the leading country, followed by Taiwan (3.2200 per cent), Hong-Kong (3.0371 per cent) and Thailand (2.8788 per cent). Mauritius had the lowest labor productivity growth in the sample with an average rate of change of 0.7755 per cent annually. Among the countries with the lowest labor productivity growth are also Sri Lanka (0.8017 per cent), Turkey (0.8138 per cent), Malawi (0.8232 per cent) and Philippines (0.8969 per cent). For North America and Oceania group, the countries with the higher and lower rate of labor productivity growth were found to be Canada (1.3133 per cent) and Australia (1.0331 per cent), respectively, while the corresponding countries for Europe were Iceland (1.3406 per cent) and UK (1.1128 per cent). Jamaica (1.0255) was the country with the lower increase in labor productivity among the South and Central America countries, while Dominican Republic (1.2533 per cent) presents the highest score. Finally, the leading country for the Asia group was found to be Israel (1.1515 per cent), while Sri Lanka is found in the last position with a 0.8017 per cent growth in labor productivity.

Table 6 shows the decomposition of the weighted average of labor productivity growth across countries during the 1965-90 period. Labor productivity growth is following an increasing pattern over time, experiencing however three falling sub-periods during 1970-71, 1974-75 and 1981-1983 which were due to decreases in scale effect and human capital effect that took place in these periods. The decreases in scale effect were

caused mainly by decreases in the relative output growth of many countries during the above-mentioned periods which more or less coincide with the first oil crises. Moreover, as it was expected, technical change was found to be constantly progressive over time, while labor technical efficiency effect and substitution effect do not appear significant variations during the period analyzed.

Tables 7 and 8 present the decomposition of measured labor productivity growth per group of country for the five sub-periods. The values reported therein are the within groups weighted average for each sub-period. Our results indicate that Asian Tigers (2.7546) experienced the higher labor productivity growth during 1965-90 time period that is almost two times higher than the next two groups, namely North America and Oceana (1.2920 per cent) and Europe (1.1782 per cent) and approximately three times higher than the two lower groups namely, Asia (0.9344 per cent) and Africa (0.9344 per cent). In addition, South and Central America was found to have on average a 1.1432 per cent growth rate of labor productivity. Technical change was found to be the driving force of labor productivity for all groups, together with the scale effect which was more significant for Asian Tigers. Labor technical efficiency improvements had a significant contribution to labor productivity growth especially for the groups of more developed countries. Scale effect was estimated to be negative for African and Asian countries and positive for all other groups. The effect of human capital on labor productivity growth was greater for North America and Oceana and surprisingly about three times lower for the European countries. Finally, Asian Tigers and African countries were found to experience the highest gains in labor productivity growth by the extended labor biased technological change effect, while the lower corresponding value is observed for South and Central America Group.

The evolution of labor productivity growth for the different groups of countries is illustrated in Figure 3. As we can observe, all groups seem to have similar variations in labor productivity growth following an increasing trend. However, we can notice two sharp decreases in labor productivity growth during the years 1971 and 1975. The fall of labor productivity was found to be more intense for Asian Tigers and African countries and this is due decreases in the relative scale effects, while Asian countries seem to not have been affected. During the first fifteen years, North America and Oceana group was

found to achieve greater labor productivity growth than Europe but this changed in the early 80's.

2.4. CONCLUDING REMARKS

In this paper, based on Kuroda's (1995) dual approach of partial factor productivity measurement, incorporating human capital into our decomposition analysis and relaxing at the same time the restrictive assumption of labor specific technical efficiency we present a detailed decomposition of labor productivity growth. Our empirical aggregate production frontier model was based on the generalized Cobb-Douglas functional specification suggested by Fan (1991) and was extended into a "multilateral" production structure using Jorgenson and Nishimizu (1978) context of bilateral production functions. The measurement of labor technical efficiency was based on Kopp's (1981) orthogonal non-radial index of factor-specific technical efficiency modified in a parametric frontier framework. Finally, following Griliches (1963), human capital proxied by Hall and Jones (1999) construction was introduced into the analysis as a multiplicative augmentation of labor input.

The model was then applied to a sample of 52 countries around the world covering a time period from 1965-1990. The data used in the analysis were retrieved by Penn World Tables and by Barro and Lee's (1996) educational data. Our empirical results indicated that the average annual rate of labor productivity growth was 1.4018 per cent over the period analyzed. Technical change was found to be the driving force of labor productivity contributing 40.98 per cent to changes in labor productivity growth, followed by scale effect with 13.79 percentage contribution. Furthermore, improvements in labor technical efficiency and human capital were found to explain about 20 per cent of labor productivity growth, indicating that their absence from the analysis would lead in biased results.

Providing a comparison between the unweighted and the weighted average of worldwide labor productivity, we then showed that the higher scores of labor productivity were generated mainly by the bigger countries in the sample. Using the same weighting scheme applied within groups, we calculated labor productivity growth separately for each one of the groups. We found Asian Tigers (2.7546) to have experienced the higher labor productivity growth during 1965-90 time period that was almost two times higher than the next two groups, namely North America and Oceana (1.2920 per cent) and Europe (1.1782 per cent) and approximately three times higher than the two lower groups

namely, Asia (0.9344 per cent) and Africa (0.9344 per cent). In addition, South and Central America was found to have on average a 1.1432 per cent rate of labor productivity growth.

2.5. TABLES AND FIGURES

Table 1. Parameter Estimates of the Multilateral Cobb-Douglas Production Frontier.

Par.	N. America&Oceania		S.&C. America		Europe		Africa		Asia		Asian Tigers	
					Estimate	StdError						
Common Coefficient Estimates												
β^0					0.6469	(0.0350)*						
β^t					0.1250	(0.0151)*						
β^{tt}					0.0356	(0.0042)*						
	Estimate	StdError	Estimate	StdError	Estimate	StdError	Estimate	StdError	Estimate	StdError	Estimate	StdError
Multilateral Structure												
β^l	0.4234	(0.1879)*	0.5783	(0.3408)**	0.3943	(0.0478)*	0.4627	(0.0428)*	0.5768	(0.0742)*	0.7403	(0.0814)*
β^k	0.6182	(0.1500)*	0.5138	(0.0256)*	0.6162	(0.0278)*	0.4921	(0.0213)*	0.3728	(0.0520)*	0.4848	(0.0343)*
β^{lt}	0.2795	(0.0540)*	-0.0240	(0.0114)*	0.0060	(0.0092)	-0.0772	(0.0416)**	-0.0457	(0.0094)*	-0.0849	(0.0161)*
β^{kt}	-0.2780	(0.0542)*	0.0226	(0.0075)*	-0.0203	(0.0083)*	0.0673	(0.0260)*	0.0144	(0.0133)	0.1542	(0.0112)*
ζ_{i0}	0.6828	(0.1323)*	0.5312	(0.1121)*	0.6431	(0.1558)*	0.5124	(0.1422)*	0.5388	(0.1254)*	0.6718	(0.1087)*
ζ_{i1}	0.1274	(0.0356)*	0.1101	(0.0298)*	0.1243	(0.0321)*	0.0964	(0.0301)*	0.1010	(0.0331)*	0.1198	(0.0376)*
ζ_{i2}	0.0259	(0.0120)*	0.0179	(0.0084)*	0.0237	(0.0112)*	0.0161	(0.0054)*	0.0187	(0.0088)*	0.0287	(0.0137)*
$\bar{R}^2$						0.4690						

Note: *l* refers to labor, *c* to capital and, *t* to time. In the lower panel of the table are reported the ζ parameters of the country with the maximum efficiency score. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively.

Table 2. Model Specification Tests

Hypothesis	LR-test	Critical Value (a=0.05)
Multilateral Structure Testing		
$\beta_j^l = \beta^l$, $\beta_j^k = \beta^k$, $\beta_j^{lt} = \beta^{lt}$ and $\beta_j^{kt} = \beta^{kt}$	37.61	$\chi_4^2 = 9.49$
$\beta_j^{lt} = \beta^{lt}$ and $\beta_j^{kt} = \beta^{kt}$	25.69	$\chi_2^2 = 5.99$
$\beta_j^l = \beta^l$ and $\beta_j^k = \beta^k$	23.40	$\chi_2^2 = 5.99$
$\beta_j^l = \beta^l$	14.26	$\chi_1^2 = 3.84$
$\beta_j^k = \beta^k$	16.30	$\chi_1^2 = 3.84$
$\beta_j^{lt} = \beta^{lt}$	12.55	$\chi_1^2 = 3.84$
$\beta_j^{kt} = \beta^{kt}$	13.21	$\chi_1^2 = 3.84$
Technological Specification		
Constant returns-to-scale: $\beta_j^l + \beta_j^k = 1 \ \wedge \ \beta_j^{lt} + \beta_j^{kt} = 0, \ \forall j$	64.20	$\chi_2^2 = 5.99$
Hicks-neutral technical change: $\beta_j^{lt} = \beta_j^{kt} = 0, \ \forall j$	49.28	$\chi_2^2 = 5.99$
Zero-technical change: $\beta_T = \beta_{TT} = \beta_j^{lt} = \beta_j^{kt} = 0, \ \forall j$	75.60	$\chi_4^2 = 9.49$
Labor-neutral technical change: $\beta_j^{lt} = 0, \ \forall j$	13.78	$\chi_1^2 = 3.84$
Technical Inefficiency Specification		
Zero output technical efficiency: $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0, \ \forall i$	144.58	$\chi_{156}^2 \approx 71.52$
Time invariant output technical efficiency: $\zeta_{i1} = \zeta_{i2} = 0, \ \forall i$	118.28	$\chi_{104}^2 \approx 69.85$
Common temporal pattern of technical efficiency across countries: $\zeta_{i1} = \zeta_1 \ \wedge \ \zeta_{i2} = \zeta_2 \ \forall i$	106.37	$\chi_{104}^2 \approx 69.85$
Time-invariant labor technical efficiency: $\zeta_{i1} = \zeta_{i2} = 0 \ \wedge$ $\beta_j^{lt} = 0, \ \forall j$	123.21	$\chi_{105}^2 \approx 69.92$

Table 3. Frequency Distribution of Output and Labor-Specific Technical Efficiency.

%	N. America&Oceania	S.&C. America	Europe	Africa	Asia	Asian Tigers	All Countries
Output Technical Efficiency							
<40	0	0	0	2	0	0	2
40-50	0	0	0	0	1	0	1
50-60	0	2	0	2	0	0	4
60-70	0	3	3	2	2	2	12
70-80	0	3	5	0	2	1	11
80-90	4	4	5	0	1	2	16
90>	0	1	5	0	0	0	6
Mean	86.82	71.80	85.12	57.00	66.00	80.53	71.58
Min	82.57	55.60	61.19	32.37	43.57	58.55	32.37
Max	88.61	92.06	93.07	67.98	88.6	87.58	93.07
Labor Specific Technical Efficiency							
<40	0	1	0	0	0	0	1
40-50	0	2	1	2	1	0	6
50-60	0	2	5	1	0	1	9
60-70	1	1	3	2	2	2	11
70-80	3	4	4	1	2	1	15
80-90	0	2	5	0	1	1	9
90>	0	1	0	0	0	0	1
Mean	74.14	64.67	72.05	53.61	60.25	70.18	64.89
Min	65.64	42.52	47.26	40.91	45.79	52.62	40.91
Max	78.66	90.15	87.28	73.89	84.81	86.51	90.15
N	4	13	18	6	6	5	52

Figure 1. Average Output Technical Efficiency per Group of Countries.

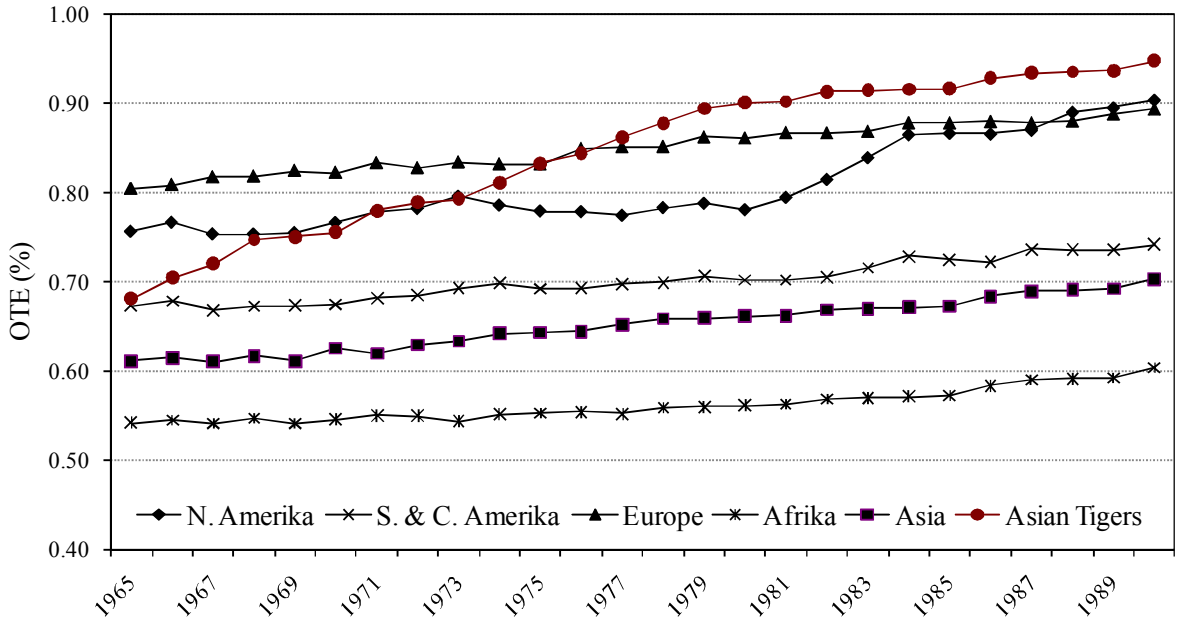


Figure 2. Average Labor Technical Efficiency per Group of Countries.

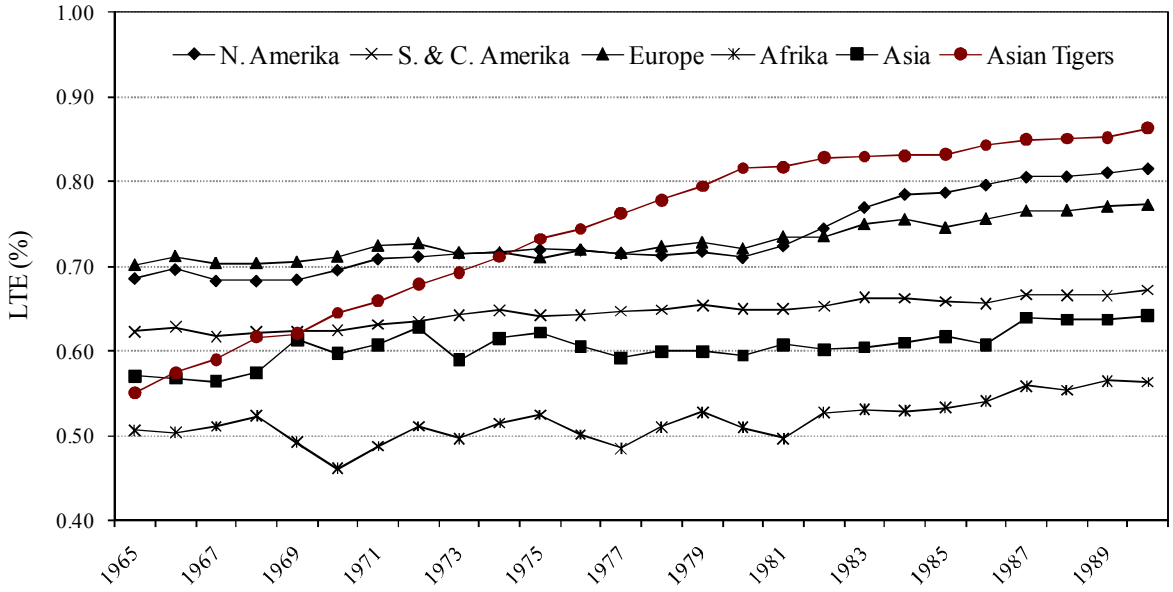


Table 4. Decomposition of Labor Productivity Growth (average values over the 1965-1990 period).

	Unweighted Average	Weighted Average
Labor Productivity Growth	1.3038	1.4018
	(100)	(100)
Changes in Labor Technical Efficiency	0.1203	0.1630
	(9.23)	(11.62)
Scale Effect	0.1611	0.1933
	(12.36)	(13.79)
Substitution Effect	0.1441	0.1162
	(11.05)	(8.29)
Capital	0.0479	0.0352
	(3.67)	(2.51)
Labor	0.0962	0.0810
	(7.38)	(5.78)
Human Capital Effect	0.1118	0.1258
	(8.57)	(8.97)
Rate of Technical Change	0.6594	0.6987
	(50.57)	(49.84)
Autonomous Part	0.6108	0.6445
	(46.84)	(45.98)
Biased Part	0.0486	0.0542
	(3.73)	(3.86)
Extended Labor Biased TC Effect	0.1071	0.1049
	(8.22)	(7.48)

Note: The weighted average rate of labor productivity change was calculated using Olley and Pakes (1996) output share weighting. The values in parenthesis indicate the percentage contribution of each effect to labor productivity change.

Table 5a. Decomposition of Labor Productivity Growth (Average Values over the 1965-90 time period)

Countries	LP	LTE	SE	SUBE	HC	TC	ELBTC
Argentina	1.1308	0.0276	0.1663	0.1488	0.1286	0.6066	0.0529
Australia	1.0331	0.1103	0.1412	0.0532	0.0532	0.6217	0.0533
Austria	1.2538	0.1109	0.0468	0.2870	0.0361	0.6853	0.0877
Belgium	1.2455	0.1183	0.0440	0.2984	0.0137	0.6834	0.0877
Bolivia	1.0364	0.0578	0.2177	0.0879	0.0458	0.5743	0.0529
Canada	1.3133	0.1304	0.1316	0.1438	0.1252	0.6597	0.1227
Chile	1.0284	0.0452	0.2126	0.0203	0.1193	0.5780	0.0529
Columbia	1.1734	0.0938	0.2262	0.0947	0.1100	0.5958	0.0529
Denmark	1.2065	0.1330	0.0361	0.2334	0.0327	0.6835	0.0877
Dominican Reb	1.2533	0.0340	0.2493	0.2191	0.1292	0.5689	0.0529
Ecuador	1.2202	0.0814	0.2004	0.1465	0.1733	0.5656	0.0529
Finland	1.3024	0.1521	0.0353	0.2342	0.1124	0.6807	0.0877
France	1.1756	0.1534	0.0430	0.1322	0.0652	0.6940	0.0877
Germany	1.1276	0.1734	0.0343	0.1212	0.0158	0.6951	0.0877
Greece	1.2326	0.1508	0.0493	0.1565	0.1048	0.6834	0.0877
Guatemala	1.1292	0.0494	0.1838	0.1885	0.0834	0.5712	0.0529
Hondura	1.2314	0.0636	0.2267	0.1704	0.1471	0.5707	0.0529
Hong Kong	3.0731	0.3880	1.3248	0.1675	0.1706	0.8015	0.2207
Iceland	1.3406	0.1568	0.0500	0.2991	0.0782	0.6688	0.0877
India	0.9802	0.0654	-0.1947	0.0198	0.1644	0.8190	0.1062
Ireland	1.2678	0.1576	0.0472	0.2272	0.0710	0.6772	0.0877
Israel	1.1515	0.2136	-0.0992	0.2367	0.1556	0.4886	0.1562
Italy	1.1918	0.1789	0.0554	0.1265	0.0528	0.6905	0.0877
Jamaica	1.0255	0.0542	0.1562	0.0788	0.1190	0.5642	0.0529
Japan	2.6249	0.3226	0.8951	0.0661	0.0894	1.0310	0.2207
Kenya	0.9107	0.0828	-0.1827	0.0666	0.1057	0.6424	0.1960

Note: LP column refers to Labor productivity changes, LTE to labor technical efficiency changes, SE to scale effect, SUBE to Substitution effect, HC to human capital effect, TC to technical change and ELBTC to extended labor biased technological change effect. The last row of the table presents the weighted average of each column using Olley and Pakes (1996) output share weighting.

Table 5b. Decomposition of Labor Productivity Growth (Average Values over the 1965-90 time period)

Countries	LP	LTE	SE	SUBE	HC	TC	ELBTC
Korea Rep	3.3022	0.3361	1.5515	0.0696	0.2210	0.9025	0.2214
Malawi	0.8232	0.0490	-0.1754	0.0793	0.0546	0.6194	0.1962
Mauritius	0.7755	0.0474	-0.1242	0.0178	0.1044	0.5340	0.1962
Mexico	1.1202	0.0479	0.1415	0.0814	0.1919	0.6050	0.0524
Netherlands	1.3323	0.1559	0.0457	0.2436	0.1133	0.6859	0.0879
New Zealand	1.2287	0.1860	0.0785	0.0228	0.1737	0.6396	0.1281
Norway	1.2917	0.0992	0.0476	0.2273	0.1462	0.6835	0.0879
Panama	1.1911	0.0534	0.1729	0.2025	0.1600	0.5498	0.0524
Paraguay	1.0991	0.0560	0.1335	0.1504	0.1360	0.5707	0.0524
Peru	1.2233	0.0403	0.2272	0.1492	0.1645	0.5897	0.0524
Philippines	0.8969	0.0578	-0.1400	0.0381	0.1645	0.6710	0.1055
Portugal	1.3238	0.1556	0.0552	0.2425	0.0998	0.6828	0.0879
Sierra Leone	1.2019	0.0227	-0.0787	0.3561	0.0443	0.6613	0.1962
Spain	1.1726	0.0988	0.0500	0.1574	0.0933	0.6853	0.0879
Sri Lanka	0.8017	0.0685	-0.1481	0.0702	0.0967	0.6088	0.1055
Sweden	1.3278	0.1384	0.0387	0.3268	0.0483	0.6878	0.0879
Switzerland	1.1206	0.0935	0.0313	0.1545	0.0694	0.6840	0.0879
Syria	0.9028	0.0709	-0.1112	0.1178	0.2166	0.5032	0.1055
Taiwan	3.2200	0.3827	1.4302	0.1304	0.2043	0.8509	0.2214
Thailand	2.8788	0.3678	1.1601	0.0402	0.1307	0.9586	0.2214
Turkey	0.8138	0.0535	-0.1666	0.0357	0.1408	0.6448	0.1055
UK	1.1128	0.1077	0.0358	0.1111	0.0752	0.6951	0.0879
USA	1.3039	0.1755	0.1294	0.1203	0.1931	0.6015	0.0841
Yugoslavia	1.1594	0.1213	0.0533	0.1129	0.0965	0.6875	0.0879
Zambia	1.0114	0.0228	-0.0950	0.1794	0.1283	0.5796	0.1962
Zimbabwe	0.9248	0.0424	-0.1618	0.1307	0.1131	0.6043	0.1962
Mean	1.4018	0.1630	0.1933	0.1162	0.1258	0.6987	0.1049

Note: LP column refers to Labor productivity changes, LTE to labor technical efficiency changes, SE to scale effect, SUBE to Substitution effect, HC to human capital effect, TC to technical change and ELBTC to extended labor biased technological change effect. The last row of the table presents the weighted average of each column using Olley and Pakes (1996) output share weighting

Table 6. Decomposition of Labor Productivity Growth (Weighted Average over 1965-90 time period)

Year	LP	LTE	SE	SUBE	HC	TC	ELBTC
1966	0.8860	0.1293	0.1793	0.1225	0.1143	0.2976	0.0429
1967	0.9231	0.1375	0.1498	0.1216	0.1135	0.3328	0.0679
1968	1.1240	0.1493	0.2511	0.1208	0.1123	0.3679	0.1225
1969	1.1630	0.1447	0.2480	0.1210	0.1105	0.4043	0.1345
1970	1.1392	0.1395	0.2468	0.1193	0.1086	0.4398	0.0852
1971	1.0788	0.1317	0.1693	0.1195	0.0875	0.4691	0.1017
1972	1.2539	0.1302	0.2617	0.1224	0.0877	0.5034	0.1486
1973	1.2229	0.1217	0.2487	0.1265	0.0879	0.5416	0.0966
1974	1.0034	0.1321	0.0143	0.1270	0.0875	0.5712	0.0898
1975	1.0649	0.1423	0.0140	0.1210	0.0884	0.5979	0.0945
1976	1.4509	0.1753	0.2096	0.1199	0.2191	0.6187	0.0984
1977	1.4552	0.1812	0.2066	0.1188	0.2202	0.6541	0.0742
1978	1.5069	0.1725	0.2227	0.1211	0.2210	0.6914	0.0781
1979	1.5903	0.1763	0.2422	0.1244	0.2201	0.7238	0.1034
1980	1.5794	0.1875	0.1984	0.1240	0.2177	0.7546	0.0971
1981	1.4345	0.1742	0.1675	0.1163	0.0731	0.7863	0.1171
1982	1.3152	0.1914	0.0167	0.1086	0.0736	0.8160	0.1088
1983	1.4946	0.1878	0.1772	0.1050	0.0739	0.8541	0.0966
1984	1.6242	0.1807	0.2671	0.1038	0.0738	0.8902	0.1086
1985	1.6052	0.1754	0.2227	0.1011	0.0740	0.9280	0.1040
1986	1.7142	0.1813	0.1846	0.1056	0.1358	0.9684	0.1387
1987	1.7881	0.1815	0.2319	0.1080	0.1359	1.0074	0.1235
1988	1.8538	0.1798	0.2656	0.1099	0.1360	1.0465	0.1160
1989	1.8804	0.1875	0.2308	0.1075	0.1360	1.0820	0.1364
1990	1.8931	0.1833	0.2084	0.1083	0.1361	1.1202	0.1368
Mean	1.4018	0.1630	0.1933	0.1162	0.1258	0.6987	0.1049

Note: LP column refers to Labor productivity changes, LTE to labor technical efficiency changes, SCE to scale effect, SUBE to Substitution effect, HC to human capital effect, TC to technical change and ELBTC to extended labor biased technological change effect. The last row of the table presents the weighted average of each column using Olley and Pakes (1996) output share weighting.

Table 7a. Decomposition of Labor Productivity Growth per group of Countries (Weighted Average Values for each Sub-Period)

	1966-70	1971-75	1976-80	1981-85	1986-90	1966-90
North America & Oceania						
LP Change	0.9956	1.0365	1.4854	1.2997	1.6427	1.2920
LTE	0.1500	0.1214	0.1783	0.1973	0.1979	0.1690
SE	0.1286	0.0862	0.1842	0.1239	0.1250	0.1296
SUBE	0.1540	0.1340	0.1157	0.1000	0.0858	0.1179
HC	0.1714	0.1362	0.3775	0.0556	0.1652	0.1812
TC	0.3176	0.4646	0.5759	0.7389	0.9412	0.6076
ELBTC	0.0741	0.0941	0.0537	0.0841	0.1277	0.0867
Europe						
LP Change	0.8109	0.8859	1.2243	1.3734	1.5968	1.1782
LTE	0.1119	0.0751	0.1534	0.1835	0.1949	0.1438
SE	0.0840	0.0555	0.0317	0.0173	0.0251	0.0427
SUBE	0.1273	0.1530	0.1666	0.1499	0.1674	0.1529
HC	0.0706	0.0040	0.0909	0.0669	0.0686	0.0602
TC	0.3295	0.5110	0.6934	0.8679	1.0526	0.6909
ELBTC	0.0875	0.0872	0.0882	0.0879	0.0881	0.0878
Asian Tigers						
LP Change	2.5105	2.4900	2.8622	2.6385	3.1519	2.7546
LTE	0.3015	0.4225	0.4026	0.2854	0.2472	0.3318
SE	1.2687	0.7602	0.9913	0.8604	1.1784	1.0118
SUBE	0.0465	0.0584	0.0749	0.0756	0.0981	0.0707
HC	0.0602	0.1422	0.1767	0.0838	0.1236	0.1173
TC	0.7683	0.8829	1.0070	1.1029	1.2461	1.0014
ELBTC	0.1857	0.2237	0.2096	0.2305	0.2584	0.2216

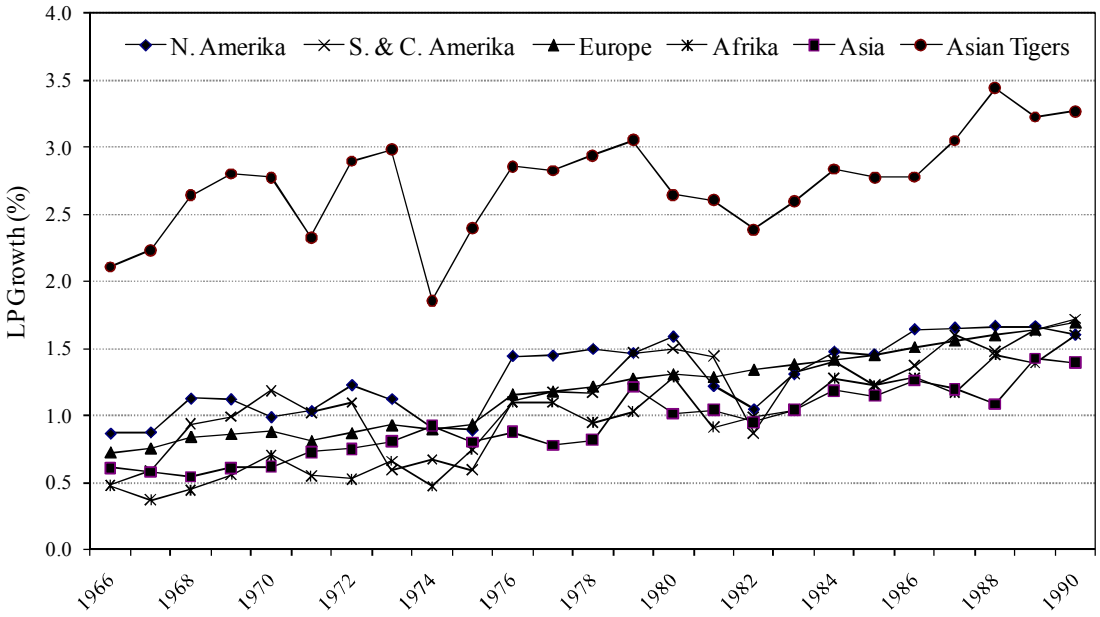
Note: LP column refers to Labor productivity changes, LTE to labor technical efficiency changes, SE to scale effect, SUBE to Substitution effect, HC to human capital effect, TC to technical change and ELBTC to extended labor biased technological change effect. Output shares within the groups were used as weights for the calculation of the weighted average values (Olley and Pakes, 1996).

Table 7b. Decomposition of Labor Productivity Growth per group of Countries (Weighted Average Values for each Sub-Period)

	1966-70	1971-75	1976-80	1981-85	1986-90	1966-90
South and Central America						
LP Change	0.8333	0.7938	1.2801	1.2503	1.5587	1.1432
LTE	0.0457	0.0240	0.0482	0.0577	0.0618	0.0475
SE	0.1565	0.0775	0.3029	0.1919	0.1761	0.1810
SUBE	0.1106	0.1245	0.1212	0.1022	0.0807	0.1078
HC	0.2017	0.0830	0.1578	0.0808	0.2582	0.1563
TC	0.2672	0.4328	0.5990	0.7629	0.9276	0.5979
ELBTC	0.0516	0.0520	0.0509	0.0547	0.0543	0.0527
Africa						
LP Change	0.5090	0.5883	1.0915	1.0871	1.3784	0.9309
LTE	0.0668	0.0196	0.0654	0.0450	0.0682	0.0530
SE	-0.1204	-0.1983	-0.1559	-0.1247	-0.1835	-0.1566
SUBE	0.1223	0.1313	0.1447	0.1132	0.1126	0.1248
HC	0.0607	0.0569	0.2265	0.0224	0.1334	0.1000
TC	0.2050	0.4055	0.6236	0.8139	1.0210	0.6138
ELBTC	0.1746	0.1732	0.1872	0.2172	0.2267	0.1958
Asia						
LP Change	0.5900	0.8003	0.9394	1.0721	1.2703	0.9344
LTE	0.0813	0.0783	0.0451	0.0531	0.0664	0.0649
SE	-0.1346	-0.1300	-0.1534	-0.2238	-0.2792	-0.1842
SUBE	0.0267	0.0356	0.0350	0.0327	0.0299	0.0320
HC	0.1505	0.1513	0.1621	0.1515	0.1849	0.1601
TC	0.3680	0.5566	0.7489	0.9506	1.1555	0.7559
ELBTC	0.0980	0.1086	0.1016	0.1080	0.1129	0.1058

Note: LP column refers to Labor productivity changes, LTE to labor technical efficiency changes, SE to scale effect, SUBE to Substitution effect, HC to human capital effect, TC to technical change and ELBTC to extended labor biased technological change effect. Output shares within the groups were used as weights for the calculation of the weighted average values (Olley and Pakes, 1996).

Figure 3. Weighted Average Labor Productivity Growth.



PART II: Identifying the Worker and Quality Effects of Human Capital on Farm Production

3. INTRODUCTION

Since the early 60's, a lot of empirical papers have been published analyzing the role of human capital in agriculture, initiated by the early theoretical developments of Schultz (1961) and the empirical findings of Griliches (1963; 1964). Initially, economists focused primarily on the role of education as the most important aspect of human capital in farm production (Griliches, 1963; Welch, 1970). However, the notably improvements in educational levels recorded by these studies could not explain the losses in farmers' human capital observed in both developed and developing countries at the same period. These unexplained reductions in farmers' ability turned the attention of economists on the investigation of another important aspect of human capital, namely, health impairment. Indeed, the empirical results revealed a significant deterioration of farmers' health status which was caused by various reasons. In developed countries, impairments in farmers' health were found to be due to exposure in chemical elements of farm inputs, *e.g.* insecticides and herbicides (Coye, 1985)[17], while, on the other hand, low consumption in terms of calories intake and deteriorations in nutritional status were found to be the main causes in developing country agriculture (Bliss and Stern, 1978; Strauss, 1986; Croppenstedt and Muller, 2000).

Despite the voluminous literature in this field, most studies seem to have two common shortcomings. First, they are limited in investigating only the role played by only one of these two elements of human capital neglecting the other, and second, they ignore possible multidimensional impacts of human capital on farm production. Both education and health and also the potential connection among them[18] may affect farmers' capabilities and individual productivity levels. The absence of either of these two important elements of human capital from the analysis provides an incomplete picture about the real magnitude of human capital and leads in biased and controversial conclusions regarding their impact on farmers' productivity. On the other hand, the assumption of a one-dimensional impact of human capital on agricultural production is quite restrictive, since the productive value of human capital has its roots in various phenomena.

In particular, human capital may affect directly farms' productivity as a separate factor of production (Welch, 1970). Improvements in human capital may permit farm laborers to accomplish more work with the available resources. This the "worker

effect" noted by Welch (1970) which can be viewed simply as the marginal product of human capital elements. Further, improvements in human capital result in an increase in effective labor units on field as consequence of the reduction in sick time and prolongations of life. This can be considered as a rightward shift of the labor supply curve which increases labor productivity (Ram and Schultz, 1979). Finally, human capital also affects the rate of diffusion of new technologies. One dimension of human capital is the ability to innovate and to adjust in changing conditions (Nelson and Phelps, 1966). Human capital alone may enhance the development of more productive and cost efficient technologies and enable the adoption of human capital demanding innovations.

Nevertheless, improvements in human capital may also cause qualitative adjustments in labor input, increasing the daily amount of effective work per farmer (Schultz; 1961, 1980). Human quality components such as education and health affect human capabilities and increase the value productivity of labor effort. For instance, improvements in farmers' health may reduce weakness, fatigue, lassitude and disability and enhance farmers' vigor and vitality, increasing thus farmers' productivity (Ram and Schultz, 1979). This can be regarded as a rightward shift of the demand curve of labor that raises farm productivity. Gains in education and health constitute additions to the stock of farm workers' human capital. Increased human capital enhances farmers' physical abilities to engage in work and increases their intellectual abilities to acquire and decode information about potential costs and productive characteristics of other inputs. Hence, different aspects of human capital improve the quality of human effort, which in turn has qualitative impacts on farmers' productivity.

However, the qualitative effects of different aspects of human capital on labor may be not proportional (Deolalikar (1988). More specifically, the relative impact of education and health on the effective units of labor may differ, since a per unit change in education would result in a different impact on labor quality than an equal change in health. Further, the contribution of these changes to labor quality is also depending on the relative level of education and health. Highly educated farmers in bad health will utilize qualitatively more a percentage raise in their health status than an equal raise in their educational level and *vice versa*. Hence, the impact of education and health on both laborers' quality and productivity performance may significantly vary.

In this paper, we attempt to integrate the existent relative literature assessing the impact of both aspects of human capital, i.e., education and health, on farmers' productivity, taking into account both the worker and the qualitative effects of human capital on TFP growth along with their impact on the rate of technical change. In particular, following Welch (1970) work and the ideas of Schultz (1961), we treat education and health as separate factors of production, which also affect the diffusion rate of new technologies (Nelson and Phelps, 1966). We further assume that both aspects of human capital have impacts on the quality of labor. Specifically, we follow Griliches (1963) and Deolalikar (1988) specification, expressing effective labor as a multiplicative augmentation of physical labor and human capital aspects, establishing however a not proportional link between education, health and effective labor.

Then, using Chan and Mountain (1983) findings, we end up to decompose farmers' total factor productivity growth into five components, namely, scale economies, changes in production technology, technical efficiency changes, worker effect, and, labor quality changes. On the basis of the decomposition analysis, we further examine how different assumptions regarding the specification of human capital would modify the results. Finally, the empirical model is based on a generalized Cobb Douglas production frontier suggested by Fan (1991) which is applied to a panel data set of 50 greenhouse farms observed during the 2003-07 period obtained from a primary survey in the region of Ierapetra, Greece.

The remaining paper is organized as follows. In the next section, we present the theoretical framework. Next, the empirical model is described, followed by the estimation results. Finally, the conclusions and the summary of the results follow next and the last section includes the tables.

3.1. THEORETICAL FRAMEWORK

Let assume that farmers in period t utilize a vector of variable inputs, $\mathbf{x} = \{x_1, x_2 \ldots, x_j\} \in \Re_+^J$, labor, $l \in \Re_+$, and human capital, $c \in \Re_+$, to produce a single aggregate output, $y \in \Re_+$, through a well-behaved technology described by the following non-empty, closed set that allows for free disposability of variable inputs:

$$T^t = \{(\mathbf{x}, l, c, y) : y \leq f^p(\mathbf{x}, l, c, t)\} \tag{25}$$

where $f^p(\mathbf{x},l,c,t): \Re_+^{J+2} \rightarrow \Re_+$, is a continuous and, strictly increasing, differentiable concave production function, representing the maximal farm output from variable inputs and labor use given farms' human capital and technological constraints.

Human quality components affect farmers' capabilities and enhance the productivity of labor effort (Schultz; 1961, 1980). In particular, increased human capital may enhance farmers' physical abilities to engage in farm work and also their intellectual abilities to acquire and decode information about potential costs and productive characteristics of other inputs. This implies that different aspects of human capital may be considered as qualitative adjustment of labor input. To capture these quality adjustments, we follow Griliches (1963) and Bliss and Stern (1978) assuming that human capital augments uneffective working hours devoted to labor. Specifically, assuming that human capital is determined by farmers' education and health status, *i.e.,* $c = \{h, \varepsilon\} \in \Re_+^2$, we may define effective labor as follows:[19]

$$l^e = f^l(l, h, \varepsilon) \tag{26}$$

where $l \in \Re_+$ denotes labor input, $\varepsilon \in \Re_+$ and $h \in \Re_+$ are the education level and health status of farm laborers, respectively[20] and, $f^l(l, h, \varepsilon) \in \Re_+^3 \rightarrow \Re_+$ is assumed to be a continuous and, strictly increasing concave in all its arguments, differentiable function representing effective labor given uneffective labor input and farmers' health status and education level.

Nevertheless, besides the labor quality adjustments effects, human capital may also affect directly farm production. First, according to Welch (1970) human capital may permit farm laborers to accomplish more work with the available resources that it can be viewed as the marginal product of human capital. Welch (1970) named that marginal product of human capital as the "worker effect", that is increases in output per unit change in human capital given the quantities of the other inputs. Second, as Nelson and Phelps (1966) argued another dimension of human capital is the increased ability of farmers to innovate and to adjust in changing technological conditions. Human capital alone may enhance the development of more productive and cost efficient technologies and allowing the adoption of higher demanding innovations.

Hence, we may assume that farm laborers' education and health have also a direct impact on production as separate factors of production and on technical change affecting the adoption of new farm technologies. Under these assumptions, we may redefine the technology set in relation (25) as:

$$T^t = \left\{ \left(\mathbf{x}, l, h, \varepsilon, y \right) : y \leq f^p \left(\mathbf{x}, l^e, h, \varepsilon, t \right),\ l^e = f^l \left(l, h, \varepsilon \right) \right\} \tag{27}$$

Using relation (27) we may then define the input correspondence set $L(y) = \left\{ \left(\mathbf{x}, l, h, \varepsilon \right) : \left(\mathbf{x}, l, h, \varepsilon, y \right) \in T^t \right\}$ as all input combinations capable of producing $y \in \Re_+$. The input set is assumed to be closed and convex satisfying strong disposability of labor and variable inputs. Since we allow for free disposability of variable inputs, farmers may not be technical efficient, failing to maximize output for a given bundle of variable inputs, given the technological constraints and human capital variables. This implies that:

$$y = f^p \left(\mathbf{x}, l^e, h, \varepsilon, t \right) \cdot TE^O \tag{28}$$

where TE^O is farm's output technical efficiency defined as:[21]

$$TE^O = \left[\max_{\theta} \left\{ \theta : \theta y = f^p \left(\mathbf{x}, l^e, h, \varepsilon, t \right),\ l^e = f^l \left(l, h, \varepsilon \right) \right\} \right]^{-1} \tag{29}$$

Taking logarithms in both sides of equation (28) and totally differentiating with respect to time, we get:

$$\dot{y} = TC + \dot{TE}^O + \sum_j e_j^x \dot{x}_j + e^l \dot{l} + \left(e^h \dot{h} + e^\varepsilon \dot{\varepsilon} \right) + e^{l^e} \left(e_h^{l^e} \dot{h} + e_\varepsilon^{l^e} \dot{\varepsilon} \right) \tag{30}$$

where a dot over a variable indicates its time rate of change, $e_j^x = \partial ln\, f^p(\bullet) / \partial ln\, x_j$ is the output elasticity of the jth variable input, $e^l = e^{l^e} \cdot e_l^{l^e}$ is the output elasticity of uneffective labor with $e^{l^e} = \partial ln\, f^p(\bullet) / \partial ln\, l^e$ and $e_l^{l^e} = \partial ln\, f^l(\bullet) / \partial ln\, l$ being the

output elasticity of effective labor and the effective labor elasticity of uneffective labor, respectively, and $e^{\varepsilon} = \partial ln f^{p}(\bullet)/\partial ln \varepsilon$ and $e^{h} = \partial ln f^{p}(\bullet)/\partial ln h$ are the output elasticities with respect to laborers' education and health. Finally, $e_{\varepsilon}^{l^e} = \partial ln f^{l}(\bullet)/\partial ln \varepsilon$ and $e_{h}^{l^e} = \partial ln f^{l}(\bullet)/\partial ln h$ are the effective labor elasticities of farmers' education level and health status, respectively.

To make relation (30) operational we need some assumption concerning the relationship between both education and health status and effective labor units. Since the relative impact of education and health on the effective units of labor may differ, we need to establish a specification which will allow for a not proportional relation between education and health, and uneffective labor input. To deal with this, we follow Deolalikar (1988) specification, expressing effective labor as a multiplicative augmentation of physical labor and human capital, assuming however that the relative contribution of the different aspects of human capital to the effective labor is not proportional. Hence, following Deolalikar (1988) formulation, we may specify equation (26) as:

$$l^{e} = l \cdot h^{d_h} \cdot \varepsilon^{d_\varepsilon} \tag{31}$$

where $d_h \in \Re_+$ and $d_\varepsilon \in \Re_+$ denote the proportional impact of health and education on effective labor, respectively. Relation (31) implies that the effective labor elasticity with respect to farmers' health status and education level equals the corresponding magnitudes of the proportional factors, *i.e.*, $e_{h}^{l^e} = d_h$ and $e_{\varepsilon}^{l^e} = d_\varepsilon$, and that the output elasticity of effective labor equals the output elasticity of the uneffective labor input as $e^{l} = e^{l^e} \cdot e_{l}^{l^e} \Rightarrow e^{l} = e^{l^e}$. Hence, relation (30) becomes:

$$\dot{y} = TC + \dot{TE}^{O} + \sum_{j} e_{j}^{x} \dot{x}_{j} + e^{l^e} \dot{l} + \left(e^{h} \dot{h} + e^{\varepsilon} \dot{\varepsilon} \right) + e^{l^e} \left(d_h \dot{h} + d_\varepsilon \dot{\varepsilon} \right) \tag{32}$$

decomposing, thus, output growth into five main effects, that is, the technical change effect (first term), the technical efficiency effect (second term), the scale effect (third and fourth term), worker effect (fifth term) and labor quality effect (last term).

Having identified the different components of output growth, we can now proceed with the decomposition of farmers' TFP growth. Since the quantitative effects of human capital on production are captured by the data in the part of the input growth, the qualitative effects of human capital appearing in the last two terms of equation (8) should be part of the productivity changes (Schultz, 1961). Hence, we introduce at this point Kendrick's (1961) *divisia index* of TFP growth *i.e.,* $\dot{TFP} = \dot{y} - \sum_j S_j^x \dot{x}_j - S^l \dot{l}$ that allows for the identification of these qualitative effects in the productivity growth component, where S_j^x and S^l are the cost shares of the *j* variable and uneffective labor inputs, respectively. Solving the corresponding dual cost minimization problem

$$C(\mathbf{w}, y, h, \varepsilon) = \left\{ \sum_j w_j^x x_j + w^l l : y \leq f^p\left(\mathbf{x}, l^e, h, \varepsilon, t\right),\ l^e = l \cdot h^{d_h} \cdot \varepsilon^{d_\varepsilon} \right\} \tag{33}$$

where $\mathbf{w} \in \Re_{++}^{j+1}$ is a vector of strictly positive variable and labor input prices and using the first-order conditions,[22] we end up with similar to Chan and Mountain (1983) results, *i.e.*, $S_j^x = e_j^x / E$ and $S^l = e^{l^e} / E$, where $E = \sum_j e_j^x + e^{l^e}$ are the returns of scale. Substituting the conventional divisia index of TFP growth into (32) and using Chan and Mountain (1983) results, it yields:

$$\begin{aligned} TFP^D = \left(\frac{E-1}{E}\right)\left(\sum_j e_j^x \dot{x}_j + e^{l^e} \dot{l}\right) + TC + \dot{TE}^O \\ + \left(e^h \dot{h} + e^\varepsilon \dot{\varepsilon}\right) + e^{l^e}\left(d_h \dot{h} + d_\varepsilon \dot{\varepsilon}\right) \end{aligned} \tag{34}$$

which is the final decomposition formula of TFP growth under Deolalikar (1988) non-proportional augmentation of labor input. The first term on the right hand side of equation (34) is the scale effect that is positive (negative) under increasing (decreasing) returns to scale as long as inputs increase and *vice versa*, while it is zero under constant return to scale. Next is the technical change effect that captures shifts in the production frontier. It is positive (negative) under progressive (regressive)

technical change and zero under no technical change. The third term is the effect of technical efficiency changes which refers to movements towards or away from the production frontier. It affects positively (negatively) productivity growth, as long as technical efficiency increases (decreases) over time. The last two components in equation (34) measure the relative contribution of human capital to farms' TFP growth. The fourth term refers to the worker effect that corresponds to the direct impact of education and health on production as separate factors of production (Schultz, 1961; Welch 1970), while the fifth term indicates changes in the quality of labor input via the indirect effect of human capital on the effective units of labor. The worker effect is positive (negative) as long as education and health contribute positively (negatively) to production, *i.e.*, $e^h > (<) 0$ and $e^\varepsilon > (<) 0$ and farmers' education and health improve over time and *vice versa*. Further, the quality effect of labor input has a positive (negative) impact on TFP growth as long farmers' educational level and health status improve (deteriorate) over time. Finally both worker and labor quality effects vanish when human capital (i.e. education and health) remains unchanged over time.

Nevertheless, in order to identify the total effect of human capital on TFP growth, we have also to take into account its relative impact on technical change (Nelson and Phelps, 1966). The latter is captured by the biased part of technical change related with education level and health status that is included into the second term of equation (10). Furthermore, rearranging the terms in equation (34), we can discriminate the effects of education and health on TFP growth. Thus, under Deolalikar (1988) formulation, the overall human capital effect *i.e.,* $T\dot{F}P_C$, on productivity can be expressed as:

$$TFP_C^D = \underbrace{\left(e^h + e^{l^e} d_h\right)\dot{h} + TC_h}_{Health\ Effect} + \underbrace{\left(e^\varepsilon + e^{l^e} d_\varepsilon\right)\dot{\varepsilon} + TC_\varepsilon}_{Education\ Efect} \tag{35}$$

where TC_h, and TC_ε are the biased technical change effects related with education and health, respectively. The first part of equation (35) is the overall health effect on farms' productivity growth and it is consisted by three terms that are the direct effect of farmers' health on production (worker effect), the indirect health effect of on the

effective units of labor (quality effect) and the biased technical change effect related with health. The overall effect is positive (negative) under health using (saving) technical change as long as laborers' health status affect positively (negatively) farm production and health improves over time and *vice versa*, while it is zero when farmers' health status does not change over time and technical change is health neutral. Similarly, the overall education effect (second part of equation (35)) on TFP growth is positive (negative) under education using (saving) technical change, a long as laborers' education level have a positive (negative) impact on farm production and laborers' education increases over time and *vice versa*, while it is zero when education levels remain constant over time and technical change is education neutral. In other cases, the effects of education and health on TFP growth depend on the magnitudes of the various components. Finally, under health and education neutral technical change, the overall human capital effect is zero as long laborers education level and health status remain unchanged over time.

Finally, we examine how different formulations of human capital would modify the components in equations (34) and (35). First, we consider the case of the equal impact of education and health on effective labor that is though not proportional to physical labor input, *i.e.,* $d = d_h = d_\varepsilon$. In this case, the technical change effect and the worker effect remain unchanged in equation (34), while the quality effect is slightly modified since the proportional factor affects equally education and health components and thus it can be seen as a common multiplicative factor of the last term, *i.e.,*

$$TFP^{DP} = \left(\frac{E-1}{E}\right)\left(\sum_j e_j^x \dot{x}_j + e^{l^e}\dot{l}\right) + TC + T\dot{E}^O + \left(e^h \dot{h} + e^\varepsilon \dot{\varepsilon}\right) + e^{l^e} d\,\dot{c} \tag{36}$$

where $c = h \cdot \varepsilon$. Similarly relation (35) turns into:

$$TFP_C^{DP} = \underbrace{\left(e^h + e^{l^e} d\right)\dot{h} + TC_h}_{Health\ Effect} + \underbrace{\left(e^\varepsilon + e^{l^e} d\right)\dot{\varepsilon} + TC_\varepsilon}_{Education\ Efect} \tag{37}$$

implying that the relative contributions of health and education quality effects to TFP growth are determined only by the growth rates of the two aspects of human capital.

Second, we consider the impacts of human capital on farmers human capital, under Griliches (1963) formulation, that is, when $d_h = d_\varepsilon = 1$. In this case, the proportional factors of health and education vanish and relation (34) turns into the following:

$$TFP^G = \left(\frac{E-1}{E}\right)\left(\sum_j e_j^x \dot{x}_j + e^{l^e}\dot{l}\right) + TC + T\dot{E}^O + \left(e^h \dot{h} + e^\varepsilon \dot{\varepsilon}\right) + e^{l^e}\dot{c} \tag{38}$$

where $c = h \cdot \varepsilon$. Similarly the human capital effect in relation (35) turns into:

$$TFP_C^G = \underbrace{\left(e^h + e^{l^e}\right)\dot{h} + TC_h}_{Health\ Effect} + \underbrace{\left(e^\varepsilon + e^{l^e}\right)\dot{\varepsilon} + TC_\varepsilon}_{Education\ Efect} \tag{39}$$

Removing the assumptions of Welch (1970) and Nelson and Phelps (1966), the worker effect in equation (34) vanishes (fourth term) and all other terms remain the same under the different specifications of effective labor input augmentation. Concerning the human capital effect in (35) the biased technical change components of both education and health are zero, *i.e.*, $TC_h = TC_\varepsilon = 0$:

$$TFP_C^W = e^{l^e}\left(d_h \dot{h} + d_\varepsilon \dot{\varepsilon}\right) \tag{40}$$

Equation (40) indicates that under this specification, the impact of human capital effect on TFP growth is consisted only by the quality effects of farmers' health and education. Improvements in human capital have positive impacts on farmers' productivity, while the relative contributions of health and education are determined by their corresponding proportional factors and their growth rates. Again, we examine the two alternative specifications. Considering an equal impact of education and health on effective labor that is though not proportional to physical labor input, the relative contributions of health and education are determined only by their corresponding growth rates. Further, their total impact is determined also by the common proportional factor and the output elasticity of labor input, *i.e.,*

$TFP_C^W = e^{l^e} d\dot{c}$. Finally, under Griliches (1963) formulation, the proportional factors of health and education vanish, *i.e.,* $TFP_C^W = e^{l^e}\dot{c}$ and thus the overall effect of human capital on TFP growth is depended by labor output elasticity and the growth rates of laborers' health and education. As the latter increase over time, the contribution of human capital on farm productivity is positive.

3.2. EMPIRICAL MODEL

For the quantitative measurement and decomposition of farmers' TFP growth we utilized a balanced data set of 50 greenhouse farms located in the island of Crete in Greece covering the period from 2003 to 2007. For aggregate output, variable inputs and labor, we used directly the production data provided by a primary survey, while human capital was proxied by the construction of educational and health indexes. Specifically, laborers' education index was calculated as the product of the years of formal education times an index of seminars duration related with agricultural production, *i.e.,* $\varepsilon_{it} = \varepsilon_{it}^F \times \left(1 + \varepsilon_{it}^I / 365\right)$ where $\varepsilon_{\mathrm{it}}^{\mathrm{F}} \in \Re_+$ is formal education measured in years of schooling and $\varepsilon_{it}^I \in \Re_+$ is informal education measured in days of seminars attained. This formulation allows for more educated farmers to utilize more sufficient seminar related with agricultural production, since the latter may require a level of general education (Antle and Capablo, 1994). Further, laborers' health index was defined as the unity minus the ratio of the farmer's days required to recuperate from illnesses divided by the total days of the year *i.e.,* $h = \left(1 - \text{Days of recuperation}/365\right)$. This formulation implies that farmers in excellent health will obtain a unity health index since the days of recuperation will be zero for them, while less healthy farmers will have a positive health index but below one.

Our empirical model is based on a Cobb-Douglas type of aggregate production function. Specifically, we adopt a generalized Cobb-Douglas (or quasi-translog) production frontier, proposed by Fan (1991) and Karagiannis and Tzouvelekas (2001). Although, this functional specification is not flexible enough like the translog, it allows for variable returns to scale, input-biased technical change, and time varying output and demand elasticities, but it restricts the latter to be unchanged over farmers. Moreover, it permits statistical testing for various features of the aggregate production

technology. Specifically, the generalized Cobb-Douglas production frontier model expressed in logarithms has the following form:

$$\begin{aligned} ln\, y_{it} &= \beta_{it}^{0} + \beta_t t + 0.5\beta_{tt} t^2 + \sum_j \beta_j^x \, ln\, x_{jit} + \beta^{l^e} \, ln\, l_{it}^e + \beta^h \, ln\, h_{it} + \beta^{\varepsilon} \, ln\, \varepsilon_{it} \\ &+ \beta^{h\varepsilon} \, ln\, h_{it} \, ln\, \varepsilon_{it} + \sum_j \beta_{jt}^x \, ln\, x_{jit} t + \beta_t^{l^e} \, ln\, l_{it}^e t + \beta_t^h \, ln\, h_{it} t + \beta_t^{\varepsilon} \, ln\, \varepsilon_{it} t + v_{it} \end{aligned} \tag{41}$$

and

$$ln\, l_{it}^e = ln\, l_{it} + d_h \, ln\, h_{it} + d_{\varepsilon} \, ln\, \varepsilon_{it} \tag{42}$$

where $i = 1,\ldots,N$ are the farmers in the sample, $t = 1,\ldots,T$ are the time periods, $j = 1,\ldots,J$ are variable inputs used in the production process, l_{it}^e is effective labor, and, ε_{it} and h_{it} are indexes proxying the educational level and health status of farmer *i* at year *t*. β 's are the parameters to be estimated and v_{it} is a symmetric and normally distributed error term, $v_{it} \sim N\left(0, \sigma_v^2\right)$, (*i.e.*, statistical noise), representing the omitted explanatory variables and measurement errors in the dependent variable.

We examine at this point the effects of different human capital specifications on the empirical model. Under Welch (1970) and Nelson and Phelps (1966) assumptions, the two alternative specifications described in the last part of the theoretical model modify only equation (42) as follows:

$$ln\, l_{it}^e = ln\, l_{it} + d\left(ln\, h_{it} + ln\, \varepsilon_{it}\right) \tag{43}$$

and

$$ln\, l_{it}^e = ln\, l_{it} + ln\, h_{it} + ln\, \varepsilon_{it} \tag{44}$$

Equation (43) represents the case of a proportional impact of education level and health status on effective labor that is though not proportional to physical labor input, while equation (44) represents Griliches (1963) formulation where the relation between physical labor, health status and education level is proportional. Further, the production frontier model in (41) also changes, removing Welch (1970) and Nelson and Phelps (1966) assumptions, since the direct effects of both education level and

health status on production vanish. Hence, relation (41) could be written in this case as:

$$\begin{aligned} ln\, y_{it} = \beta_{it}^{0} + \beta_{t} t + 0.5\beta_{tt} t^{2} + \sum_{j} \beta_{j}^{x}\, ln\, x_{jit} \\ + \beta^{l^{e}}\, ln\, l_{it}^{e} + \sum_{j} \beta_{jt}^{x}\, ln\, x_{jit} t + \beta_{t}^{l^{e}}\, ln\, l_{it}^{e} t + v_{it} \end{aligned} \tag{45}$$

Equation (45) represents the case where human capital affects only the units of effective labor under Deolalikar (1988) formulation. Again, the two alternative specifications for human capital cause similar modifications in equation (45), as they interpreted in equations (43) and (44). In all specifications followed here, effective labor is introduced into the production in a structural form. This implies that a bi-dimensional grid search should be conducted around the 0-2 range for the identification of the proportional factors in line with Greene (2000, pp. 329-334) suggestions.

Following Cornwell, Schmidt and Sickles (1990) fixed effects specification, $\beta_{it}^{0} = \beta_{t}^{0} - \xi_{it}$ are assumed to be farm and period specific intercepts introduced into (41) and (45) in order to capture temporal variations in output technical efficiency. According to this formulation output technical inefficiency is assumed to follow a quadratic pattern over time, *i.e.*,

$$\xi_{it} = \zeta_{i0} + \zeta_{i1} t + \zeta_{i2} t^{2} \tag{46}$$

where, ζ_{i0}, ζ_{i1} and ζ_{i2} are the $(N \times 3)$ unknown parameters to be estimated. If $\zeta_{i1} = \zeta_{i2} = 0 \quad \forall i$, then output technical efficiency is time-invariant, while when $\zeta_{i1} = \zeta_{1}$ and $\zeta_{i2} = \zeta_{2}\ \forall i$ then output technical efficiency is time-varying following, however, the same pattern for all farms in the sample.

Under expected profits maximization, we may introduce a two step procedure to estimate the models in equations (41), (42) and (46) which will allow the distinction between technical change and time-varying technical efficiency. Specifically, in a first stage *β's* parameters in (41) and (42) are estimated using an OLS regression and then the residuals of the regressions for each farmer in the panel are regressed on time

and time-squared as in (46) to obtain estimates of ζ's for each farm in the sample. Then, defining $\beta_t^0 = \max_i \{\xi_{it}\}$ as the estimated intercept of the production frontier in period t, the output technical efficiency of each farm in period t is estimated as

$$TE_{it}^O = exp\left(-\xi_{it}\right) \tag{47}$$

where $\xi_{it} = \left(\hat{\beta}_t^0 - \hat{\beta}_{it}\right)$. A direct implication of the above specification is that in each period at least one farm is fully efficient, although the identity of this farm may vary through years. The advantages of this specification are its parsimonious parameterization regardless of functional form, its straightforward estimation, its independence of distributional assumptions, and that it allows output technical inefficiency to vary across farms and time. Moreover, since the expression in (46) is linear to its parameters, the statistical properties of individual farmers-effects are not affected.

Having introduced specific functional forms for the production frontier, we can now proceed with the quantification of the various terms appearing in (34). Since, effective labor input is introduced into the production frontier in a structural form, the different specifications for the impact of human capital on effective labor do not affect the computation of the various features of the production structure. However, the different specifications regarding the impact of human capital on production do affect it.

First, we proceed with the derivation of the output elasticities from equation (41), in order to identify the scale and worker effect (first and fourth terms in equation (34)). As a direct implication of the generalized Cobb Douglas production frontier adopted here, the output elasticities with respect to all inputs are time varying but constant over farms, while the output elasticities with respect to human capital is time and farm varying due the interaction term between education and health. In particular, under Deolalikar (1988) specification, the output elasticities are the following:

$$e_j^x = \frac{\partial ln\, y_{it}}{\partial ln\, x_{jit}} = \beta_j^x + \beta_{jt}^x t \tag{48}$$

$$e^{l^e} = \frac{\partial ln\, y_{it}}{\partial ln\, l_{it}^e} = \beta^{l^e} + \beta_t^{l^e} t \tag{49}$$

$$e^h = \frac{\partial ln\, y_{it}}{\partial ln\, h_{it}} = \beta^h + \beta_t^h t + \beta^{h\varepsilon}\, ln\, \varepsilon_{it} \tag{50}$$

$$e^\varepsilon = \frac{\partial ln\, y_{it}}{\partial ln\, \varepsilon_{it}} = \beta^\varepsilon + \beta_t^\varepsilon t + \beta_t^{h\varepsilon}\, ln\, h_{it} \tag{51}$$

Moreover, considering equation (45), the output elasticities of variable inputs and labor remain the same as in equations (48) and (49), but the output elasticities with respect to health and education are zero (equations (50) and (51)).

The hypothesis of constant returns-to-scale can be statistically tested by imposing the restrictions in (41) that $\sum_j \beta_j^x + \beta^{l^e} = 1$, $\beta^h = \beta^\varepsilon = \beta^{h\varepsilon} = 0$ and $\sum_j \beta_{jt}^x + \beta_t^{l^e} + \beta_t^h + \beta_t^\varepsilon = 0\ \forall\, j$, while for equation (45) the corresponding restrictions are $\sum_j \beta_j^x + \beta^{l^e} = 1$ and $\sum_j \beta_{jt}^x + \beta_t^{l^e} = 0\ \forall\, j$. If the hypotheses cannot be rejected then the underlying technology exhibits constant returns-to-scale and the scale effect in equation (34) is zero.

For the estimation of the technical change effect (second terms in (34)), we need to compute the primal rate of technical change, that is,

$$TC = \frac{\partial ln\, y_{it}}{\partial t} = \beta_t + \beta_{tt} t + \sum_j \beta_{jt}^x\, ln\, x_{jit} + \beta_t^{l^e}\, ln\, l_{it}^e + \beta_t^h\, ln\, h_{it} + \beta_t^\varepsilon\, ln\, \varepsilon_{it} \tag{52}$$

The hypotheses of *Hicks*-neutral and zero technical change can be tested, imposing the following parameter restrictions in (41): $\beta_{jt}^x = \beta_t^l = \beta_t^h = \beta_t^\varepsilon = 0$ and $\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_t^l = \beta_t^h = \beta_t^\varepsilon = 0\ \forall\, j$, respectively. If health and education have only qualitative impacts on production via the labor quality adjustments, then technical change is computed by equation (45). In this case the last two terms in (52) are eliminated, while the rest terms remain as they are and the corresponding restrictions for *Hicks*-neutral and zero technical change are: $\beta_{jt}^x = \beta_t^l = 0$ and

$\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_t^l = 0 \ \forall \ j$. If the hypotheses fail to be rejected, then technical change effect is zero in TFP decomposition analysis.

3.3. EMPIRICAL RESULTS

A primary survey has been conducted for the purposes of this study involving 50 small greenhouse farms randomly selected from Ierapetra Region located in Crete island in Greece. The survey covered a five-year period from 2003 to 2007. All surveyed farms included to the dataset were asked to provide analytical information about their farm production, outputs produced, variable inputs employed and human capital information focusing on education and health. One output and six variable inputs were identified. Output was measured in euros as the total revenues coming up from greenhouse production, including three crops, namely, tomatoes, cucumbers and peppers. The five variable inputs that were taken into consideration were: *a*) land measured in stremmas (one stremma equals 0.1 ha), *b*) pesticides measured in Euros *c*) all kinds of chemical fertilizers measured in euros, *d*) intermediate inputs including energy, fuels, and irrigation water measured in euros and *e*) labor measured in working hours. Since all farmers in the sample indicated that do not occupy hired workers, human capital variables were calculated as the average educational and health status of the family members employed in farm production.

All monetary variables were converted into 2000 constant prices using the agricultural production price index published by the National Statistical Service of Greece. All outputs and inputs used in the analysis were aggregated using Divisia indices with revenues and cost shares used as weights during the aggregation procedure. Furthermore, to avoid errors associated with measurement units, all variables were converted into indices, using the corresponding variables' mean values as the basis of the normalization. Table 1 presents descriptive statistics of output, inputs and human capital variables used in the estimation procedure.

The fixed effects parameter estimates of the generalized Cobb-Douglas production frontier are shown in tables 2 and 3. Table 2 presents the parameter estimates of the model in equations (41) and (42), where it is assumed that human capital affects the production both directly as a separate factor of production and indirectly as a qualitative adjustment factor of labor input (Full Model). On the other hand, table 3 presents the parameter estimates of the model in equation (45), where it

considers only the qualitative effects of human capital on labor input (Reduced Model). In both tables, model 1 illustrates the fixed effects parameter estimations when Deolalikar (1988) formulation is adopted in the modeling of effective labor, while model 2 illustrates the corresponding estimations when a proportional impact of education and health on effective labor is assumed that is though not proportional to uneffective labor. Finally, model 3 illustrates the fixed effects parameter estimations when Griliches formulation (1963) is adopted. The first-order parameters in all six models *i.e.,* β_j^x and β^{l^e}, were found to have the expected positive sign, while their magnitudes were found to vary between zero and one, implying that the bordered *Hessian* matrix of the first- and second-order partial derivatives is negative semi-definite indicating that all regularity conditions hold at the point of approximation, *i.e.*, sample means. In turn, this implies that all marginal products are positive and diminishing and that the production frontier is locally quasi-concave. In the low panels of tables 2 and 3 are also reported the parameters of the Cornwell, Schmidt and Sickles (1990) inefficiency effects model for the farm with the maximum efficiency score. All the ζ_{i0} parameters were found to have positive signs with their magnitude to range from zero to one. The ζ_{i1} and ζ_{i2} parameters were found to be positive for the majority of the farms in the sample implying improvements in output technical efficiency over time. Finally, in the last row of the tables are reported the estimates of the proportional factors for health and education variables *i.e.,* d_h and d_ε, which were identified through the conduction of Grid Search. For model 3, these factors are equal to one, while for model 2 the factors are different than one but equal between education and health.

Based on the parameter estimates, we have computed basic features of the various production structures considered in this study. The output elasticities and the returns-to-scale, for each structure are presented in tables 4 and 5. Output elasticity estimates in all cases were found to be statistical significant at least at the 5 per cent level, revealing land as the most important input, contributing the most to Green-house production and followed by effective labor, pesticides, intermediate inputs, and fertilizers. In the full model, the output elasticity of education was found to be greater than the output elasticity of health, indicating education as the most important aspect of human capital as far as their direct contribution to farm production. Furthermore, the returns-to-scale were found to be decreasing on average in all models, implying

that a proportional percentage increase in all inputs would result in a lower increase in output. Comparing full and reduced models, the returns to scale were estimated to be less decreasing in the reduced models, while no significant variations are observed between different specifications.

Several hypotheses concerning model specification have been tested and the results are presented in Tables 6 and 7.[23] First the hypothesis of constant returns to scale was tested for the different specifications in the full model case *i.e* $\sum_j \beta_j^x + \beta^{l^e} = 1$, $\beta^h = \beta^\varepsilon = \beta^{h\varepsilon} = 0$ and $\sum_j \beta_{jt}^x + \beta_t^{l^e} + \beta_t^h + \beta_t^\varepsilon = 0 \ \forall j$, using the generalized likelihood ratio test and then for the reduced model case *i.e.,* $\sum_j \beta_j^x + \beta^{l^e} = 1$ and $\sum_j \beta_{jt}^x + \beta_t^{l^e} = 0 \quad \forall j$, respectively. The hypothesis was rejected at the 5 per cent level, implying that the scale effect contributes significantly to farmer's productivity growth. Next, the hypotheses of zero technical change and *Hicks*-neural technical change were examined for the different full and reduced model specifications. Both hypotheses were rejected in all cases at 5 per cent level, revealing also technical change as a significant source of farmer's productivity. The parameter estimates related with the neutral component of the rate of technical change *i.e.,* β_t and β_{tt} were found positive in all models, implying that technical change was progressive over the period under consideration. On the other hand, the parameter estimates related with the biased component of the rate of technical change *i.e.,* β_{jt}^x and β_{kt}^l were estimated to vary across different specifications. In the full model specifications, technical change was pesticides and labor saving, while for the reduced model specifications technical change was found fertilizers and intermediate inputs using for the time period under consideration. Finally, technical change was estimated to be human capital neutral in all models.

The final set of statistical testing refers to the specification of output technical efficiency and it's temporal pattern. The results are reported in the lower panel of tables 6 and 7. Statistical testing using LR-test rejects in all models the hypotheses of zero and time invariant technical efficiency *i.e.,* $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0 \ \forall i$, and $\zeta_{i1} = \zeta_{i2} = 0, \ \forall i$, respectively, at a 5 per cent significant level, implying that changes in output technical efficiency contribute significantly to farmers' TFP growth for the period under consideration. Moreover, the temporal pattern of output technical

efficiency was found to vary across farmers in the sample, since the hypothesis that $\zeta_{i1} = \zeta_1$ and $\zeta_{i2} = \zeta_2 \ \forall i$ was also rejected from the generalized LR-test for the different specifications under investigation. The estimates of the output technical efficiency obtained via equation (46) are reported in the form of frequency distribution within a decile range in tables 8. Farmers' output technical efficiency was found to vary slightly among different structural specifications, ranging from 77.36 to 81.02, indicating that output could have been increased approximately from 19 to 23 per cent if technical inefficiency was eliminated.

Using the obtained estimates, we have computed the various components of farmer's TFP growth. Table 9 presents the average values of TFP changes under the different full model specifications and it's decomposition over both farms and time periods. First in the table appears the average annual rate of farmer's productivity growth and then the relative percentage contribution of each effect. Using Deolalikar (1988) specification (Model 1 in the table), the average annual rate of farmers' TFP growth was found to be 1.0704 per cent during the five-year period analyzed, while the corresponding values for the second and third model are 1.0072 and 1.1439 per cent, respectively. In all cases, the greatest share of that growth (about 70 per cent) was due to the rate of technical change, driven mainly by the neutral part, while the smallest shares were due to the inputs and human capital biased technical change effects. On the other hand, scale economies were found to have affected negatively farmers' productivity during the period analyzed. Under Griliches (1963) specification, scale effect was found to contribute less to TFP growth in comparison with the other two models. Changes in technical efficiency were also found to be a significant source of productivity growth, causing about 12 per cent increases to TFP growth. The relative significance of technical efficiency do not vary importantly for different specifications. Further, the worker effect was also estimated to account significantly for changes in farmers' productivity driven by changes in education, while impairments in farmers' health were found to decrease weakly TFP growth. Worker effect was estimated to be greater under Deolalikar (1988) specification and smaller under Griliches (1963) specification. Finally, labor quality effect was also found to have an important impact on farmers' productivity, which is though much greater under Griliches (1963) specification (21.53 per cent). The labor quality effect

was driven mainly by improvements in farmers' education, while deteriorations in farmers health had a weak impact on it.

Finally, table 10 presents the average values of TFP growth under the different specifications for the reduced model. Under Deolalikar (1988) specification, the average TFP growth was found to be 0.9125 per cent during the five-year period under consideration, while the corresponding values for the second and third model are 0.8788 and 1.0942 per cent, respectively. The driving force of farmers' productivity growth was found to be again technical change explained mainly by the neutral part and less by the input biased component. Scale economies were also found to contribute negatively to TFP growth but their impact is less significant than in the full model. Further, the impact of technical efficiency effect was found to be quite steady among the different specifications, explaining about 17 per cent of the TFP growth. Finally, Labor quality effect was also identified to be an important source of productivity changes especially under Griliches (1963) specification (23.67 per cent), powered by educational improvements, while health impairments reduced the measured TFP growth.

Our results confirm the importance role of human capital in farm production. Considering the full (reduced) model case, the absence of human capital from the analysis would result in about 28 (10) per cent underestimation of farmers' TFP growth under Deolalikar (1988) specification, while under Griliches (1963) specification the corresponding downward bias would be about 35 (26) per cent. Furthermore, ignoring the role of health as an important aspect of human capital would result in an upward bias of 6 (8) per cent on the measured productivity growth under Deolalikar (Griliches) specification in the full model case, while in the reduced model the corresponding percentage would be 3 (6) per cent. Finally, the empirical evidence do not provide any important effect of human capital on technical change in any specification.

Useful insights are provided, comparing the full and the reduced model but also the different specifications followed in this study. Neglecting the worker effect from the analysis would lead in about 14 per cent underestimation of the TFP growth for Greek greenhouse farmers under Deolalikar (1988) specification, while under Griliches (1963) formulation the downward bias would be about 11 per cent. Finally, overlooking the not proportional relation of human capital and labor would result in

about 6.5 per cent overestimation of the TFP growth in full model and about 19 per cent in the reduced model.

3.4. CONCLUSIONS

Since the early 60's, a lot of empirical studies have been emerged aimed to investigate the role of education and health on agricultural production. However, the majority of these studies are limited in investigating only the role played by education in production neglecting health and conversely, and they further ignore possible multidimensional impacts of human capital on farm production. Human capital may affect directly the production as a separate factor of production (Welch, 1970) and further the rate of diffusion of new technologies (Nelson and Phelps, 1966). Moreover, improvements in human capital may also cause qualitative adjustments in labor input, increasing the daily amount of effective work per farmer (Schultz; 1961, 1980)

In this paper, we attempted to integrate the existent relative literature assessing the impact of both aspects of human capital, i.e., education and health, on farmers' productivity, and taking into account the worker and the qualitative effects of human capital on TFP growth along with their impact on the rate of technical change. In particular, following Welch (1970) work and the ideas of Schultz (1961), we introduced education and health as separate factors of production, allowing also to affect the diffusion rate of new technologies (Nelson and Phelps, 1966). We further assumed that both aspects of human capital cause quality adjustments in labor input. Specifically, we followed Griliches (1963) specification, expressing effective labor as a multiplicative augmentation of physical labor and human capital aspects, establishing however a not proportional link between education, health and effective labor (Deolalikar, 1988).

Then, using Chan and Mountain (1983) findings, we decomposed farmers' total factor productivity growth into five components, namely, scale economies, changes in production technology, technical efficiency changes, worker effect, and, labor quality changes. On the basis of the decomposition analysis, we examined how different assumptions regarding the specification of human capital would modify the results. Finally, we applied the empirical model to a panel data set of 50 greenhouse farms

observed during the 2003-07 period, using a generalized Cobb Douglas production frontier suggested by Fan (1991).

The results confirmed the importance role of education and health in farm production and provided useful insights about the different impacts of human capital on productivity. We found that neglecting the worker effect from the analysis would lead in about 14 per cent underestimation of the TFP growth for Greek greenhouse farmers under Deolalikar (1988) specification, while under Griliches (1963) formulation the downward bias would be about 11 per cent. Finally, overlooking the not proportional relation of human capital and labor would result in about 6.5 per cent overestimation of the TFP growth in the full model case and about 19 per cent in the reduced model case.

3.5. TABLES

Table 1. Descriptive Statistics of the Variables used to estimate the Cobb-Douglas Production Frontier Function for Greenhouse Farms in Greece, 2003-07.

Variable	Mean	Min	Max	StDev
Output (in Euros)	41,545	9,524	212,230	29,898
Inputs				
Land (in Acres)	4.87	1.78	16.18	2.95
Fertilizers (in Euros)	4,574	837	15,547	2,911
Pesticides (in Euros)	2,624	358	9,857	2,271
Intermediate Inputs (in Euros)	17,619	1,021	92,144	18,033
Labor (in Hours)	5,000	920	11,320	2,560
Human Capital				
Education Index	9.35	3.1	14.3	2.99
Health Index	0.98	0.94	1.00	0.007

Table 2. Parameter Estimates of the Generalized Cobb Douglas Production Function (Full Model).

Par.	Model 1	Model 2	Model 3	Par.	Model 1	Model 2	Model 3
β^0	3.3218	3.2091	3.2623	β_t	0.4449	0.4411	0.4395
	(5.6452)*	(5.1264)*	(5.4230)*		(1.8556)**	(1.8247)**	(2.6093)*
β_A^x	0.4243	0.4411	0.4365	β_{tt}	0.0653	0.0661	0.0548
	(5.2377)*	(5.6052)*	(4.4911)*		(0.6876)	(0.6917)	0.6790
β_Z^x	0.1451	0.1321	0.1458	β_{At}^x	-0.0367	-0.0302	-0.0310
	(1.6546)**	(1.7352)**	(1.8230)**		(0.5544)	(0.3891)	(0.0466)
β_F^x	0.0689	0.0642	0.0684	β_{Zt}^x	-0.0252	-0.0221	-0.0260
	(1.8191)**	(1.7781)**	(1.7881)**		(2.1140)**	(2.0318)**	(1.6435)**
β_I^x	0.1217	0.1403	0.1235	β_{Ft}^x	0.0695	0.0673	0.0718
	(2.3276)*	(2.4291)*	(1.6736)**		(1.0342)	(0.9824)	(0.1058)
β^{l^e}	0.1702	0.1645	0.1723	β_{It}^x	0.0126	0.0103	0.0144
	(1.6723)**	(1.6129)**	(1.6531)**		(0.0614)	(0.1345)	(0.0696)
β^h	0.0768	0.0855	0.0824	$\beta_t^{l^e}$	-0.1212	-0.1186	-0.1222
	(1.6738)**	(1.7245)**	(1.7134)*		(1.8272)**	(1.7981)**	(1.7993)**
β^ε	0.0925	0.0893	0.0671	β_t^h	-0.0029	-0.0033	-0.0045
	(3.8266)*	(3.3523)*	(2.7715)**		(0.0188)	(0.0213)	(0.3745)
$\beta^{h\varepsilon}$	0.0175	0.0100	0.0138	β_t^ε	-0.0148	-0.0132	-0.0142
	(0.3604)	(0.2981)	(0.3111)		(1.7984)**	(1.7133)**	(1.6618)**
ζ_{i0}	0.5270	0.5082	0.5413	ζ_{i2}	0.0512	0.0621	0.0665
	(1.9390)**	(1.8211)**	(1.9724)**		(1.7990)**	(1.8014)**	(1.8321)**
ζ_{i1}	0.1236	0.1187	0.1234	$\bar{R}^2$	0.5588	0.5412	0.5523
	(1.9111)**	(1.8342)**	(1.9041)**				
d_h	0.3600	0.4400	1.0000	d_ε	0.5500	0.4400	1.0000

Note: Numbers in parenthesis report t-statistic value. *A* refers to land, Z to pesticides use, *F* to fertilizers use, *I* to intermediate inputs, *l* to labor input, *h* to health and *ε* to education. Model 1 was estimated adopting Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 was estimated assuming a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 was estimated adopting Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively. In the low panel of the Table are reported the *ζ* parameters of the farm with the maximum efficiency score.

Table 3. Parameter Estimates of the Generalized Cobb Douglas Production Function (Reduced Model)

Par.	Model 1	Model 2	Model 3	Par.	Model 1	Model 2	Model 3
β^0	3.5796	3.6921	3.4234	β_{tt}	0.0656	0.0687	0.0755
	(4.8791)*	(4.9792)*	(4.3453)*		(0.4341)	(0.4613)	(0.4812)
β_A^x	0.3748	0.3804	0.3983	β_{At}^x	-0.0157	-0.0162	-0.0139
	(4.9858)*	(4.9919)*	(4.3749)*		(0.2576)	(0.2987)	(0.2564)
β_Z^x	0.1546	0.1532	0.1627	β_{Zt}^x	-0.0134	-0.0158	-0.0125
	(1.7455)**	(1.7140)**	(1.8937)**		(0.0857)	(0.0881)	(0.0790)
β_F^x	0.0731	0.0743	0.0627	β_{Ft}^x	0.0427	0.0425	0.0401
	(2.6613)*	(2.6870)*	(2.4672)*		(1.6466)**	(1.6391)**	(1.6876)**
β_I^x	0.1222	0.1239	0.1189	β_{It}^x	0.0568	0.0549	0.0598
	(2.3323)*	(2.3890)*	(2.1532)*		(1.8965)**	(1.8656)**	(1.7513)**
β^{l^e}	0.1857	0.1789	0.1922	$\beta_t^{l^e}$	-0.0339	-0.0353	-0.0255
	(1.9262)**	(1.9018)**	(2.0123)**		(0.2050)	(0.2127)	(0.2980)
β_t	0.4009	0.4252	0.4372				
	(2.5236)*	(2.5024)*	(2.2983)*				
ζ_{i0}	0.5184	0.5165	0.5222	ζ_{i2}	0.0863	0.0736	0.0893
	(2.0213)**	(2.0105)**	(2.0820)**		(1.6325)**	(1.6129)**	(1.6518)**
ζ_{i1}	0.1467	0.1458	0.1489	$\bar{R}^2$	0.5211	0.5199	0.5341
	(1.9875)**	(1.9814)**	(1.9938)**				
d_h	0.4200	0.4200	1.0000	d_ε	0.4100	0.4200	1.0000

Note: Numbers in parenthesis report t-statistic value. *A* refers to land, Z to pesticides use, *F* to fertilizers use, *I* to intermediate inputs, and *l* to labor input. Model 1 was estimated adopting Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 was estimated assuming a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 was estimated adopting Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively. In the low panel of the Table are reported the ζ parameters of the farm with the maximum efficiency score.

Table 4. Output Elasticities and Returns-to-Scale for Greenhouse farms in Greece, 2003-2007. (Full Model)

Variable	Model 1		Model 2		Model 3	
	Mean	StdError	Mean	StdError	Mean	StdErr
Output elasticities						
e^A	0.3334	(0.1193)*	0.3427	(0.1349)*	0.3395	(0.1274)*
e^Z	0.1849	(0.0884)*	0.1784	(0.0837)*	0.1915	(0.0903)*
e^F	0.0950	(0.0372)*	0.0913	(0.0329)*	0.0945	(0.0392)*
e^I	0.1353	(0.0468)*	0.1403	(0.0503)*	0.1397	(0.0483)*
e^{l^e}	0.2039	(0.0941)*	0.1974	(0.0891)*	0.2084	(0.0983)*
e^h	0.0823	(0.0546)**	0.0902	(0.0598)**	0.0878	(0.0490)**
e^ε	0.1138	(0.0539)*	0.1034	(0.0488)*	0.0956	(0.0438)*
Returns-to-Scale	0.9525	(0.2321)*	0.9501	(0.2209)*	0.9736	(0.2338)*

Note: *A* refers to land, Z to pesticides use, *F* to fertilizers use, *I* to intermediate inputs, *l* to labor input, *h* to health and ε to education. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively. Model 1 was estimated adopting Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 was estimated assuming a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 was estimated adopting Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$.

Table 5. Output Elasticities and Returns-to-Scale for Greenhouse farms in Greece, 2003-2007. (Reduced Model)

Variable	Model 1		Model 2		Model 3	
	Mean	StdError	Mean	StdError	Mean	StdErr
Output elasticities						
e^A	0.3182	(0.1010)*	0.3244	(0.1223)*	0.3328	(0.1358)*
e^Z	0.1988	(0.0904)*	0.1924	(0.0921)*	0.2014	(0.1064)*
e^F	0.1123	(0.0408)*	0.1156	(0.0436)*	0.1080	(0.0446)*
e^I	0.1348	(0.0496)*	0.1355	(0.0506)*	0.1285	(0.0510)*
e^{l^e}	0.2139	(0.0983)*	0.2081	(0.0953)*	0.2171	(0.1034)*
Returns-to-Scale	0.9780	(0.2541)*	0.9760	(0.2525)*	0.9878	(0.2601)*

Note: *A* refers to land, Z to pesticides use, *F* to fertilizers use, *I* to intermediate inputs, and *l* to labor input. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively. Model 1 corresponds to Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 to a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 to Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$.

Table 6. Model Specification Tests. (Full Model)

Hypothesis	LR test-statistic			
	Model 1	Model 2	Model 3	Critical Value (a=0.05)
Farm Technology				
Constant returns-to-scale: $\sum_j \beta_j^x + \beta^{l^e} = 1,\ \beta^h = \beta^\varepsilon = \beta^{h\varepsilon} = 0$ and $\sum_j \beta_{jt}^x + \beta_t^{l^e} + \beta_t^h + \beta_t^\varepsilon = 0\ \forall j$	43.36	45.04	48.90	$\chi_5^2 = 11.07$
Zero-technical change: $\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_t^l = \beta_t^h = \beta_t^\varepsilon = 0$, $\forall j$	46.98	38.78	52.06	$\chi_9^2 = 16.91$
Hicks-neutral technical change: $\beta_{jt}^x = \beta_t^l = \beta_t^h = \beta_t^\varepsilon = 0\ \forall j$	52.98	42.10	48.33	$\chi_7^2 = 14.07$
Output Technical Efficiency				
Zero output technical efficiency, *i.e.*, $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0,\ \forall i$	103.20	120.10	111.23	$\chi_{150}^2 \simeq 71.40$
Time invariant output technical efficiency: $\zeta_{i1} = \zeta_{i2} = 0,\ \forall i$	96.41	102.32	88.36	$\chi_{100}^2 \simeq 69.52$
Common temporal pattern of technical efficiency across farms: $\zeta_{i1} = \zeta_1\ \forall i$ and $\zeta_{i2} = \zeta_2\ \forall i$	88.34	94.40	92.33	$\chi_{100}^2 \simeq 69.52$

Note: Model 1 corresponds to Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 to a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 to Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$.

Table 7. Model Specification Tests. (Reduced Model)

Hypothesis	LR test-statistic			
	Model 1	Model 2	Model 3	Critical Value (a=0.05)
Farm Technology				
Constant returns-to-scale: $\sum_j \beta_j^x + \beta^{l^e} = 1,\ \sum_j \beta_{jt}^x + \beta_t^{l^e} = 0\ \forall\, j$	50.92	52.90	46.70	$\chi_2^2 = 5.99$
Zero-technical change: $\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_t^l = 0\ \forall\, j$	58.40	56.42	60.12	$\chi_7^2 = 14.07$
Hicks-neutral technical change: $\beta_{jt}^x = \beta_t^l = 0\ \forall\, j$	65.40	57.98	55.34	$\chi_5^2 = 11.07$
Output Technical Efficiency				
Zero output technical efficiency, *i.e.*, $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0,\ \forall i$	122.12	114.54	102.80	$\chi_{150}^2 \simeq 71.40$
Time invariant output technical efficiency: $\zeta_{i1} = \zeta_{i2} = 0,\ \forall i$	100.89	93.40	98.50	$\chi_{100}^2 \simeq 69.52$
Common temporal pattern of technical efficiency across farms: $\zeta_{i1} = \zeta_1\ \forall i$ and $\zeta_{i2} = \zeta_2\ \forall i$	94.40	89.90	90.12	$\chi_{100}^2 \simeq 69.52$

Note: Model 1 corresponds to Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 to a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 to Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$.

Table 8. Frequency Distribution of Output Technical Efficiency – Average values for 2003-07 tim period (Full and Reduced Model)

TE^O	Full Model			Reduced Model		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
<40	0	0	0	0	0	0
40-50	0	0	0	0	0	0
50-60	1	2	0	1	2	0
60-70	7	6	6	7	6	6
70-80	17	17	18	18	18	17
80-90	16	16	17	16	16	17
90>	9	9	9	8	8	10
Mean	78.69	76.54	81.02	79.82	77.36	80.13
Min	58.34	57.12	61.48	58.65	58.23	62.08
Max	95.12	96.22	96.78	95.36	96.23	97.04

.*Note:* Model 1 corresponds to Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 to a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 to Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$.

Table 9. Decomposition of TFP Growth for Greek Greenhouse Farms - Average Values for the 2003-07 period. (Full Model)

	Average Annual Rate of Change (%)		
	Model 1	Model 2	Model 3
TFP Growth (Accounted-%)	1.0223	1.0223	1.0223
TFP Growth (Estimated-%)	1.0704	1.0072	1.1439
	(100)	(100)	(100)
Scale Effect	-0.0609	-0.0531	-0.0382
	(-5.69)	(-5.27)	(-3.34)
Rate of Technical Change	0.7085	0.7046	0.6896
	(66.19)	(69.96)	(60.28)
Neutral	0.6847	0.6781	0.6610
	(63.97)	(67.33)	(57.78)
Biased Input	0.0264	0.0281	0.0302
	(2.47)	(2.79)	(2.64)
Education	-0.0045	-0.0038	-0.0042
	(-0.42)	(-0.38)	(-0.37)
Health	0.0019	0.0022	0.0026
	(0.18)	(0.22)	(0.23)
Technical Efficiency Changes	0.1328	0.1268	0.1310
	(12.41)	(12.59)	(11.45)
Worker Effect	0.1447	0.1265	0.1155
	(13.52)	(12.56)	(10.10)
Education	0.1721	0.1565	0.1447
	(16.08)	(15.54)	(12.65)
Health	-0.0274	-0.0300	-0.0292
	(-2.56)	(-2.98)	(-2.55)
Labor Quality Effect	0.1453	0.1024	0.2460
	(13.57)	(10.17)	(21.51)
Education	0.1696	0.1314	0.3153
	(15.84)	(13.05)	(27.56)
Health	-0.0243	-0.0290	-0.0693
	(-2.27)	(-2.88)	(-6.06)

Note: Model 1 corresponds to Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 to a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 to Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$. The values in parenthesis indicate the percentage contribution of each effect to total factor productivity change.

Table 10. Decomposition of TFP Growth for Greek Greenhouse Farms - Average Values for the 2003-07 period. (Reduced Model)

	Average Annual Rate of Change (%)		
	Model 1	Model 2	Model 3
TFP Growth (Accounted-%)	1.1203	1.1203	1.1203
TFP Growth (Estimated-%)	0.9125	0.9188	1.0942
	(100)	(100)	(100)
Scale Effect	-0.0333	-0.0386	-0.0242
	(-3.65)	(-4.39)	(-2.21)
Rate of Technical Change	0.6797	0.6944	0.6916
	(74.49)	(79.02)	(63.21)
Neutral	0.6439	0.6548	0.6604
	(70.56)	(74.51)	(60.35)
Biased Input	0.0358	0.0396	0.0312
	(3.92)	(4.51)	(2.85)
Technical Efficiency Changes	0.1618	0.1564	0.1678
	(17.73)	(17.80)	(15.34)
Labor Quality Effect	0.1043	0.1066	0.2590
	(11.43)	(7.58)	(23.67)
Education	0.1327	0.1323	0.3284
	(14.54)	(15.05)	(30.01)
Health	-0.0284	-0.0257	-0.0694
	(-3.11)	(-3.23)	(-6.34)

Note: Model 1 corresponds to Deolalikar (1988) formulation ,*i.e,* $d_h \neq d_\varepsilon$, Model 2 to a proportional impact of education and health on effective labor that is though not proportional to physical labor *i.e.,* $d_h = d_\varepsilon \neq 1$ and Model 3 to Griliches (1963) formulation, *i.e.,* $d_h = d_\varepsilon = 1$. The values in parenthesis indicate the percentage contribution of each effect to total factor productivity change.

PART III: The Effect of Pesticides Use on Farmer's Productivity Levels

4. INTRODUCTION

Since the seminal paper on the investments in human capital by Schultz (1961), a lot of studies emerged aimed to analyze the effect of human capital improvements on worker's productivity and efficiency (*e.g.*, Becker, 1975; Grossman, 1972). Investments in human capital such as education, health or nutrition were identified to enhance human capabilities to do productive work and therefore to promote economic growth. Investments into the stock of human capital affect the productivity of workers at least in three ways (Ram and Schultz, 1979; Schultz, 1980): *i*) there is a clear implication of an increase in the vitality and the physical ability to engage in work for day to day and a reduction in days lost because of illness, which increase the daily amount of effective work, *ii*) there is an additional incentive to acquire schooling as investment in future earnings accruing over a longer period and, *iii*) there is an increase in entrepreneurial and managerial ability that contributes to efficiency in acquiring information and applying management practices.

Although economists initially focused on human capital investments aimed to explain economic growth at an aggregate level, the investigation of the relationship between human capital and productivity in agricultural sector have also gained interest. Significant losses observed in the stock of farmer's human capital have gradually attracted economists who attempted to identify the causes of these reductions and their consequences on farmer's productivity growth. First, Bliss and Stern (1978) and Strauss (1986) focused on the nutritional level as the most important aspect of farmer's human capital. Their findings indicate that improvements in farmer's nutritional status, in terms of calorie consumption, would have a highly significant effect on labor productivity. Their findings were also established by Deolalikar (1988) and Croppenstedt and Muller (2000) who used the ratio of weight divided by height as a proxy of the nutritional status.

However, nutritional status is the one side of the coin as far as the explanation of the losses in farmer's human capital are concerned. Coye (1985) found out that farm laborers have experienced a much higher rate of illness than any other sector of the economy, due to their systematically exposure to hazardous chemicals. Indeed, pesticides and other chemicals used extensively in agricultural production pose serious health hazards to farm laborers. Unsafe handling, storage and application can cause serious chronic health distortions to farm workers. Affected farmers experience

productivity losses due to impaired work capacity in the field and reduced management abilities due to impaired intellectual capacity. Focusing on pesticides, there is a notably feature that characterizes their relationship with farm or labor productivity. On one hand, pesticides act as a productive input that controls damage from pests, enhancing thus farmers' production, while on the other hand pesticides cause serious health problems to farmers, reducing their productivity performance. This implies that the economic benefits from the pesticides use could be offset by productivity losses from impaired health conditions. The identification of this trade off has important economic and policy implications, since it is the own decision of the farmers regarding pesticides use that determines the magnitude of the two opposite effects on production.

A lot of studies have attempted to identify these tradeoffs. Combining a health function with a crop cost function, Antle and Pingali (1994) analyzed the value of the health effects of pesticides on Philippine rice production. They concluded that the health costs of pesticides outweigh the associated production benefits, revealing a strong impact of pesticides on farmer's health. Using the same data but a different methodological approach, Rola and Pingali (1993) came up with similar results. Using Antle and Pingali's (1994) methodological work, Crissman, Cole, and Carpio (1994) investigated the health effects of pesticides on Ecuadorian potato production, pointing out among others that education and incentives for protective equipment use would enhance farmer's productivity. Along these lines, Antle, Cole and Crissman (1998) conducted a joint estimation of a health production function and a crop production technology in Ecuadorian potato production to show that reductions in the most hazardous pesticides would lead in a win-win outcome in terms of productivity and health gains.

One salient feature stands out from the existent empirical work on the health effects of pesticides, as it was drawn above. Most studies ignore completely the important role of education that contributes significantly to agricultural production (Griliches 1963, 1964; Welsh 1970). As it was argued by Schultz (1961), education and extension programs notably in agriculture, enhance the quality and the productive capacity of farmers. Furthermore, education can help farmers to protect themselves from health damages either by reducing their exposure to health risks or by digesting more easily technical information concerning appropriate pesticide use. Hence, the general level of education together with education related with safe use of pesticides

may provide additional information to farmers about the health consequences of pesticides and be important for their safe use during applications, especially in developing countries (Antle and Capablo, 1994). Nevertheless, not all farmers are affected equally by pesticide exposure. For instance, the health effects of pesticides may vary between field workers and managers, since both the duration of the exposure and the nature of contact with chemicals is different. Furthermore field workers and managers may utilize differently various aspects of human capital. Improvements in health, education and nutrition would affect managers' organizational abilities since educated deciders in good health would have better intellectual abilities. On the other hand, such improvements would enhance field workers capacity in a different manner, increasing their physical ability to engage in manual work and reducing the days lost because of illnesses.

In this paper, we attempt to provide an integrated analysis of the effect of human capital on farmers total factor productivity growth taking into account both the direct and indirect effect of pesticide use in farm production. Inspired by the early ideas of Schultz (1961, 1980), and using the methodological advantages developed by Griliches (1963, 1964) and Antle and Pingali (1994), we provide an analytical decomposition of farmer's TFP growth. The decomposition analysis allows for the identification of the human capital effects along with the pesticides effects on farmers productivity growth. Specifically, assuming that field and management labor are not perfect substitutes (Mundlak, 1961), we augment both labor categories by different amounts of human capital considering two aspects of it, namely education and health. Following Griliches (1963) formulation, we incorporate human capital into our analysis using education and farmer's health as multiplicative augmentations of labor inputs. Laborers' health status is proxied by a health impairment index suggested by Antle and Pingali (1994) extended though to capture pesticides effects related with long exposure and interactions between education and health. Then, using Chan and Mountain (1983) findings, we end up to decompose farmers' total factor productivity growth into four components, namely, scale economies, technical efficiency changes, changes in production technology and, finally, field and management labor quality changes. The empirical model is based on a translog production frontier which is applied to a panel data set of 50 greenhouse farms observed during the 2003-07 period obtained from a primary survey in the region of Ierapetra, Greece.

The remaining paper is organized as follows. In the next section, we present the theoretical framework. Next, the health data and the health impairment model are described, followed by the empirical model. Production data description and the estimation results are presented then. Finally, the conclusions and the summary of the results follow next and the last section contains the tables.

4.1. THEORETICAL FRAMEWORK

Let assume that farmers in period t utilize a vector of variable inputs $\mathbf{x} = \{x_1, x_2 \ldots, x_j\} \in \Re_+^J$, human capital $c \in \Re_+$, labor $l \in \Re_+$, and pesticides $z \in \Re_+$ to produce a single aggregate output $y \in \Re_+$ through a well-behaved technology described by the following non-empty, closed set:

$$T = \{(\mathbf{x}, l, z, c, y) : y \leq f^p(\mathbf{x}, l, z, c, t)\} \tag{53}$$

where $f^p(\mathbf{x}, l, z, c, t) : \Re_+^{J+3} \rightarrow \Re_+$, is a continuous and, strictly increasing, differentiable concave production function, representing the maximal farm output from variable inputs, labor and, pesticides use given farms' human capital and technological constraints. At this point we may assume that field and management labor are not perfectly substitutes, having therefore a different impact on farm productivity growth (Mundlak, 1961). Hence, we may divide the total labor hours devoted to farm production into two categories: *i*) field labor[24] *i.e.,* $l_f \in \Re_+$, denoting the hours worked on farming activities, *e.g.*, harvesting, planting, pruning and, *ii*) management labor, *i.e.,* $l_m \in \Re_+$, denoting the hours devoted to decisions related with on farm production.

Following Griliches (1963), Bliss and Stern (1978) and Strauss (1986) we further assume that human capital augments ineffective working hours devoted in either field or management labor. Specifically, we assume that effective labor units (*i.e.*, field or management) are determined by both the educational level and the health status of farm laborers. Hence, effective labor units can be expressed as:

$$l_k^e = f_k^l(l_k, h_k, \varepsilon_k), \;\; k = f, m \tag{54}$$

where $l_k \in \Re_+ \ \forall k = f, m$ denotes field and management labor, $\varepsilon_k \in \Re_+$ and $h_k \in \Re_+$ are the education level and health status of farm laborers, respectively[25] and, $f_k^l\left(l_k, h_k, \varepsilon_k\right) \in \Re_+^3 \to \Re_+$ is assumed to be a continuous and, strictly increasing concave in all its arguments, differentiable function representing effective field or management labor units given ineffective labor, health status and education level.

According to Antle and Pingali (1994) farmer's health status is assumed to be affected by pesticide use. Introduction of pesticide materials constituted a breakthrough chemical innovation that raised land productivity in both developed and developing countries (Hayami and Ruttan, 1985). However, both anecdotal evidence and available data worldwide indicate that farmers do not typically utilize recommended doses of pesticides nor do they utilize recommended practices for safe storage, handling and application (Rola and Pingali, 1993; Cowan and Gunby, 1996). Therefore pesticide application has two effects on farms' productivity: a *direct effect* as a variable input to control damage from pests and, an *indirect effect* on human health through the chronic effects that pesticide exposure has on laborers' health. These adverse effects are lessened though when more farmers follow recommended practices which is directly linked with their educational level. Obviously more educated farmers may protect themselves from health damages either by reducing their exposure to health risks or by digesting more easily technical information concerning appropriate pesticide use. Further, farmer-specific characteristics like nutritional status or habits like smoking or drinking may also deteriorate health problems caused by inappropriate pesticide application. Hence, individual health status for both field and management labor can be proxied by the following *health* function:

$$h_k = f_k^h\left(\varepsilon_k, z, \mathbf{d}_k\right), k = f, m \tag{55}$$

where $\varepsilon_k \in \Re_+$ is an education index for the kth labor input, $z \in \Re_+$ is pesticides use and $\mathbf{d}_k = \left\{d_{k1}, d_{k2}, \ldots, d_{ks}\right\} \in \Re_+^s$ are laborer-specific nutritional or other characteristics that affect individual health status. The health function $f_k^h\left(\varepsilon_k, z, \mathbf{d}_k\right) \in \Re_+^{S+2} \to \Re_+$ is assumed to be continuous and differentiable function non-decreasing in the education

level $\left(i.e.,\ \partial f_k^h / \partial \varepsilon_k \geq 0\right)$ and non-increasing in pesticide use $\left(i.e.,\ \partial f_k^h / \partial z \leq 0\right)$. It's monotonicity property with respect to the **d**-vector depends on the choice of variable included therein and whether these enhance or deteriorates health status. This in turn implies that, farms' human capital is determined by laborers individual education levels, pesticide use in farm production and laborer-specific characteristics.

Under these assumptions, we may redefine the technology set in (53) as:

$$T = \left\{\left(\mathbf{x}, l_k, z, \varepsilon_k, \mathbf{d}_k, y\right) : y \leq f^p\left(\mathbf{x}, l_k^e, z, t\right),\ l_k^e = f_k^l\left(l_k, z, \varepsilon_k, \mathbf{d}_k\right)\right\},\ k = f, m \tag{56}$$

with all terms as defined earlier. Using (56) we may define the input correspondence set $L(y) = \left\{\left(\mathbf{x}, l_k, z, \varepsilon_k, \mathbf{d}_k\right) : \left(\mathbf{x}, l_k, z, \varepsilon_k, \mathbf{d}_k, y\right) \in T\right\},\ k = f, m$ as all input combinations capable of producing $y \in \Re_+$. The input set is assumed to be closed and convex satisfying strong disposability of field and management labor, pesticides and variable inputs. Since we allow for free disposability inputs, farmers may not be technical efficient, failing to maximize output for a given bundle of inputs, given the technological constraints and human capital variables. This implies that:

$$y = f^p\left(\mathbf{x}, l_k^e, z, t\right) \cdot TE^O,\ k = f, m \tag{57}$$

where TE^O is farm's output technical efficiency defined as:[26]

$$TE^O = \left[\max_{\theta}\left\{\theta : \theta y = f^p\left(\mathbf{x}, l_k^e, z, t\right),\ l_k^e = f_k^l\left(l_k, z, \varepsilon_k, \mathbf{d}_k\right)\right\}\right]^{-1},\ k = f, m \tag{58}$$

Taking logarithms in both sides of equation (57) and totally differentiating with respect to time, we get:

$$\begin{aligned} \dot{y} = TC + \dot{TE}^O + \sum_j e_j^x \dot{x}_j + \sum_k e_k^l \dot{l}_k + e^z \dot{z} \\ + \sum_k e_k^{l^e}\left[\left(e_{k\varepsilon}^{l^e} + e_{kh}^{l^e} e_{k\varepsilon}^h\right)\dot{\varepsilon}_k + \sum_s e_{kh}^{l^e} e_{ks}^h \dot{d}_{ks}\right] \end{aligned} \tag{59}$$

where a dot over a variable indicates its time rate of change, $e_j^x = \partial ln\, f^p(\bullet)/\partial ln\, x_j$ is the output elasticity of the jth variable input, $e_k^l = e_k^{l^e} \cdot e_{kl}^{l^e}$ is the output elasticity of field and management labor inputs with $e_k^{l^e} = \partial ln\, f^p(\bullet)/\partial ln\, l_k^e$ and $e_{kl}^{l^e} = \partial ln\, f_k^l(\bullet)/\partial ln\, l_k$ being the output elasticity of effective labor and the effective labor elasticity of ineffective labor, respectively, $e^z = e_z^D + e_z^I$ is the total output elasticity of pesticides and $e_z^D = \partial ln\, f^p(\bullet)/\partial ln\, z$, $e_z^I = \sum_k \partial ln\, f_k^l(\bullet)/\partial ln\, z$ are the direct and indirect output elasticities of pesticides, respectively. The latter is further decomposed into $e_z^I = \sum_k e_k^{l^e} e_{kh}^{l^e} e_{kz}^h$ with $e_{kh}^{l^e} = \partial ln\, f_k^l(\bullet)/\partial ln\, h_k$ and $e_{kz}^h = \partial ln\, f_k^h(\bullet)/\partial ln\, z$ being the effective labor elasticity of health status and the health elasticity of pesticides use, respectively. Finally, $e_{k\varepsilon}^{l^e} = \partial ln\, f_k^l(\bullet)/\partial ln\, \varepsilon$ is the effective labor elasticity of education, $e_{k\varepsilon}^h = \partial ln\, f_k^h(\bullet)/\partial ln\, \varepsilon$ is the health elasticity of education level and, $e_{ks}^h = \partial ln\, f_k^h(\bullet)/\partial ln\, d_{ks}$ is the health elasticity of laborer-specific characteristics.

Following Griliches (1963; 1964) we may assume that field and management labor and human capital are perfect substitutes (Acemoglu and Zilibotti, 2001). Then the effective labor units can be expressed as multiplicative augmentations of the corresponding physical labor units and human capital, *i.e.*, education level and health status.[27] Thus, under Griliches (1963) formulation, relation (55) can be specified as:

$$l_k^e = l_k \cdot h_k(\varepsilon_k, z, \mathbf{d}_k) \cdot \varepsilon_k, \quad k = f, m \tag{60}$$

Relation (60) implies that the effective labor elasticity of ineffective field and management labor and the effective labor elasticity of health status are equal to one, *i.e.*, $e_{kl}^{l^e} = e_{kh}^{l^e} = 1\ \forall k$, and that the output elasticities of effective labor units equal the corresponding output elasticities of the ineffective labor units as $e_k^l = e_k^{l^e} \cdot e_{kl}^{l^e} \Rightarrow e_k^l = e_k^{l^e}\ \forall k$. Hence, relation (59) becomes:

$$\dot{y} = TC + \dot{TE}^{O} + \sum_{j} e_{j}^{x}\,\dot{x}_{j} + \sum_{k} e_{k}^{l}\,\dot{l}_{k} + e^{z}\,\dot{z} + \sum_{k} e_{k}^{l}\left[\left(1+e_{k\varepsilon}^{h}\right)\dot{\varepsilon}_{k} + \sum_{s} e_{ks}^{h}\,\dot{d}_{ks}\right] \qquad (61)$$

decomposing, thus, output growth into four main effects, that is, the technical change effect (first term), the technical efficiency effect (second term), the scale effect (next three terms) and the field and management labor quality effect (last term).

Since the qualitative effect of labor contribute to productivity changes (Schultz, 1961), the labor quality effect appearing in the last term of equation (61) should be part of the productivity growth rather than part of the input growth. Thus, we introduce at this point Kendrick's (1961) divisia index of TFP growth *i.e.,* $\dot{TFP} = \dot{y} - \sum_{j} S_{j}^{x}\,\dot{x}_{j} - \sum_{k} S_{k}^{l}\,\dot{l}_{k} - S^{z}\,\dot{z}$, that allows for the identification of those qualitative effects in the productivity growth component, where S_{j}^{x}, S_{k}^{l} and S^{z}, are the cost shares of the *j* variable inputs, field and management labor inputs, and pesticides, respectively. Solving the dual cost minimization problem defined as

$$C\left(\mathbf{w}, y, \varepsilon_{k}, \mathbf{d}_{k}\right) = \left\{\sum_{j} w_{j}^{x} x_{j} + \sum_{k} w_{k}^{l} l_{k} + w^{z} z : y \le f^{p}\left(\mathbf{x}, l_{k}^{e}, z, t\right),\ l_{k}^{e} = f_{k}^{l}\left(l_{k}, z, \varepsilon_{k}, \mathbf{d}_{k}\right)\right\} \qquad (62)$$

and using the first-order conditions,[28] we end up with similar to Chan and Mountain (1983) results, *i.e.*, $S_{j}^{x} = e_{j}^{x}/E$, $S_{k}^{l} = e_{k}^{l}/E$ and $S^{z} = e^{z}/E$, where $E = \sum_{j} e_{j}^{x} + \sum_{k} e_{k}^{l} + e^{z}$ are the returns of scale. Substituting the divisia index of TFP growth into (61) and using Chan and Mountain (1983) findings, yields:

$$\begin{aligned} \dot{TFP} = \left(\frac{E-1}{E}\right)\left(\sum_{j} e_{j}^{x}\,\dot{x}_{j} + \sum_{k} e_{k}^{l}\,\dot{l}_{k} + e^{z}\,\dot{z}\right) + TC + \dot{TE}^{O} \\ + \sum_{k} e_{k}^{l}\left[\left(1+e_{k\varepsilon}^{h}\right)\dot{\varepsilon}_{k} + \sum_{s} e_{ks}^{h}\,\dot{d}_{ks}\right] \end{aligned} \qquad (63)$$

which constitutes the final decomposition formula of TFP growth. The first term measures the relative contribution of scale economies to TFP growth. The term is

zero under constant returns to scale while it is positive (negative) under increasing (decreasing) returns to scale as long as inputs increase over time and *vice versa*. The second term is the technical change effect, capturing shifts of the production frontier. It is positive (negative) under progressive (regressive) technical change while it is zero under no technical change. Next is the effect of technical efficiency changes that refers to movements toward or away from the production frontier. It contributes positively (negatively) to TFP growth as long as technical efficiency increases (decreases) over time. The last term is the quality effect of field and management labor on TFP growth which is further decomposed into two components. The first component measures the effect of changes in laborers' education level on the effective labor units as well as on their relative health status. The term vanishes when laborer's educational level remain constant over time. The second component refers to the effect of laborers' personal characteristics on their state of health. The term have a positive (negative) impact on TFP growth, when positive changes in laborer's personal characteristics affect positively (negatively) their state of health and *vice versa*. Finally, the overall quality effect on TFP growth is zero as long as both education and laborer's characteristics remain unchanged over time.

Using relation (63) we can identify the total effect of pesticides on farmers' individual TFP growth. First, there is a direct associated with the damage control of pest population mitigating the negative impacts of pest infestation on farm and, an indirect effect arising from inappropriate use of pesticides by farmers and the associated health problems that reduce farmers' human capital. Second, there is an another effect coming from changes in production technology over time which may enhances or not pesticide use (*e.g.*, introduction of integrated pest management techniques may affect pesticide use on farm). Under Griliches (1963) formulation of farm production frontier model, these effects can be shown from the following relation:

$$\dot{TFP}_z = \left(\frac{E-1}{E}\right)\left(e_z^D + \sum_k e_k^l e_{kz}^h\right)\dot{z} + TC_z \qquad (64)$$

where $\dot{TFP}_z$ stands for the overall effect of pesticides on farms' TFP growth. The first term on the right hand side of equation (64) refers to the total scale effect of

pesticides which is composed of two components. The first component is the direct scale effect that is positive (negative) under increasing (decreasing) returns to scale as long pesticides use increase over time and *vice versa*. It is the damage control effect of pesticide use arising from mitigating pest infestation on crop production. The second component is the indirect scale effect of pesticides, capturing impairments in laborers' health (field workers and managers) due to pesticides use. The term is positive (negative) under decreasing (increasing) returns to scale as long as pesticides affect negatively laborer's health and pesticides use increases over time and *vice versa*. The total scale effect of pesticides is zero as long pesticides use remains constant over time or under constant returns to scale. The last component of equation (64) is the biased part of technical change related with pesticides use. It is positive (negative) under pesticides using (saving) technical change and zero under pesticides neutral technical change.

Under constant returns to scale, the overall pesticides effect on TFP growth is positive (negative) as long as technical change is pesticides using (saving). In the case of variable returns to scale, the overall effect is unclear, depending on the relative contribution of the various terms. Specifically, under decreasing (increasing) returns to scale and pesticides using (saving) technical change, the overall pesticide effect is positive (negative) as long as pesticides use increases over time and impairments in laborers' health due to pesticides use dominate the direct scale effect of pesticides. Finally, the overall effect of pesticides on farmers' TFP growth is zero under constant returns to scale and pesticides neutral technical change.

4.2. HEALTH IMPAIREMENT INDEX MODELS

A health data survey has been conducted for the purposes of this study involving 50 small greenhouse farms randomly selected from Ierapetra Region located in the Southern part of the island of Crete in Greece. The survey covers a five years period from 2003 to 2007. Greenhouse farmers in this region of Greece are using extensively hazardous chemical pesticides over the last decades, neglecting though to use or using insufficiently protective equipments. Due to space limitations in greenhouses, pesticides are applied by farmers using backpack sprayers instead of tractors or other aerial applications, rendering themselves more likely to excessive exposure. The lack of air refreshment in greenhouses contributes further to the

aggravation of the problem. As a result, it has been recorded an important number of farmers who suffered systematically from serious health problems associated with exposure to chemical elements. Beside social problem of deteriorating farmers health status, these problems have also important economic implications since they could be interpreted as losses in farmers' stock of human capital that could decrease farmer's productivity as a consequence of the decrease in their physical ability to engage in work from day to day and the increase in the days lost because of illness.

During the survey, repeated personal interviews were carried out by a team of experts consisted by an agronomist, a specialist doctor and an agricultural economist in order to obtain an accurate data set and to minimize measurement errors.[29] The medical records of all active members of the included households were examined in detail and additional medical information together with production data information were asked for five crop seasons from 2003-07. Following Antle and Pingali (1994), we have examined five categories of health problems related with exposure to pesticides, namely, eye problems, dermal problems, respiratory problems, neurological problems and kidney problems.[30] These categories are also identified by World Health Organization as the main consequences of inappropriate pesticide use. The clinical symptoms accompanied the health problems were deeply investigated by the specialist doctor after personal meetings with each farmer and the health problems related with pesticides applications were therefore identified.

Table 1 presents the summary statistics of the health problems observed in each category during the period under consideration. Over the five-year period, 313 cases of illnesses were totally recorded to be related with the use of pesticides.[31] The most frequent met category was found to be the respiratory problems observed in 176 cases, followed by dermal problems (55 cases) and eye problems (40 cases), while the less frequent observed categories were found to be the neurological and kidney problems (4 cases in total). The third column of table 1 contains the average recuperate days that is the days required for the farmer to fully recover from an illness. The average value was found to be 18.9 days, while not significant variations were observed across the different categories. The next two columns in table 1 provide information about the average days that farmers did not work because of illnesses and their personal perceptions about the percentage reduction of their efficiency performance for the days that although they suffer from a specific health problem, they still worked. The mean not-work days were calculated to be 9.9 while

their personal perceptions regarding the percentage reduction of their efficiency was found to be 55% on average. The last column in table 1 includes the mean medical cost of treatment for each category. The average medical cost was measured to be 217 Euros, while again not important cost differences are met along the different categories, except of the kidney category that appears a very low medical cost (100 Euros) which is though generated by only two observations.

The total cost of treatment discussed above was used in this study as the basis for the approximation of farmer's health impairment. Although, this measure ignores important dimensions of health impairment such as losses of leisure and changes in life expectancy (Cropper and Freeman, 1991), it still remains a reliable measure of farmer's health status since the aim of this analysis is mainly to capture the potential disabilities of farmers to engage in field work and management because of illnesses. Averting expenditures are also likely to account for health impairment, but since no significant variation in averting behavior among farmers was observed, their importance is minimum. However, still our measure may suffer by a downward bias since not all health problems are reported by the farmers and not all chronic effects of pesticides are captured. Therefore, the measure of health impairment may provide an underestimation of the real health status of the farmers.

Following the environmental economics literature and the work of Antle and Pingali (1994), a health production function was estimated for each labor category using laborer's education, exposure to pesticides, and laborer's nutritional status and age as explanatory variables. Unlike with Anlte and Pingali (1994), personal habits of farmers such as smoking and drinking were omitted since there is no empirical economic evidence to support their significance on farmer's health. On contrary, education was included among the variables explaining laborer's health impairment, since the general level of education together with education related with safe use of pesticides may provide additional information to farmers about the health consequences of pesticides and be conducive for their safe use during applications, especially in developed countries (Antle and Capablo, 1994).[32] Furthermore, pesticides exposure was proxied by the value of pesticides used instead of the number of application, since the doses may vary among applications over time. Five different types of chemicals were found among the pesticides used by the greenhouse farmers in the sample for the period analyzed. All chemicals identified, were belonging in the first category of the most hazardous chemicals as it is provided by World Health

Organization. Thus, one category of pesticides was considered in this study to account for laborer's health impairment.[33]

Two health impairment index models have been estimated for field and management labor, respectively, since both the duration of the exposure to pesticides and the nature of contact with chemicals may vary between field workers and managers. Despite the high data requirements associated with the collection of human capital information for field workers and management labor, our approach is accurate enough since the data has been collected mainly by small farms that did not occupy hired workers. Furthermore, in all cases the manager of the farm was found to be the male head of the household, who divided his work hours between field work and management. This allows for the identification of human capital data into the active family members which enhances the reliability of the obtained data. Moreover, the data allow the estimation of health impairment for a five-year period, instead of a single season, enabling the identification of health problems associated with long term exposure to pesticides. This may further reduce any bias in the results.

Specifically, we have estimated the following log-linear regression model to approximate both field workers and managers' health impairment index:

$$-ln\, h_{kit} = b_k^0 + b_k^{\varepsilon}\, ln\, \varepsilon_{kit} + b_k^z\, ln\, z_{it} + b_k^A\, ln\, A_{kit} + b_k^N\, ln\, N_{kit} + v_{kit}^h \qquad (65)$$

where $k = f, m$ is family field labor and management, $i = 1,\ldots,N$ are the farms in the sample, $t = 1,\ldots,T$ are the time periods and h_{kit} is the health impairment of the ith laborer in category k in time t, defined as the average sum of the treatment cost plus the opportunity cost of the laborer's time required to recuperate.[34] Similarly, ε_{kit} is an index of the average laborer's education,[35] z_{it} is pesticides use, A_{kit} is the average age of laborer's and N_{kit} is the average nutritional status of laborer's, defined as the ratio of weight divided by the height. Finally v_{kit} is assumed to be a normally distributed error term with zero mean and a constant variance, *i.e.,* $v_{kit}^h \sim N\left(0, \sigma_{v^h}^2\right)$

Descriptive statistics for the variables used to estimate the health impairment indexes are presented in table 2. Since management was always conducted by the head of the family, the values presented in the lower panel of the table constitute the means of the corresponding variables for the head of the family in the sample. The

upper panel of the table illustrates the mean values for the family members working on field. In each farm, these values were calculated as the weighted average of the family members (including the head of the family) using as weight the time share devoted in field work. The mean value of the education index was calculated to be 9.6 (9.2) for family field labor (manager), presenting significant variations across farms for both labor categories but being about the same between the two categories. The average pesticides use measured in euros is varying into a range from 358 to 9,857 Euros with the mean value to be 2,624 Euros. The mean age of the family field labor (manager) was found to move from 20 (21) to 60 (69) years with the mean value to be 39 (46) years, while the average nutritional levels were measured to be 0.47 and 0.52 for family field labor and the household heads, respectively.

The OLS estimation results of the health impairment index models are illustrated in Table 3. All the parameters in both models were found to be statistically significant at least on the 5% level, while the signs of the coefficients were identified to be as expected, indicating a positive relation between health and, education and nutritional status. The results also reveal a strong negative effect of pesticides and aging on farmers' health. Comparing the estimation results from the two models, useful conclusions can be obtained about the relative impact of the different explanatory variables on the health status of the two labor categories. Specifically, increases in education were found to improve more manager's health status, while pesticides have almost the half impact on the health of family field labor in comparison with manager's health. Finally, improvements in nutritional status have a greater impact on manager's health, while aging effect does not present any significant variation between labor categories, contributing insignificantly to their health status.

4.3. FARM PRODUCTION FRONTIER MODEL

For the decomposition of farmer's TFP growth and the quantitative measurement of overall pesticide use effect we hinge on a translog specification of the production frontier model in (57). This particular flexible functional specification allows for variable returns to scale, input-biased technical change and farm- and time-varying output elasticities, permitting at the same time the conduction of statistical testing for various features of farm production technology. Human capital is introduced into the

production function following Griliches approach (1963) as it is shown in equation (60). Laborer's health status is proxied by the exponential value of the predicted health impairment index, while education is proxied by an index of formal and informal education, the same used for the estimation of the health impairment model (see endnote 12). Specifically, the following translog production frontier model was considered:

$$\begin{aligned} ln\, y_{it} = {} & \beta^0 + \beta_t t + \sum_j \beta_j^x \, ln\, x_{jit} + \sum_k \beta_k^l \, ln\, l_{kit}^e + \beta^z \, ln\, z_{it} + \sum_j \beta_{jt}^x \, ln\, x_{jit} t + \\ & \sum_k \beta_{kt}^l \, ln\, l_{kit}^e t + \beta_t^z \, ln\, z_{it} t + 0.5 \Bigg[\beta_{tt} t^2 + \sum_j \sum_\rho \beta_{j\rho}^{xx} \, ln\, x_{jit} \, ln\, x_{\rho it} + \\ & \sum_k \sum_\lambda \beta_{k\lambda}^{ll} \, ln\, l_{kit}^e \, ln\, l_{\lambda it}^e + \sum_j \sum_k \beta_{jk}^{xl} \, ln\, x_{jit} \, ln\, l_{kit}^e + \sum_j \beta_j^{xz} \, ln\, x_{jit} \, ln\, z_{it} + \\ & \sum_j \beta_k^{lz} \, ln\, l_{kit}^e \, ln\, z_{it} + \beta^{zz} \, ln\, z_{it}^2 \Bigg] + v_{it}^p \end{aligned} \tag{66}$$

and

$$ln\, l_{kit}^e = ln\, l_{kit} + ln\, \hat{h}_{kit} + ln\, \varepsilon_k, \quad k = f, m \tag{67}$$

where $i = 1, \ldots, N$ are the farmers in the sample, $t = 1, \ldots, T$ are the time periods, $j = 1, \ldots, J$ are variable inputs used in the production process, $k = f, m$ is field and management labor, z_{it} is the quantity of pesticides used on farm production, $\hat{h}_{kit}$ is the predicted health impairment index for the kth labor input obtained from (43), β's are the parameters to be estimated and, v_{it}^p is a symmetric and normally distributed error term, $v_{it}^p \sim N\left(0, \sigma_{v^p}^2\right)$, (*i.e.*, statistical noise), representing the omitted explanatory variables and measurement errors in the dependent variable.

Following Cornwell, Schmidt and Sickles (1990) fixed effects specification, β^0 are assumed to be farm and period specific intercepts introduced into (44) in order to capture temporal variations in output technical efficiency as $\beta_{it}^0 = \beta_t^0 - \xi_{it}$. According to this formulation output technical inefficiency is assumed to follow a quadratic pattern over time, *i.e.*,

$$\xi_{it} = \zeta_{i0} + \zeta_{i1} t + \zeta_{i2} t^2 \tag{68}$$

where, ζ_{i0}, ζ_{i1} and ζ_{i2} are the $(N \times 3)$ unknown parameters to be estimated.

The model in (66) and (67) was estimated in two-steps allowing the distinction between technical change and time-varying technical efficiency. Specifically, *β's* parameters in (66) are estimated using a simple OLS regression on the within-means transformed variables and then the residuals for each farmer in the panel are regressed on time and time-squared as in (68) to obtain estimates of *ζ*'s for each farm in the sample. Then, defining $\beta_t^0 = \max_i \{\xi_{it}\}$ as the estimated intercept of the production frontier in period *t*, the output technical efficiency of each farm in period *t* is then estimated as:

$$TE_{it}^{O} = exp(-\xi_{it}) \tag{69}$$

where $\xi_{it} = \left(\hat{\beta}_t^0 - \hat{\beta}_{it}\right)$. A direct implication of the above specification is that in each period at least one farm is fully efficient, although the identity of this farm may vary through years. The advantages of this specification are its parsimonious parameterization regardless of functional form, its straightforward estimation, its independence of distributional assumptions, and that it allows output technical inefficiency to vary across farms and time. Moreover, since the expression in (68) is linear to its parameters, the statistical properties of individual farmers-effects are not affected.

Using (69) the effect of changes in output technical efficiency on individual TFP growth is measured as (Fecher and Pestieau, 1993):

$$\dot{TE}_{it}^{O} = \frac{\partial \xi_{it}}{\partial t} = \zeta_{1i} + 2\zeta_{2i} t \tag{70}$$

If $\zeta_{i1} = \zeta_{i2} = 0 \quad \forall i$, then output technical efficiency is time-invariant, while when $\zeta_{i1} = \zeta_1$ and $\zeta_{i2} = \zeta_2 \; \forall i$ then output technical efficiency is time-varying following, however, the same pattern for all farms in the sample.

Having introduced a specific functional form for the farm production frontier, we can identify all terms appearing in (66) and (68). First, we derive the health elasticities from equation (65) as:

$$e_{k\varepsilon}^{h} = \frac{\partial \ln f_k^h}{\partial \ln \varepsilon_k} = b_k^{\varepsilon} \tag{71}$$

$$e_{kz}^{h} = \frac{\partial \ln f_k^h}{\partial \ln z} = b_k^{z} \tag{72}$$

$$e_{kA}^{h} = \frac{\partial \ln f_k^h}{\partial \ln A_k} = b_k^{A} \tag{73}$$

$$e_{kN}^{h} = \frac{\partial \ln f_k^h}{\partial \ln N_k} = b_k^{N} \tag{74}$$

Equations (71), (73) and (74) are necessary for the identification of the field and management quality effect appearing in the last term of (63) while equation (72) is required for the estimation of the indirect scale effect of pesticides in the first term of (63).

Next, the output elasticities necessary to identify the scale effect in (63) are estimated under Griliches (1963) augmentation of ineffective labor $\left(i.e.,\ e_k^l = e_k^{l^e}\right)$ from the following relations:

$$\begin{aligned} e_j^x = \frac{\partial \ln y_{it}}{\partial \ln x_{jit}} &= \beta_j^x + \beta_{jt}^x t + \beta_j^{xx} \ln x_{jit} + \\ &0.5\left(\sum_{\rho} \beta_{\rho j}^{xx} \ln x_{\rho it} + \sum_{k} \beta_{jk}^{xl} \ln l_{kit}^e + \beta_j^{xz} \ln z_{it} \right) \end{aligned} \tag{75}$$

$$\begin{aligned} e_k^l = \frac{\partial \ln y_{it}}{\partial \ln l_{kit}^e} &= \beta_k^l + \beta_{kt}^l t + \beta_{kk}^{ll} \ln l_{kit}^e + \\ &0.5\left(\sum_{j} \beta_{jk}^{lx} \ln x_{jit} + \sum_{\lambda} \beta_{k\lambda}^{ll} \ln l_{\lambda it}^e + \beta_k^{lz} \ln z_{it} \right) \end{aligned} \tag{76}$$

$$\begin{aligned} e_z^D = \frac{\partial \ln y_{it}}{\partial \ln z_{it}} &= \beta^z + \beta_t^z t + \beta^{zz} \ln z_{it} + \\ &0.5\left(\sum_{j} \beta_j^{xz} \ln x_{jit} + \sum_{k} \beta_k^{lz} \ln l_{kit}^e \right) \end{aligned} \tag{77}$$

$$e_z^I = \sum_k \Big[\beta_k^l + \beta_{kt}^l t + \beta_{kk}^{ll} \ln l_{kit}^e + 0.5\left(\sum_j \beta_{jk}^{lx} \ln x_{jit} + \sum_{\lambda \neq k} \beta_{k\lambda}^{ll} \ln l_{\lambda it}^e + \beta_k^{lz} \ln z_{it} \right) \Big] b_k^z \tag{78}$$

with $e^z = e_z^D + e_z^I$. The hypothesis of constant returns-to-scale can be statistically tested by imposing the restriction that $\sum_j \beta_j^x + \sum_k \beta_k^l + \beta^z = 1$, $\beta_{j\rho}^{xx} = \beta_{k\lambda}^{ll} = \beta_{jk}^{xl} = \beta_j^{xz} = \beta_k^{lz} = \beta^{zz} = 0$, and $\sum_j \beta_{jt}^x + \sum_k \beta_{kt}^l + \beta_t^z = 0$, $\forall\, j,\, k,\, \rho,\, \lambda$. If this hypothesis cannot be rejected then the underlying technology exhibits constant returns-to-scale and the scale effect in equation (63) vanishes.

Finally, for the estimation of the technical change effect, we need to compute the rate of technical change from equation (66), that is:

$$TC = \frac{\partial \ln y_{it}}{\partial t} = \beta_t + \beta_{tt} t + \sum_j \beta_{jt}^x \ln x_{jit} + \sum_k \beta_{kt}^l \ln l_{kit}^e + \beta_t^z \ln z_{it} \tag{79}$$

The hypothesis of *Hicks* neutral and zero technical change, is tested by imposing $\beta_{jt}^x = \beta_{kt}^l = \beta_t^z = 0$ and $\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_{kt}^l = \beta_t^z = 0 \;\forall\, j,\, k$, respectively, in (79). Finally, the biased pesticide component necessary for the identification of the last term in (64) on the decomposition of overall pesticide effect is calculated as $TC_z = \beta_t^z \ln z_{it}$.

4.4. PRODUCTION DATA AND EMPIRICAL RESULTS

All surveyed farms included to the dataset were asked to provide analytical information about their farm production, outputs produced and variable inputs employed. Particular emphasis was placed on the use of pesticides and on the allocation of their time between management and field labor. One output and six variable inputs were distinguished. Output was measured in euros as the total revenues coming up from greenhouse production, including three crops, namely,

tomatoes, cucumbers and peppers. The six variable inputs that were taken into consideration were: *a*) land measured in stremmas (one stremma equals 0.1 ha), *b*) all kinds of chemical fertilizers measured in euros, *c*) intermediate inputs including energy, fuels, and irrigation water measured in euros, *d*) field labor measured in working hours, *e*) management labor measured in working hours devoted to management decision related to farm activities, and *f*) pesticides measured in Euros.[36]

All monetary variables were converted into 2000 constant prices using the agricultural production price index published by the National Statistical Service of Greece. All outputs and inputs used in the analysis were aggregated using Divisia indices with revenues and cost shares used as weights during the aggregation procedure. Furthermore, to avoid errors associated with measurement units, all variables were converted into indices, using the corresponding variables' mean values as the basis of the normalization. Table 4 presents the descriptive statistics of the variables used in the estimation procedure.

The fixed effects parameter estimates of the translog production frontier in equation (66) and (67) are presented in Table 5. All the first-order parameter *i.e.,* β_j^x, β_k^l and β^z, were found to have the expected positive sign, while their magnitudes were found to vary between zero and one, implying that the bordered *Hessian* matrix of the first- and second-order partial derivatives is negative semi-definite indicating that all regularity conditions hold at the point of approximation, *i.e.*, sample means. In turn, this implies that all marginal products are positive and diminishing and that the production frontier is locally quasi-concave. In the lower panel of Table 5 are also reported the parameters of the Cornwell, Schmidt and Sickles (1990) inefficiency effects model for the farm with the maximum efficiency score. All the ζ_{i0} parameters were found to have positive signs with their magnitude to range from zero to one. The ζ_{i1} and ζ_{i2} parameters were found to be positive for the majority of the farms in the sample implying improvements in output technical efficiency over time.

Based on the parameter estimates, we have computed basic features of the production structure for Greek greenhouse farms, namely, output elasticities and returns-to-scale, that are presented in Table 6. All output elasticity estimates were found to be statistical significant at least at the 5 per cent level, revealing land as the most important input, contributing the most to Green-house production and followed by pesticides, intermediate inputs, fertilizers, effective field labor, and effective

management. The results of the estimated output elasticities imply that *ceteris paribus*, 1 per cent increase in land, fertilizers, intermediate inputs, effective labor, effective management and pesticides would have as a result a percentage increase of 0.343, 0.088, 0.184, 0.076, 0.050 and 0.226 in farmers' output, respectively. Furthermore, the returns-to-scale were found to be decreasing (0.969) on average, implying that a proportional percentage increase in all inputs would result in a 3 per cent lower increase in output.

Several hypotheses concerning model specification have been tested and the results are presented in Table 7.[37] First the hypothesis of constant returns to scale *i.e.,* $\sum_j \beta_j^x + \sum_k \beta_k^l + \beta^z = 1$, $\beta_{j\rho}^{xx} = \beta_{k\lambda}^{ll} = \beta_j^{xz} = \beta_k^{lz} = \beta^{zz} = 0$ and $\sum_j \beta_{jt}^x + \sum_k \beta_{kt}^l + \beta_t^z = 0$ $\forall\, j,\, k\, ,\rho,\lambda$ was tested using the generalized likelihood ratio test. The hypothesis was rejected at 5 per cent level, implying that the scale effect contributes significantly to farmer's productivity growth. Next, the hypothesis of zero technical change *i.e.,* $\beta^t = \beta^{tt} = \beta^{jt} = \beta^{l_k t} = \beta^{zt} = 0\ \forall\, j,\, k$ and *Hicks*-neural technical change *i.e.,* $\beta_{jt}^x = \beta_{kt}^l = \beta_t^z = 0\ \forall\, j,\, k$ were examined. Both hypotheses were rejected at 5 per cent level, revealing also technical change as a significant source of farmer's productivity. The parameter estimates related with the neutral component of the rate of technical change *i.e.,* β_t and β_{tt} were found to be positive, implying that technical change was progressive over the period under consideration. On the other hand, the parameter estimates related with the biased component of the rate of technical change *i.e.,* β_{jt}^x, β_{kt}^l and β_t^z indicate that technical change was fertilizer, management and pesticides using and field labor saving for the time period under consideration.

The final set of statistical testing refers to the specification of output technical efficiency and it's temporal pattern. The results are reported in the lower panel of table 7. Statistical testing using LR-test rejects the hypotheses of zero and time invariant technical efficiency i.e., $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0\ \forall i$, and $\zeta_{i1} = \zeta_{i2} = 0,\ \forall i$, respectively, at a 5 per cent significant level, implying that changes in output technical efficiency contribute significantly to farmers' TFP growth for the period under consideration. Moreover, the temporal pattern of output technical efficiency was found to vary across farmers in the sample, since the hypothesis that $\zeta_{i1} = \zeta_1$ and $\zeta_{i2} = \zeta_2\ \ \forall i$ was also rejected from the generalized LR-test. The estimates of the

output technical efficiency obtained via equation (69) are reported in the form of frequency distribution within a decile range in Table 8. Farmers' output technical efficiency was found to be slightly increasing for the five-year period. It's mean score was estimated to be 81.03 per cent, indicating that output could have been increased approximately by 19 per cent if technical inefficiency was eliminated.

Using the obtained estimates, we have computed the various components of farmer's TFP growth as they appear in equation (63). Table 9 presents the average values of TFP changes and it's decomposition over both farms and time periods. First in the table appears the average annual rate of farmer's productivity growth and then the relative percentage contribution of each effect. During the five-year period, the mean annual TFP growth for the Greek Greenhouse farms was 1.282 per cent. The greatest share of that growth (53.24 per cent) was due to the rate of technical change, driven mainly by the neutral part (50.48 per cent), while the smallest share was due to the biased technical change effect (2.76 per cent). Field labor and management quality effects were found to be the next most important sources, explaining about 20.77 and 17.84 per cent of the increase in productivity growth. The greatest portion of the quality effects was due to improvements in field workers and managers' education that were found to contribute 23.45 and 20.10 per cent to farmers' productivity, respectively, while impairments in their health status were found to account for 2.68 and 2.26 per cent reductions in farmers' productivity. The effects of health impairment on TFP were found to be explained more by deteriorations in nutritional status and much less by aging for both labor categories. Increases in technical efficiency were also a significant component of TFP growth for this period, contributing 11.92 per cent to farmers' productivity, while scale effect (-3.77 per cent) was found to reduce the rate of TFP growth.

Finally, we have estimated the overall pesticides effect (equation (64)) on farmers' productivity growth and the results are presented in Table 10. The average annual pesticides effect and its' subcomponents appear first in the table, and then the relative percentage contribution of each component to TFP growth is reported. The percentage contribution of pesticides to the productivity of the Greenhouse farmers in Greece was 5.79 per cent for the period analyzed. The biased part of technical change related with pesticides use was found to have the greater impact on TFP growth, followed by the direct scale effect that caused a 1.72 per cent reduction to productivity. The indirect scale effect that captures the health effects of pesticides use

was found to have a weak positive effect (0.86 per cent) on TFP growth. The unexpected positive sign of the indirect scale effect can be explained by the existence of decreasing returns to scale. Specifically, increases in pesticides use deteriorate farmer's health which in turn results in a reduction of effective labor use. Due to decreasing returns to scale, the reduction in effective labor use will cause a lower reduction in output given the use of the other inputs, and thus productivity will be increased.

4.5. CONCLUSIONS

In their influential works Ram and Schultz (1979) and Schultz (1961; 1980) indicated the important role of human capital in productivity growth. They argued among others that additions into the stock of human capital affect the productivity of workers in various ways: i) there is a clear implication of an increase in the physical ability to engage in work that increase the amount of effective work, ii) there is an additional incentive to acquire schooling as investment in future earnings which accrue over a longer period due either to improvements in managerial ability or to adopt new more profitable technologies. On the other hand, individual decisions on the use of certain variable inputs affect the quality of human capital engaged in production process. A notable example in agricultural sector is the use of damage control inputs, i.e., pesticides, that although enhance farm yields at the same time deteriorates farmer's human capital through the adverse effects on their health status.

In his paper, we built upon the early ideas of Schultz (1961; 1980) and on the methodological advantages of Griliches (1963) and Antle and Pingali (1994) in order to identify the effects of human capital along with the effects of pesticides use on farmers' productivity growth. Following Griliches (1963) specification, we incorporated human capital into our analysis using education and health as multiplicative augmentations of labor inputs, while the adverse health effects of pesticides use on farmer's health were captured through a development of a health impairment index. We provided thus a decomposition of farmers total productivity growth into four components, namely, scale effect, technical efficiency effect, technical change effect and labor and management quality effect.

The empirical model was applied to a panel data set of 50 greenhouse farms observed during the 2003-07 period obtained from a primary survey in the region of

Ierapetra, Greece. The results indicate that greenhouse farm productivity increased 1.2826 per cent over the period analyzed. The main source of productivity growth was found to be technical change contributing (53.24 per cent) to TFP changes. Changes in labor quality due to human capital improvements were found to account for about 38.5 per cent of TFP growth, indicating the important role of human capital in Greenhouse production. Furthermore, the pesticides effect on TFP growth was 5.49 per cent, driven mainly by the biased technical change of pesticides. Finally, the health effect of pesticides on productivity was found to be weak but positive (0.86 per cent) due to the existence of decreasing returns to scale.

4.6. TABLES

Table 1. Descriptive Statistics per Health Problem Category.

Health Problem	No of Cases	Recuperate Days	Not-Work Days	Decrease in Efficiency %	Cost of Treatment
1. Eyes	20	20.2	9.7	57	225
2. Dermal	33	18.9	9.8	55	216
3. Respiratory	156	18.7	9.9	54	217
4. Neurological	3	20.0	10.0	50	200
5. Kidney	1	15.0	10.0	40	100
Mean	-	18.9	9.9	55	217

Table 2. Descriptive Statistics of the Variables used to estimate Health Impairment Indexes.

Variable	Mean	Min	Max	StDev
Family Field Labor				
Log Health Impairment	4.75	0	6.23	0.23
Education Index	9.6	3.2	14.3	3.14
Pesticides (in Euros)	2,624	358	9,857	2,271
Age (in years)	39	20	60	10.20
Nutritional Status (weight/height)	0.47	0.39	0.78	0.06
Manager				
Log Health Impairment	5.67	0	7.06	0.29
Education Index	9.1	3.1	14.1	2.94
Pesticides (in Euros)	2,624	358	9,857	2,271
Age (in years)	46	21	69	11.59
Nutritional Status (weight/height)	0.52	0.40	0.88	0.07

Table 3. Parameter Estimates of the Health Impairment Indexes.

Par.	Estimate	StdError	Par.	Estimate	StdError
b_f^0	-5.3484	(1.0272)*	b_m^0	-4.8485	(1.1067)*
b_f^ε	0.4543	(0.1145)*	b_m^ε	0.6145	(0.1591)*
b_f^z	-0.2591	(0.1026)*	b_m^z	-0.4986	(0.1353)*
b_f^A	-0.0167	(0.0083)*	b_m^A	-0.0127	(0.0075)**
b_f^N	0.2975	(0.0838)*	b_m^N	0.4864	(0.1167)*

Note: f refers to field labor, m to management, ε to education, z to pesticides use, A to age and N to nutritional status. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively.

Table 4. Descriptive Statistics of the Variables used to estimate the translog production function.

Variable	Mean	Min	Max	StDev
Output (in Euros)	41,545	9,524	212,230	29,898
Inputs				
Land (in stremmas)	4.87	1.78	16.18	2.95
Labor (in hours)	4,028	802	10,328	2,272
Management (in hours)	972	78	3,114	796
Fertilizers (in Euros)	4,574	837	15,547	2,911
Pesticides (in Euros)	2,624	358	9,857	2,271
Intermediate Inputs (in Euros)	17,619	1,021	92,144	18,033

Note: the reported statistics for labor inputs refer to ineffective field labor and management.

Table 5. Parameter Estimates of the Translog Production Function

Parameter	Estimate	t-Statistic	Parameter	Estimate	t-Statistic
Stochastic Frontier Model					
β^0	0.4883	(2.7988)*	β^{xl}_{Lf}	0.0420	(0.2680)
β^x_L	0.4024	(5.3844)*	β^{xl}_{Lm}	-0.0156	(-0.1003)
β^x_C	0.0724	(2.2553)*	β^{xz}_L	0.0599	(1.7852)**
β^x_I	0.1304	(2.2213)*	β^{ll}_{ff}	-0.0370	(-1.7731)**
β^l_f	0.1023	(1.7243)**	β^{ll}_{fm}	0.0255	(0.3445)
β^l_m	0.0774	(1.8794)**	β^{lx}_{fC}	0.0670	(0.7434)
β^z	0.1555	(1.6877)**	β^{lz}_f	-0.0824	(-1.0019)
β_t	0.4124	(2.2837)*	β^{lx}_{fI}	0.1715	(1.6769)**
β_{tt}	0.0709	(-1.6830)**	β^{ll}_{mm}	-0.0017	(-0.0395)
β^x_{Lt}	0.0213	(0.2173)	β^{lx}_{mC}	-0.1150	(-2.1231)*
β^x_{Ct}	0.1356	(1.6877)**	$\beta^{l_m z}$	0.0802	(1.0672)
β^x_{It}	0.0140	(0.1974)	β^{lx}_{mI}	-0.1335	(-1.6880)**
β^l_{ft}	-0.0877	(-1.7849)**	β^{xx}_{CC}	-0.1120	(-2.2634)*
β^l_{mt}	0.1252	(2.3361)*	β^{xz}_C	0.0109	(0.1518)
β^z_t	0.1212	(1.6985)**	β^{xx}_{CI}	-0.1745	(-1.6193)**
β^{xx}_{LL}	-0.1145	(-2.1891)*	β^{zz}	-0.1176	(-1.9908)**
β^{xx}_{LC}	0.0393	(0.2402)	β^{zx}_I	-0.0236	(-0.2742)
β^{xx}_{LI}	0.0255	(0.1757)	β^{xx}_{II}	0.0069	(0.1200)
ζ_{i0}	0.7411	(0.2565)*	ζ_{i2}	0.0144	(0.0087)**
ζ_{i1}	0.1348	(0.0481)*	$\bar{R}^2$	0.5324	

Note: *A* refers to land, *C* to fertilizers use, *I* to intermediate inputs, *f* to effective field labor, *m* to effective management input and *z* to pesticides use. * and ** indicate statistical significance at the 1 and 5 per cent level, respectively. In the lower panel of the Table are reported the ζ parameters of the farm with the maximum efficiency score.

Table 6. Output Elasticities and Returns-to-Scale for Greenhouse Farms, 2003-07.

Variable	Mean Value	Standard Error
Output elasticities		
Land	0.3430	(0.0974)*
Fertilizers	0.0885	(0.0940)**
Intermediate Inputs	0.1844	(0.1129)*
Field Labor	0.0765	(0.0333)**
Management	0.0509	(0.0368)**
Pesticides	0.2263	(0.0389)*
Returns-to-Scale	0.9696	(0.1577)*

Table 7. Model Specification Tests.

Hypothesis	LR test-statistic	Critical Value (a=0.05)
Farm Technology		
Constant returns-to-scale: $\sum_j \beta_j^x + \sum_k \beta_k^l + \beta^z = 1$, $\beta_{j\rho}^{xx} = \beta_{k\lambda}^{ll}$ $\beta_{jk}^{xl} = \beta_j^{xz} = \beta_k^{lz} = \beta^{zz} = 0$, $\sum_j \beta_{jt}^x + \sum_k \beta_{kt}^l + \beta_t^z = 0 \ \forall j,k,\lambda,\rho$	78.28	$\chi_{23}^2 = 35.17$
Zero-technical change: $\beta_t = \beta_{tt} = \beta_{jt}^x = \beta_{kt}^l = \beta_t^z = 0 \ \forall \ j, \ k$	68.60	$\chi_8^2 = 15.50$
Hicks-neutral technical change: $\beta_{jt}^x = \beta_{kt}^l = \beta_t^z = 0 \ \forall \ j, \ k$	61.77	$\chi_6^2 = 12.59$
Output Technical Efficiency		
Zero output technical efficiency, *i.e.*, $\zeta_{i0} = \zeta_{i1} = \zeta_{i2} = 0, \ \forall i$	41.90	$\chi_{150}^2 \simeq 71.40$
Time invariant output technical efficiency: $\zeta_{i1} = \zeta_{i2} = 0, \ \forall i$	25.81	$\chi_{100}^2 \simeq 69.52$
Common temporal pattern of technical efficiency across farms: $\zeta_{i1} = \zeta_1 \ \forall i$ and $\zeta_{i2} = \zeta_2 \ \forall i$	23.42	$\chi_{100}^2 \simeq 69.52$

Table 8. Frequency Distribution of Output Technical Efficiency

TE^O	2003	2004	2005	2006	2007	2003-07
<40	0	0	0	0	0	0
40-50	0	0	0	0	0	0
50-60	0	0	0	0	0	0
60-70	6	6	6	5	5	6
70-80	19	18	17	17	16	17
80-90	15	16	17	18	19	17
90>	10	10	10	10	10	10
Mean	80.59	80.81	81.03	81.25	81.46	81.03
Min	63.74	64.12	64.49	64.86	65.23	64.49
Max	97.05	97.08	97.12	97.16	97.19	97.12

Note: In the last column is reported the frequency distribution of the mean output technical efficiency for the 5 year time period.

Table 9. Decomposition of TFP Growth for Greek Greenhouse farms (Average Values for the 2003-07 period).

	Average Annual Rate of Change (%)	Percentage
TFP Growth (%)	1.2826	
Scale Effect	-0.0484	(-3.77)
Rate of Technical Change	0.6829	(53.24)
Neutral	0.6475	(50.48)
Biased	0.0354	(2.76)
Technical Efficiency Changes	0.1529	(11.92)
Field Labor Quality Effect	0.2664	(20.77)
Education Effect	0.3007	(23.45)
Health Effect	-0.0344	(-2.68)
Aging	-0.0044	(-0.34)
Nutritional Status	-0.0300	(-2.34)
Management Quality Effect	0.2288	(17.84)
Education Effect	0.2578	(20.10)
Health Effect	-0.0291	(-2.26)
Aging	-0.0040	(-0.31)
Nutritional Status	-0.0251	(-1.95)

Table 10. Overall Pesticides effect on farmers' TFP Growth (Average Values for the 2003-07 period).

	Average Annual Rate of Change	Percentage
TFP Growth (%)	1.2826	
Overall Pesticides Effect	0.0743	(5.79)
Direct Scale Effect	-0.0221	(-1.72)
Indirect Scale Effect	0.0111	(0.86)
Biased TC	0.0853	(6.65)

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ENDNOTES

[1] This is an input-conserving definition of technical efficiency which is more appropriate for measuring labor-specific technical efficiency. For the output expanding definitions of technical efficiency see Kumbhakar and Lovell (2000, pp. 30-42)

[2] For a detailed discussion of the properties of efficiency indices, see Russell (1998, pp. 30-41) and Kumbhakar and Lovell (2000, pp. 44-46).

[3] Labor-specific technical efficiency as defined in (3) and (4), has an input conserving interpretation, which however cannot be converted into a cost-saving measure due to its orthogonal non-radial nature. Akridge (1989) based on Kopp's (1981) theoretical framework incorporated factor prices suggesting a single factor technical cost efficiency index which measures the potential cost savings that can be realized by adjusting single factor use.

[4] The maintained assumption that derived demand for labor is non-increasing in ε, implies that human capital and labor inputs are substitutes in the production of aggregate output (Griliches, 1964). Therefore the labor demand elasticity with respect to human capital is negative.

[5] Our data set is the same with that used by Henderson and Russell (2005) and to some extent with Kumar and Russell (2002) and so our results are comparable with those reported by these two studies.

[6] Aggregate output is real gross domestic product multiplied by population while capital stock and labor inputs were retrieved from capital stock per worker and real GDP per worker. All variables are measured in 1985 international prices.

[7] Using the years of schooling for adult population is a good proxy for human capital given the difficulties of alternative data source. As Griliches (1963) pointed out the use of "specific" or more elegant variables does not alter significantly the econometric results as all these variables are highly correlated with years of schooling.

[8] This specification implicitly imposes perfect substitutability between human capital and physical labor (Acemoglou and Zilboti, 2001). Alternatively we could have follow Welch (1970) approach treating human capital as a separate factor of production. Following Griliches (book) we used formal statistical testing to examine both hypotheses. In doing so the production frontier model in (11) was estimated using human capital as a separate factor of production. Then using a simple *t*-test we

examined the hypothesis that the coefficients of human capital and labor are equal. The result rejects the alternative hypothesis validating our choice of using education as an augmentation factor for physical labor in the production frontier model.

[9] We have tried to introduce the multilateral structure into the temporal pattern of output technical inefficiency, but unfortunately we couldn't obtain statistical significant estimates due to small number of countries belonging to certain groups.

[10] This means that in each period at least one country is fully efficient, although the identity of this country may vary through years.

[11] Given (14) this is equivalent by testing the hypotheses that $\beta_j^{lt} = 0$ in the aggregate production function in (11).

[12] Again given (14) this is equivalent by testing the hypotheses that $\beta_j^{lt} = \beta_j^{kt} = 0$ and $\beta_j^{t} = \beta_j^{tt} = \beta_j^{lt} = \beta_j^{kt} = 0 \ \forall j$ in the aggregate production function in (11).

[13] In fact Ray (1998) based on Atkinson and Cornwell's (1998) findings suggested a similar approach with Reinhard Lovell and Thijssen (1999) for the estimation of input specific technical efficiency.

[14] Reinhard, Lovell and Thijssen (1999) in developing their approach of measuring Kopp's (1981) orthogonal input-specific technical efficiency correctly argued that under a Cobb-Douglas specification of the production function, both indices will exhibit the same ranking for countries in the sample. However, this is not true with the multilateral generalized Cobb-Douglas production model utilized herein which allows for different temporal patterns among the two efficiency measures for countries belonging to different groups as well as across time. The latter is important in appropriately identifying the sources of labour productivity growth in the sampled countries.

[15] The complete set of parameter estimates for the Cornwell, Schmidt and Sickles (1990) inefficiency effects model are available from the authors upon request.

[16] The generalized likelihood-ratio test statistic is computed as: $LR = -2\{ln\,L(H_0) - ln\,L(H_1)\}$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively.

[17] Rola and Pingali (1993), Ante and Pingali (1994), Antle, Cole and Crissman (1998) and others studied also the impacts of chemical inputs on farmers in developing countries. Their findings are similar with those of Coye (1986).

[18] On the one hand, better education may improve farmer's health since it may provide additional information to farmers about the health consequences of pesticides and be important for their safe use during applications (Antle and Capablo, 1994). On the other hand, gains in farmers' health imply a longer life span which in turn is an additional incentive for farmers to acquire education since the returns to education accrue over longer periods (Ram and Schultz, 1979).

[19] In his seminal work, Schultz (1961) indicated education, health and nutrition as the most important factors affecting workers' human capital. Since nutritional deteriorations are captured by health impairments, we may assume education and health status as the main components of human capital in agriculture.

[20] As Griliches (1963) pointed out the use of "specific" or more elegant variables than education level does not alter significantly the econometric results as all these variables are highly correlated with years of schooling.

[21] This is an output-expanding definition of technical efficiency. For the input-conserving definitions of technical efficiency see Kumbhakar and Lovell (2000, pp. 30-42).

[22] The first order conditions derived by the solution of farmer's cost minimization problem imply that laborer's with higher human capacity receive better wages. This is in consistency with efficiency wages theory.

[23] These tests were conducted using the generalized likelihood-ratio test statistic, $LR = -2\{ln\,L(H_0) - ln\,L(H_1)\}$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively.

[24] Our analysis is simplified by assuming that family and hired field labor are perfect substitutes and that labor markets are competitive so that returns to farm work and off-farm work are equilibrated. Family time is assumed to be allocated among farm production, farm work time, off-farm work and, leisure to maximize household's

income. In equilibrium, an interior solution equates the marginal value of time across these activities.

[25] As Griliches (1963) pointed out the use of "specific" or more elegant variables than education level does not alter significantly the econometric results as all these variables are highly correlated with years of schooling.

[26] This is an output-expanding definition of technical efficiency. For the input-conserving definitions of technical efficiency see Kumbhakar and Lovell (2000, pp. 30-42).

[27] Alternatively we could have follow Welch (1970) approach treating human capital as a separate factor of production. Following Griliches (book) we used formal statistical testing to examine both hypotheses. In doing so the production frontier model was estimated in a simplified form using both human capital variables, *i.e.*, health status and education, as separate factors of production. Then using a simple *t*-test we examined the hypothesis that the coefficients of human capital variables and labor were equal. The result rejected the alternative hypotheses validating our choice of using education and health status as an augmentation factor for physical field and management labor in the production frontier model.

[28] The first order conditions derived by the solution of farmer's cost minimization problem imply that laborer's with higher human capacity receive better wages. This is in consistency with efficiency wages theory.

[29] Atkinson and Crocker (1992) argued that health production studies may suffer from biases arise from measurement errors. However, as it was also argued by Antle and Pingali (1994), the data obtained in this survey were selected from a homogenous population as regard the factors influencing farmer's state of health and were based on personal interviews, that may reduce any biases.

[30] For a detailed discussion on the relationship between specific health problems, clinical symptoms and pesticides use, see Pingali, Marquez and Palis (1993).

[31] The number of reported cases includes health problems identified in both the farm owner and the household members who work on the farm.

[32] The Greek government organizes annual seminars for the safe use and storage of pesticides. All greenhouse farmers included in the sample indicated that have attend at least in one such seminar.

[33] Our analysis can be easily extended to take into account the effects of different types of pesticides, if we simply assume that variable z is a vector of different types of pesticides, *i.e.,* $\mathbf{z} = \{z_1, z_2, \ldots, z_r\} \in \Re_+^r$.

[34] The opportunity cost of the farmer's time to recuperate was calculated as the product of the off-farm wages provided by the official website of Greek Agricultural Ministry times the recuperation time.

[35] The education index used in our analysis takes into account both schooling years and informal education related with the use of pesticides. It was calculated as the product of the years of education times an index of seminars duration, *i.e.,* $\varepsilon_{kit} = \varepsilon_{kit}^F \times \left(1 + \varepsilon_{kit}^I / 365\right)$ where $\varepsilon_{kit}^F \in \Re_+$ is formal education measured in years of schooling and $\varepsilon_{kit}^I \in \Re_+$ is informal education measured in days of seminars attained. This formulation allows for more educated farmers to utilize more sufficient seminar related with pesticides use, since the later may require a level of general education. (Antle and Capablo, 1994).

[36] In table 4, the reported statistics for labor inputs refer to ineffective field labor and management.

[37] These tests were conducted using the generalized likelihood-ratio test statistic, $LR = -2\{ln\, L(H_0) - ln\, L(H_1)\}$, where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and the alternative (H_1) hypothesis, respectively.