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On the Microeconomics of Specialization: the Role of Non-Convexity

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Abstract This paper investigates the microeconomics of specialization and its effects on firm productivity. We define economies of specialization as the productivity gains obtained under greater specialization. The paper shows how scale effects and non-convex technology affect economies of specialization. Using a nonparametric approach, we present an empirical analysis applied to Korean farms. The results indicate that non-convexity is prevalent especially on large farms. We find that non-convexity generates large productivity benefits from specialization on larger farms (but not on smaller farms), providing a strong incentive for large farms to specialize. We evaluate the linkages between non-convexity, firm size and management.

Keywords Firm productivity · Scale · Non-convexity · Specialization

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Introduction

Adam Smith (1776) first pointed out that there are productivity gains from specialization. Using a pin factory as an example, Smith (1776, p. 4) argued that producing pins in a system where workers are specialized across tasks can generate very large increases in productivity. According to Smith (1776, p. 6–8), a key factor is the amount of time workers spend switching from one task to another: this time can be saved under increased specialization. Other aspects of the benefits of firm specialization relate to

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the role of knowledge and coordination cost (e.g., as emphasized by Becker and Murphy (1992), Caliendo and Rossi-Hansberg (2012) and Garicano and Rossi-Hansberg (2015)). Somewhat surprisingly, little empirical evidence has been presented documenting the source or magnitude of gains from specialization at the firm level. This suggests a need for a refined analysis of the productivity effects of specialization. The main objective of this paper is to develop new insights into the microeconomics of firm organization and the motivations for firm diversification/specialization strategies.[1]

Where do the productivity gains from firm specialization come from? This paper shows that there are two main factors that affect the benefits of specialization: returns to scale and nonconvexity of the technology. The role of returns to scale is not new: it has been noted in previous literature (e.g., Stigler 1951; Melitz 2003). But other factors also play a role. Smith's example of a pin factory provides useful insights. Smith (1776, p. 6–8) argued that the gains from specialization come in part from savings in time lost switching from one task to the next. A similar argument would apply to the time used in learning how to manage a new task (Becker and Murphy 1992; Caliendo and Rossi-Hansberg 2012; Coviello et al. 2014; Garicano and Rossi-Hansberg 2015). Since the time lost switching between tasks (or learning to manage a new task) does not contribute to any output, this introduces fixed cost in the analysis. This suggests that reductions in fixed cost can be important sources of gains from specialization. This point has been made by Baumol et al. (1982, p. 75) in their analysis of economies of scope for a multiproduct firm. Fixed cost is a well-known source of non-convexity. Perhaps more importantly, these issues can arise independently of any scale effects. For example, in his discussion of a pin factory, Smith does not mention any role for firm size. This indicates that the productivity effects of specialization can be present within a firm irrespective of scale effects. This suggests a need to explore the role of non-convexity in the microeconomics of firm specialization.

This paper explores the microeconomics of specialization, with a focus on the role of non-convexity. It is well known that a technology that exhibits increasing returns to scale (IRS) is also non-convex. Yet, in this paper we stress that non-convexity can arise in ways that are unrelated to scale effects. Indeed, IRS is a form of non-convexity that applies in a very restrictive way: returns to scale consider only proportional changes in all inputs and outputs. We show that other forms of non-convexity (besides IRS) can have a large influence on the gains from specialization. More fundamentally, we think that the common idea that IRS and non-convexity tend to go together has contributed to hiding the deeper role played by non-convexity.

This paper makes three contributions to the literature. First, it evaluates conceptually the role played by both returns to scale and non-convexity in the economics of firm specialization. Relying on a directional distance function, we propose a measure of gains from specialization and use it to identify the distinct role played by returns to scale versus non-convexity. We obtain the following key result: the gains of firm specialization are negative under IRS and a convex technology. Alternatively, the gains of firm specialization are positive under decreasing

[1] While our analysis focuses at firm level, there is an extensive literature on the aggregate benefits of specialization. The two approaches (micro versus macro) are related. Economists have stressed the linkages between benefits of specialization and the aggregate gains from trade (e.g., Ricardo 1817; Samuelson 1962). Yet, some controversy remains about the magnitude of the gains from trade. The empirical measurements of aggregate gains from trade have typically been relatively small. For example, Arkolakis et al. (2012, p. 95) have estimated that the welfare gains from trade for the U.S. have ranged from 0.7 % to 1.4 % of income. This has stimulated the search for new models that could generate larger gains from specialization and trade (e.g., Melitz 2003; Bernard et al. 2003; Melitz and Trefler 2012; Caliendo and Rossi-Hansberg 2012).

returns to scale and a non-convex technology. Thus, our analysis shows that non-convexity can be an important factor contributing to the gains from firm specialization. This indicates a need to assess empirically the nature of returns and scale and non-convexity for a firm.

Our second contribution is to study the effects of non-convexity on specialization incentives. The analysis is based on a general measure of non-convexity. The measure is evaluated empirically using a non-parametric method. The non-parametric method is flexible in the sense that it allows for the presence of non-convexity in any part of the technology.[2] It provides a good basis to evaluate the role of management in firm specialization decisions.

Our third contribution is to apply our approach to a sample of Korean farms. Note that South Korea is not a developing country: it had a gross domestic product (GDP) per capita purchasing power parity (PPP) of $33,629 in 2014 (similar to Italy or Japan). Thus, our paper is not about economic development. Rather, we take the case of South Korean farmers as an interesting case study on the economics of specialization. An application to farms is of interest as most farms produce more than one output, allowing us to observe different patterns of output specialization across farms. In addition, farms are typically family farms in Korea where the head of the household is the manager and most labor is provided by family labor. In this regard, we can expect the gains from specialization to be closely associated with the managerial skills of the farm manager, i.e. his ability to manage multiple farm production activities. In this context, an application of our approach to Korean farms sheds light on the economics of specialization or diversification and the sources of specialization benefits. Our empirical analysis documents the relative role played by returns to scale and non-convexity on Korean farms. The results identify the presence of non-convexity as well as scale effects. We show that non-convexity varies across farm types: non-convexity tends to be more common on larger farms. We also find that non-convexity effects are more important than scale effects on larger farms. It means that scale effects are not likely to be the major or single factor affecting firm specialization (as documented below). By showing how non-convexity varies with farm size, our analysis helps explain why larger farms tend to be more specialized (Chavas 2001). Finally, our application evaluates the linkages between management and non-convexity. We find that non-convexity varies with the education and experience of the farm manager. We also find that non-convexity generates large productivity benefits from specialization on larger farms (but not on smaller farms), providing a strong incentive for large farms to specialize. By evaluating the linkages between non-convexity, firm size and management, our analysis provides new insights into the role of management and the economics of specialization.

Microeconomics of Specialization

Consider a production process involving m netputs $z=(z_1,\ldots,z_m)\in\mathbb{R}^m$. Given $z=(z_1,\ \ldots,z_m)$, we use the netput notation where inputs are negative ($z_i \leq 0$ for input i) and outputs are positive $z_j \geq 0$ for output j). The production technology is represented by the feasible set $T\subset\mathbb{R}^m$, where $z\in T$ means that the netput vector z is feasible. The set T provides a global characterization of the underlying technology. Two specific properties of the technology will be examined in this

[2] This paper is a follow-up to Kim et al. (2012a). While Kim et al. (2012a) relied on parametric methods, this paper uses more flexible nonparametric methods to investigate the economics of specialization.

paper: returns to scale and convexity properties. First, the technology T is said to exhibit $\left\{\begin{matrix}\text{increasing retruns to scale (IRS)}\\ \text{constant returns to scale (CRS)}\\ \text{decreasing returns to scale (DRS)}\end{matrix}\right\}$ if $T\left\{\begin{matrix}\supset\\ =\\ \subset\end{matrix}\right\}\delta\, T$ for any scalar $\delta > 1$;

and the technology is said to exhibit variable returns to scale (VRS) if no *a priori* restriction is imposed on returns to scale. Second, the technology is said to be convex if the set T is convex, i.e. if it satisfies $[\alpha\, z^a + (1-\alpha)z^b] \in T$ for any $z^a \in T$, $z^b \in T$, and $\alpha \in [0, 1]$. A convex technology is equivalent to the intuitive concept of "decreasing marginal productivity." Alternatively, the technology is non-convex if the set T is not convex. Throughout the paper, we assume that the technology T satisfies free disposal, where free disposal means that $T = T - \mathbb{R}^m_+$.

Our analysis of the properties of the technology T will rely on specific measures. Letting $g \in \mathbb{R}^m_+$ be a reference bundle satisfying $g \neq 0$ and following Chambers et al. (1996), consider the directional distance function:[3]

$$D(z, T) = \sup_\beta\{\beta : (z + \beta g) \in T\} \text{ if there is a scalar } \beta \text{ satisfying } (z + \beta g) \in \mathrm{T}, \\ = -\infty \text{otherwise.} \tag{1}$$

The directional distance function is the distance between point z and the upper bound of the technology T, measured in number of units of the reference bundle g. It provides a general measure of productivity. In general, $D(z, T) = 0$ means that point z is on the frontier of the technology T. Alternatively, $D(z) > 0$ implies that z is technically inefficient (as it is below the frontier).[4] $D(z, T) < 0$ identifies z as being infeasible (as it is located above the frontier). Luenberger (1995) and Chambers et al. (1996) provide a detailed analysis of the properties of $D(z, T)$. First, by definition in (1), $z \in T$ implies that $D(z, T) \geq 0$ (since $\beta = 0$ would then be feasible in (1)), meaning that $T \subset \{z : D(z, T) \geq 0\}$. Second, $D(z, T) \geq 0$ in (1) implies that $[z + D(z, T)g] \in T$. When the technology T exhibits free disposal, it follows that $D(z, T) \geq 0$ implies that $z \in T$, meaning that $T \supset \{z : D(z, T) \geq 0\}$. Combining these two properties, we obtain the following result: under free disposal, $T = \{z : D(z, T) \geq 0\}$ and $D(z, T)$ provides a complete representation of the technology T. Importantly, this result is general: it allows for an arbitrary multi-input multi-output technology, and it applies with or without convexity.

The distance function $D(z, T)$ in (1) can be used to evaluate economies of specialization (Chavas and Kim 2007). To see that, consider two situations: one where netput z is produced by a single firm and one where z is produced by K more specialized firms, where the k-th firm produced z^k subject to the restriction $\sum_{k=1}^K z^k = z$. Here, the constraint $\sum_{k=1}^K z^k = z$ requires that the aggregate netputs are the same in both situations.

Definition 1: At points z and $(z^1, \ldots, z^K)$ satisfying $\sum_{k=1}^K z^k = z$, define the following measure of economies of specialization:

$$EP\left(z, z^1 \ldots, z^K, T\right) = \sum_{k=1}^K D\left(z^k, T\right) - D(z, T). \tag{2}$$

[3] The directional distance function $D(z, T)$ in (1) is the negative of Luenberger's shortage function (Luenberger 1995).

[4] Note that $D(z, T)$ includes as special cases many measures of technical inefficiency that have appeared in the literature. See the discussion presented in Chambers et al. (1996) and Färe and Grosskopf (2000).

$EP(z, z^1, \ldots, z^K, T)$ in (2) provides a measure of the potential productivity gains (expressed in number of units of the bundle g) obtained from increased specialization. Indeed, assuming that $z^k \neq z/K$ for some k, Eq. (2) evaluates a change in technical inefficiency (as measured by $D(\cdot)$) comparing two situations: one when netputs z are produced by an integrated firm and one where netputs z are produced by K "more specialized" firms. $D(z, T)$ in (2) is the distance to the frontier when netputs z are produced in an integrated production process. $\sum_{k=1}^{K} D\left(z^k, T\right)$ is the distance when netputs z are produced in K "more specialized" production processes, z^k being the netputs used in the k-th production process. Given $\sum_{k=1}^{K} z^k = z$, it follows that $EP(z, z^1, \ldots, z^K, T)$ in (2) has the following interpretation. When $EP(z, z^1, \ldots, z^K, T) > 0$, the K specialized firms $(z^1, \ldots, z^K)$ can produce EP additional units of g compared to an integrated firm, implying that specialization improves productivity. It follows that $EP(z, z^1, \ldots, z^K, T) > 0$ reflects economies of specialization. Alternatively, when $EP(z, z^1, \ldots, z^K, T) < 0$, the production potential of the K specialized firms $(z^1, \ldots, z^K)$ is reduced by $|EP|$ units of g compared to an integrated firm, implying that specialization reduces productivity. It follows that $EP(z, z^1, \ldots, z^K, T) < 0$ reflects diseconomies of specialization.

This is illustrated in Fig. 1 which considers the production of two outputs (y_1, y_2) using inputs x, where $z = (-x, y_1, y_2)$. Figure 1 involves a comparison between an integrated firm producing outputs (y_1, y_2) using inputs x and two specialized firms: a firm producing outputs $(y_1, 0)$ using inputs $x/2$, and a firm producing outputs $(0, y_2)$ using inputs $x/2$. Figure 1 compares the productivity of the integrated firm producing at point A with the productivity of two specialized firms producing respectively at point C_1 (with netputs $z^1 = (-x/2, y_1, 0)$) and point C_2 (with netputs $z^2 = (-x/2, 0, y_2)$). Note that, as defined, $z = z^1 + z^2$. The evaluation of productivity in Fig. 1 relies on the output set $Y(x) = \{(y_1, y_2) : (-x, y_1, y_2) \in T\}$. Point A in Fig. 1 is on the frontier of $Y(x)$, with $D(z, T) = 0$. Points C_1 and C_2 are below the frontier of $Y(x/2)$. Given a reference bundle g, the two specialized firms can increase production by the distances $(B_1\ C_1)$ and $(B_2\ C_2)$. From Eq. (1), these two distances are given by $D(z^1, T)$ and $D(z^2, T)$, respectively. In this case, using (2) and noting that $D(z) = 0$, it follows that $EP(z, z^1, z^2, T) = D(z^1, T) + D(z^2, T) > 0$ measures the potential gain in productivity associated with producing outputs in a specialized manner. Thus, Fig. 1

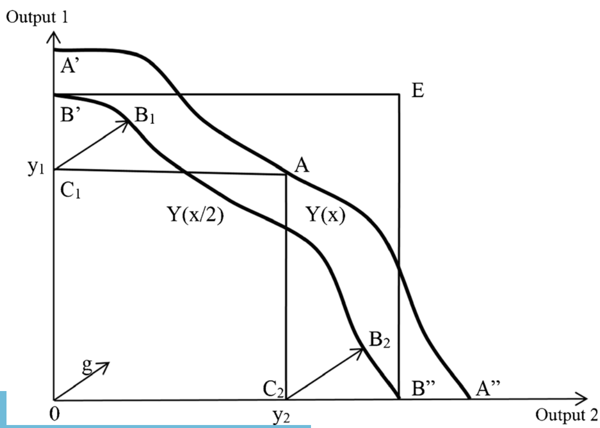

Fig. 1 Evaluating the benefit of specialization: the case of two outputs $(y_1, y_2) \in Y(x)$

illustrates a situation exhibiting economies of specialization, where specialization increases productivity.

While Eq. (2) provides a basis to evaluate the gains of specialization, it does not identify where these gains come from. We now explore the sources of these gains. We show next that economies of specialization are closely related to two fundamental concepts: economies of scale and convexity. The proof is in the Appendix.

Proposition 1: At points z and $(z^1, \ldots, z^K)$ satisfying $\sum_{k=1}^{K} z^k = z$, economies of specialization $EP(z, z^1, \ldots, z^K)$ in (2) can be decomposed as

$$EP\left(z, z^K, T\right) = ES_c(z, T) + EC_n\left(z, z\ldots, z^K, T\right), \tag{3}$$

where

$$ES_c(z, T) \equiv K\, D\left(\frac{z}{K}, T\right) - D(z, T) \begin{Bmatrix} \leq \\ = \\ \geq \end{Bmatrix} 0 \text{ under } \begin{Bmatrix} \text{IRS} \\ \text{CRS} \\ \text{DRS} \end{Bmatrix}, \tag{4}$$

$$\begin{aligned} &EC_{\text{n}}\left(z, z^1, \ldots, z^{\text{K}}, T\right) = \textstyle\sum_{k-1}^{\text{K}} D(zk, T) - \text{KD}\left(\frac{z}{K}, T.\right) \\ &\begin{Bmatrix} \leq \\ > \end{Bmatrix} .0 \begin{Bmatrix} \text{if the technology } T \text{ is convex} \\ \text{only if the technology } T \text{ is nonconvex} \end{Bmatrix} \end{aligned} \tag{5}$$

Equation (3) decomposes economies of specialization $EP(z, z^1, \ldots, z^K, T)$ into two additive components: the scale component $ES_c(z, T)$, and the convexity component $EC_n(z, z^1, \ldots, z^K, T)$. From Eq. (4), the scale component $ES_c(z, T)$ satisfies $ES_c(z, T)$ $\{\leq = \geq\}$ 0 under { IRS CRS DRS}. From Eq. (5), the convexity component $EC_n(z, z^1, \ldots, z^K, T)$ is always non-positive under a convex technology. It implies that the convexity component $EC_n(z, z^1, \ldots, z^K, T)$ can be positive only under a nonconvex technology.

By definition, diseconomies of specialization exist when $EP(z, z^1, \ldots, z^K, T) \leq 0$. From (3)-(5), this condition always holds under non-decreasing returns to scale (i.e., under either IRS or CRS) and a convex technology. In such situations, there is a disincentive for firms to specialize. Alternatively, economies of specialization exist when $EP(z, z^1, \ldots, z^K, T) \geq 0$. From (3)-(5), this can arise under DRS or under a nonconvex technology. This result indicates that DRS and nonconvexity can provide an incentive for firms to specialize. The decomposition given in Eq. (3) shows that both returns to scale and convexity can affect the gains from specialization. It indicates a need to present a separate evaluation of scale effects and nonconvexity effects in the economic investigation of specialization. This is the topic of the next section.

Evaluating Economies of Scale and Non-Convexity

The distance function in (1) provides a convenient basis to evaluate the properties of technology. First, it can be used to evaluate its convexity properties.

Definition 2: Let T^h be the convex hull of T, with $T^h = \{\alpha z^a + (1 - \alpha) z^b : z^a \in T, z^b \in T, \alpha \in [0, 1]\} \supset T$. At point z, define the following measure of non-convexity:

$$Cn(z) = D(z, T) \geq 0. \tag{6}$$

The non-negativity of $Cn(z)$ in (6) follows from (1) and $T^h \supset T$. From the definition of convexity, $Cn(z) = 0$ when the technology T is convex. Alternatively, $Cn(z) > 0$ implies the presence of non-convexity in T. Thus, $Cn(z)$ in (6) can be interpreted as a local measure (expressed in number of units of g) of the strength of departure from convexity. The measure is local in the sense that it applies at point z.

Second, the distance function in (1) can be used to evaluate scale effects.

Definition 3: Let T^c be the cone of T, with $T^c = \{\delta\, z : z \in T, \delta \in \mathbb{R}_+\} \supset T$. At point z, define the following measure of economies of scale:

$$Sc(z) = D(z, T^c) - D(z, T) \geq 0. \tag{7}$$

The non-negativity of $Sc(z)$ in (7) follows from (1) and $T^c \supset T$. From the definition of returns to scale, $Sc(z) = 0$ when the technology exhibits CRS. Alternatively, $Sc(z) > 0$ implies a departure from constant returns to scale. Thus, $Sc(z)$ in (7) can be interpreted as a local measure (expressed in number of units of g) of the strength of departure from CRS. The measure is local as it applies at point z.

Empirical Evaluation of the Technology

The empirical measurements in (6) and (7) require representations of the technology T. Consider a data set involving observations of m netputs chosen by n firms: $z_i = (z_{1i}, \ldots, z_{mi})$, where z_{ji} is the j-th netput used by the i-th firm, $i \in N = \{1, \ldots, n\}$. Following Varian (1984), Färe et al. (1994) and Banker et al. (2004), consider first the following nonparametric representations of technology:

$$T_s = \left\{ z : z \leq \textstyle\sum_{i \in N} \lambda_i\, z_i,\ \lambda_i \in \mathbb{R}_+,\ i \in N,\ \textstyle\sum_{i \in N} \lambda_i \in S_s \right. \tag{8}$$

where $s \in \{v, c\}$, with $S_v = 1$ under VRS and $S_c = \mathbb{R}_+$ under CRS. Under free disposal, T_v in (8) is the smallest convex set containing all data points; and T_c is the smallest convex cone containing all data points. The representations given in (8) have been called "Data Envelopment Analysis" (DEA). Since $S_v \subset S_c$, it follows from (8) that $T_v \subset T_c$. Note that the sets T_v and T_c are both convex.

Next, we want to consider representations of the technology that allow for non-convexity. For that purpose, define a neighborhood of $z = (z_1, \ldots, z_m) \in \mathbb{R}^m$ as $B_r(z, \sigma) = \left\{ z' : D(z, z') \leq r : z' \in \mathbb{R}^m \right\} \subset \mathbb{R}^m$, where $r > 0$ and $D(z, z') = Max_j \left\{ |z_j - z'_j| / \sigma_j : j = 1, \ldots, m \right\}$ is a weighted distance between z and z' with weights $\sigma = (\sigma_1, \ldots, \sigma_m) \in \mathbb{R}^m_{++}$. Following Chavas and Kim (2015), let $I(z, r) = \{i : z_i \in B_r(z, \sigma), i \in N\} \subset N$, where $I(z, r)$ is the set of firms in N that are located in the neighborhood $B_r(z, \sigma)$ of z.[5]

[5] The choice of the neighborhood $B_r(z, \sigma)$ is further discussed below.

Definition 4: Define a neighborhood-based representation of the technology T as

$$T^*_{rs} = \cup_{i\in N} T_{rs}(z_i), \tag{9}$$

where

$$T_{rs}(z) = \left\{ z : z \le \sum_{i\in I(z,t)} \lambda_i\, z_i,\ \lambda_i \in \mathbb{R}_+,\ i \in I(z,r),\ \sum_{i\in I(z,r)} \lambda_i \in S_s \right\} \tag{10}$$

with $s \in \{v, c\}$ and the S_s's are defined above.

The representation of technology given in (9)-(10) is obtained in two steps. In a first step, Eq. (10) defines $T_{rs}(z)$ as a local representation of the technology T in the neighborhood of point z under free disposal and returns to scale characterized by $s \in \{v, c\}$. Since $S_v \subset S_c$, it follows from (10) that $T_{rv}(z) \subset T_{rc}(z)$. Again, note that, for a given z, the sets $T_{rv}(z)$ and $T_{rc}(z)$ are convex. In a second step, Eq. (9) defines the set T^*_{rs} as the union of the sets $T_{rs}(z_i)$, $i \in N$. Since the union of convex sets is not necessarily convex, it follows that T^*_{rs} defined in (9) is not necessarily convex for each $s \in \{v, c\}$. Eq. (9) is our proposed neighborhood-based representation of technology. It allows for non-convexity to arise in any part of the feasible set.[6] The properties of T^*_{rs} are investigated in Chavas and Kim (2015) who argued that T^*_{rs} provides a generic and flexible way of introducing non-convexity in production analysis. These representations apply under alternative scale properties: under VRS when $s = v$ (with $S_v = 1$), or under CRS when $s = c$ (with $S_c = \mathbb{R}_+$).

As such, T^*_{rs} has two useful characteristics: first, it provides a flexible representation of non-convexity. Second, it is easy to implement empirically. Indeed, given $j \in N$ and $T_{rs}(z_j)$ in (10), the evaluation of the distance $D(z, T_{rs}(z_j))$ in (1) involves solving the simple linear programming problem: $D(z, T_{rs}(z_j)) = Max_{\beta,\lambda} \{\beta : (z + \beta g) \le \sum_{i\in I(z_j,r)} \lambda_i z_i,\ \lambda_i \in \mathbb{R}_+,\ i \in I(z_i, r),\ \sum_{i\in I(z_j,r)} \lambda_i \in S_s\}$. It follows from (9) that $D(z, T^*_{rs}) = \max_i \{D(z, T_{rs}(z_i)) : i \in N\}$. As noted above, $D(z, T^*_{rs})$ is a measure of technical inefficiency (expressed in number of units of the bundle g) for netput z under technology T^*_{rs}. It gives a basis to evaluate the scale effects $Sc(z)$ given in (7), with $T^c = T^*_{rc}$ and $T = T^*_{rv}$.

Empirical Analysis

The analysis presented above is general: it applies to any firm, irrespective of its institutional form or organization. This section illustrates the usefulness of our approach through an empirical application. The application is to a panel data set of production activities from a sample of Korean rice farms. Focusing on farms is of interest as most farms produce more than one output, allowing us to observe different patterns of specialization across farms. In addition, rice farms in Korea are typically family farms:

[6] Nonparametric analyses of non-convex technology have been previously analyzed by Agrell et al. (2005) and Podinovski (2005). The relationships between our approach and previous analyses are discussed in Chavas and Kim (2015).

as of 2014, the average cultivation size of a family farm is about 1.51 hectacres and the average number of people engaging in farming is about 1.85 (KREI, 2015). During 2000–2010, major sociological aspects of family farm management include the aging of farming population (the proportion of old farmers who are older than 65 has been increased from 21.7 % at 2000 to 31.8 % at 2010) and the aging of the head of farm households (the average age of farm household heads has increased from 56.3 at 2000 to 62.3 at 2010), the specialized farm management, and the diversified farming system (the proportion of rice farms has been dropped to below 50 %).[7] It is also noticeable that rice farming is mostly done by farmers with higher levels of farming experiences. Notice also that a family farm has a simple organizational structure: the head of the household is the manager. Being a family farm, most of the labor is typically provided by family labor, meaning that coordination issues among workers are minimal. To the extent that labor and management are often performed for the same person, we can expect the gains from specialization to be closely associated with the managerial skills of the farm manager. Our empirical analysis will evaluate the nature of scale effects $Sc(\cdot)$ given in (7) and non-convexity effects $Cn(\cdot)$ given in (6). In turn, we will examine the factors contributing to non-convexity.

Data

The analysis uses farm household level data from Korea, data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office (Kim et al. 2012b). This annual survey provides data on the farm household economy and agricultural management. The data come from a sample of 3140 farm households surveyed annually from 314 enumeration districts. These districts are sampled first using a proportional sampling scheme based on the number of farm households from Agricultural Census at 2000. Although this survey includes eight different farm household types which are determined by the largest proportion of the farm household revenue including paddy rice farming and vegetables farming, our empirical analysis focuses on a sample of farms classified as "paddy rice farms" located in the Jeon-Nam province in the southern part of Korea. While most farms produce more than one output, the farms in our sample have a relatively high share of farm revenue coming from rice. The reason why we focus only on rice farms in the Jeon-Nam province is that this area has an extensive irrigation network supporting rice production and is known as a rice-producing province. Moreover, being in the same region, it is relatively safe to assume that all farms face similar agro-climatic conditions. The sample includes 86, 120, 101, 101, 122 number of rice farms for the year of 2003, 2004, 2005, 2006, and 2007, respectively. This unbalanced panel dataset contains data on nine netputs: four outputs and five inputs. The outputs are: rice, vegetable, livestock and other outputs. The inputs are family labor, paddy land owned, non-paddy land owned, land rented, and other inputs. Family labor input is measured in hours, and land inputs are measured in hectares (ha). Other netputs are measured in value, assuming that all farmers face the same prices. Summary statistics are presented in Table 1. The average revenue from rice production is 14,990.5 (measured in 1000 won[8]), accounting for 64.2 % of total farm revenue. The

[7] See Kim et al. (2012b). for details.

[8] Note that 1000 won (the Korean currency) = 0.89 US dollars.

Table 1 Descriptive statistics

Variables	Number of observations	Sample mean	Standard deviation	Minimum	Maximum
rice revenue (in 1000 won)	530	14,990.6	19,413.5	603.7	161,260.9
vegetable revenue (in 1000 won)	530	3176.8	4724.3	0	39,649.2
livestock revenue (in 1000 won)	530	1659.2	3383.1	0	24,517.0
other revenue (in 1000 won)	530	3114.9	5725.3	0	73,816.2
production costs (in 1000 won)	530	10,185.9	10,763.6	617.5	72,654.9
family labor (hours)	530	891.9	565.9	71.5	3634.6
paddy land owned (in ha)	530	1.09	1.40	0	13.52
land owned except paddy land owned (in ha) land ownedupland (in ha)	530	0.48	0.66	0	6.13
land rented (in 1000 won)	530	1.01	1.51	0	16.37

1000 won (the Korean currency) is approximately equivalent to 0.89 U.S. dollar. Data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office in Korea

second largest source of revenue is vegetable production: 3177.0 (measured in 1000 won), accounting for 15.1 % of total farm revenue. The average size of a farm is 2.58 ha. The sample reflects the type of farms commonly found in Asia where farms are typically small and with some degree of specialization in rice production.

Results

The analysis relies on nonparametric representations of the technology T^*_{rs} given in (9). The distance function $D(z, T)$ in (1) is evaluated based on the bundle $g = (g_1, \dots, g_m)$ such that $g_i = 0$ for the i-th input and g_j is the sample mean for the j-th output. Thus, our reference bundle $g = (g_1, \dots, g_m)$ is associated with the outputs of an average farm, leading to a simple interpretation of our directional distance estimates.[9]

Our neighborhood-based assessment of technology T^*_{rs} requires the definition of a neighborhood. Letting $M_j = Max_{i \in N}\{z_{ji}\} - Min_{i \in N}\{z_{ji}\}$ be the sample range of the j-th netput, we considered dividing the sample range into four equally spaced intervals and defined neighborhoods as $B_r(z, \cdot) = \left\{z' : -\frac{M_j}{4} \le z_j - z'_j \le \frac{M_j}{4}; j = 1, \dots, m, z' \in \mathbb{R}^m\right\}$.[10] Based on these neighborhoods, our empirical analysis generates farm-specific estimates of technical inefficiency measured by $D\left(z_i, T^*_{rs}\right)$, $i \in N$. It permits an evaluation of farm-specific convexity effects $Cn(z_i)$ given in (6) and of scale effects $Sc(z_i)$ given in (7), $i \in N$.

The empirical analysis uses annual data on production activities from a sample of 530 Korean farms over the period 2003–2007. Our results will be evaluated for three farm types: small farms, medium farms and large farms. Small farms are defined as farms located

[9] For example, for a given T, finding that $D(_i, T) = 0.2$ means that the z_i-th farm is technically inefficient: it could move to the production frontier and increase its outputs by 20 % of the average outputs in the sample.

[10] We also conducted the analysis based of alternative choices of neighborhoods. As discussed in Chavas and Kim (2015), choosing smaller (larger) neighborhoods contributed to uncovering more (less) evidence of non-convexity. The sensitivity results are available from the authors upon request.

Table 2 Average non-convexity effects $Cn(\cdot)$ under CRS and VRS, by farm size over time

	2003	2004	2005	2006	2007
Under CRS (with $S_c = \mathbb{R}$)					
Small farm	0.021	0.012	0.017	0.016	0.007
Medium farm	0.026	0.058	0.069	0.051	0.036
Large farm	0.103	0.143	0.067	0.177	0.113
Under VRS (with $S_v = 1$)					
Small farm	0.015	0.007	0.010	0.008	0.006
Medium farm	0.030	0.062	0.068	0.053	0.038
Large farm	0.051	0.143	0.086	0.144	0.080

Farm size is identified by the size of total land. Small farms are defined as farms being in the 0 to 30 percentile of the sample distribution of farm size, medium farms are between the 30 percentile and 70 percentile, and large farms are in the 70 to 100 percentile. These results are based on data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office in Korea

in the lower 30^{th} percentile distribution of total land. Large farms are those farms located in the top 30^{th} percentile distribution of total land and medium farms are in between.

First, we evaluated the convexity effect Cn given in (6), with $T^h = T^*_{\infty s}$ and $T = T^*_{rs}$. The results are summarized in Table 2. Table 2 presents average values of Cn for each year (2003, 2004, 2005, 2006 and 2007), for each farm type (small, medium and large farms), and under both CRS ($s = c$) and VRS ($s = v$). The results show that Cn varies between 0.007 and 0.177. This documents that the non-convexity effects can be large. For example, $Cn = 0.177$ means that non-convexity effects accounts for a 17.7 % change in the mean value of all outputs. The estimates of Cn are fairly similar for CRS versus VRS, indicating that the presence of non-convexity is not related to scale effects. In general, Table 2 shows that Cn tends to be moderate for small farms (always less than 0.03) but that they increase with farm size. Indeed, with the exception of (2005, CRS), the largest Cn estimates are consistently found among large farms. This provides evidence that non-convexity effects become stronger on larger farms. It means that specialized operators tend to be more productive on larger farms. To the extent that non-convexity comes from the saving in fixed cost related to labor and managerial resources, this would imply that the productivity of specialized management improve more on large farmers. Finally, Table 2 shows that some changes in the Cn estimates over time, although not clear patterns seem to emerge. This is consistent with a slow technology change in rice production in Korea, reflected by a complete irrigation infrastructure and high-yielding rice varieties.

Second, we evaluated the scale measure Sc given in (7), with $T^c = T^*_{rc}$ and $T = T^*_{rv}$. The results are summarized in Table 3. Table 3 presents average values of Sc for each year (2003, 2004, 2005, 2006 and 2007), for each farm type (small, medium and large farms), and under both convexity (when $r \to \infty$) and non-convexity. The results show that Sc varies between 0.009 and 0.124. With the exception of (convexity, large farms,

Table 3 Average scale effects $Sc(\cdot)$ under alternative representations of the technology, by farm size over time

	2003	2004	2005	2006	2007
Under convexity: T_v versus T_c					
Small farms					
Average $Sc(\cdot)$	0.021	0.017	0.021	0.017	0.017
$Sc(\cdot)$ due to IRS	0.018	0.017	0.020	0.016	0.015
$Sc(\cdot)$ due to DRS	0.003	0.0000	0.001	0.001	0.002
Medium farms					
Average $Sc(\cdot)$	0.041	0.009	0.033	0.020	0.023
$Sc(\cdot)$ due to IRS	0.002	0.005	0.013	0.015	0.007
$Sc(\cdot)$ due to DRS	0.039	0.004	0.020	0.005	0.016
Large farms					
Average $Sc(\cdot)$	0.084	0.047	0.031	0.089	0.124
$Sc(\cdot)$ due to IRS	0.001	0.002	0.007	0.001	0.001
$Sc(\cdot)$ due to DRS	0.083	0.045	0.024	0.088	0.123
Under non-convexity: T^*_{rv} versus T^*_{rc}					
Average $Sc(\cdot)$					
For small farms	0.015	0.011	0.014	0.009	0.017
For medium farms	0.046	0.013	0.032	0.023	0.025
For large farms	0.032	0.046	0.050	0.056	0.090

Farm size is identified by the size of total land. Small farms are defined as farms being in the 0 to 30 percentile of the sample distribution of farm size, medium farms are between the 30 percentile and 70 percentile, and large farms are in the 70 to 100 percentile. These results are based on data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office in Korea

2007), the *Sc*'s are all below 0.10. This documents that scale effects are present, but that the magnitude of scale inefficiency is moderate. For example, $Sc = 0.009$ (convexity, medium farm, 2004) means that scale inefficiency amounts to a 0.9 % change in the mean value of all outputs. As might be expected, Table 3 shows that most of the scale inefficiency is due to IRS for small farms, but DRS for large farms. As discussed above, we expect DRS (IRS) to contribute positively (negatively) to economies of specialization. As a result, scale effects would provide incentives for large farms to specialize. Yet, the relative small magnitudes of *Sc* indicate that scale effects are moderate, which is consistent with long-lasting small-scale rice farming in Korea. They tend to be smaller than the non-convexity effects *Cn* reported in Table 2. It generates one of our key findings: convexity effects tend to dominate scale effects in Korean agriculture. In other words, while scale effects can affect the gains from specialization, our results point to a dominant role played by non-convexity. From Table 3, these results seem to hold both under a convex technology and a non-convex technology, indicating that scale effects appear to be unrelated to non-convexity. Finally, Table 3 shows some changes in the *Sc* estimates over time, although not clear patterns seem to emerge. This may reflect slow technology change in rice production in Korea.

Next, we examined the factors associated with non-convexity. Using our farm-specific estimates of *Cn*, we regressed them on selected explanatory variables. Since the *Cn*'s have zero as a lower bound, we use censored or Tobit regression. If non-convexity is associated with the saving in fixed cost related to labor and managerial resources, then the rise of non-convexity would likely be linked with human capital. On that basis, we include age, schooling, and their interactions as explanatory variables in the Tobit model. We also include farm size as an explanatory variable. Summary statistics for these variables are presented in Table 4.

We estimated the Tobit model using the *Cn* estimates obtained under CRS as well as VRS. The Tobit estimates are reported in Table 5. The estimates show that age, schooling and their interaction have each statistically significant effects on non-convexity. This is consistent with our interpretation of non-convexity being associated with saving in fixed cost related to labor and managerial resources. Our results indicate that managerial ability likely changes with both experience and education. Interestingly, due to the interaction effects, the marginal impacts of age or schooling on non-convexity can be either positive or negative. The marginal impact of age is found to be negative but only for "low schooling." Similarly, the impact of schooling is found to be negative but only for young individuals. Evaluated at sample mean of schooling, we found a negative relationship between age and non-convexity. This indicates that younger individuals have more incentive to specialize in rice production holding other variables constant. Evaluated at sample mean of age, we found a positive relationship between schooling and non-convexity. This implies that education contributes to specialization in rice production. To the extent that non-convexity contributes to gains from specialization, our results indicate that young and better educated individuals would have more incentive to specialize. Given the fact that larger rice farms are generally operated by relatively younger individuals seeking specialization benefits associated with rice farming by increasing the size of paddy land, this result seems plausible in a Korean rice production context. Alternatively, older and less educated individuals would have less incentive to specialize. This suggests that the pattern of specialization varies with education and with the life cycle of individuals. The Tobit estimates reported in Table 5 also show that non-convexity is more prevalent on farms that specialized in rice. This likely reflects the presence of fixed cost associated with rice production. Finally, Table 5 shows that farm size has a strong and positive relationship with non-convexity. This is consistent with the results reported in Table 2: non-convexity effects are more important for large farms, suggesting that the productivity of specialized management improves for larger farmers.

Table 4 Descriptive statistics for the analysis of non-convexity

Variable	Obs.	Sample mean	Std. deviation	Min.	Max.
Non-convexity	530	0.060	0.138	0.000	1.201
Age	530	63.29	9.32	39.00	85.00
Years of schooling	530	6.78	3.77	0.00	16.00
Farm size	530	2.57	2.69	0.18	22.62
Time trend	530	3.10	1.41	1.00	5.00
Rice revenue ratio	530	0.64	0.16	0.28	1.00

These results are based on data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office in Korea

Table 5 Tobit estimation of factors affecting non-convexity (dependent variable = *Cn*)

Variables	(a) Under CRS		(b) Under VRS	
	Coefficients	Standard errors	Coefficients	Standard errors
Intercept	0.188	0.186	0.086	0.212
Age	-0.006**	0.003	-0.006**	0.023
Schooling	-0.049**	0.020	-0.048**	0.023
Age*Schooling	0.001**	0.000	0.001**	0.000
Farm size	0.014***	0.005	0.007	0.005
Time trend	0.004	0.008	0.004	0.010
Rice revenue ratio	0.202***	0.075	0.263***	0.087
Sigma	0.230	0.011	0.252	0.014

Stars denote the significance level: *** for the 1 % significance level; ** for the 5 % significance level; and * for the 10 % significance level. These results are based on data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office in Korea

Finally, simulations of economies of specialization (*EP* given in (2)) and its scale component (*ESc* given in (4)) and convexity component (*ECn* given in (5)) are presented in Table 6 for selected farm types. Two farm types are evaluated: a moderate-size farm with 1.77 ha of land, and a large farm size with 5.23 ha of land. The simulation involves two specialization schemes ($K=2$), with z^1 being specialized in rice and z^2 being specialized in other (non-rice) activities.[11] Table 6 reports economies of specialization for the large farm (with $EP=0.608$), but diseconomies of specialization for the moderate-size farm (with $EP=-0.262$). Importantly, these specialization effects are large. For example, the reference bundle g representing average farm outputs in the sample, $EP=0.608$ measures productivity effects amounting to a 60.8 % increase in average revenue. This illustrates that the incentives to specialize are strong on large farms but not on smaller farms. Table 6 also shows that the scale component *ESc* is negative for both farm types ($ESc=-0.091$ for moderate size, and $ESc=-0.137$ for large farm). From Eq. (4), this corresponds to situations of IRS, which tends to reduce the benefit of specialization. Finally, Table 6 shows that the convexity component *ECn* is negative for the moderate-size farm ($ECn=-0.171$), but positive for the large farm ($ECn=0.745$). As stated in Eq. (5) above, *ECn* is necessarily negative under a convex technology, and it can turn positive only in the presence of non-convexity. Thus, Table 6 shows two important results: 1/ the productivity benefits of specialization come in large part from non-convexity; and 2/ non-convexity is prevalent in large farms but not in smaller farms. This documents the role of non-convexity and its effects on the incentive for farms to specialize. It reveals significant productivity benefits from specialized management on larger farms, providing a strong incentive for large farms to specialize.

[11] In the simulation, the specialized netputs z^1 and z^2 are defined as follows. Compared to the original farm (z), the farm specialized in rice (z^1) produces 70 % of the rice output, 30 % of the non-rice outputs, and 50 % of inputs. Compared to the original farm, the farm specialized in non-rice (z^2) produces 30 % of the rice output, 70 % of the non-rice outputs, and 50 % of inputs. In a way consistent with Eq. (2), this guarantees that $z=z^1+z^2$. We chose this pattern of partial output specialization as no farm in our sample was observed to be completely specialized (i.e., producing only rice or only non-rice outputs).

Table 6 Simulations of EP, ESc and ECn for selected farm types

	Economies of specialization *EP*	Scale component *ESc*	Convexity component *ECn*
	$EP = \sum_k D(z^k, T) - D(z, T)$	$ESc = K\ D(z/K, T) - D(z, T)$	$ECn = \sum_k D(z^k, T) - K\ D(z/K, T)$
Moderate-size farm	-0.262	-0.091	-0.171
Large farm	0.608	-0.137	0.745

The farm size is 1.77 ha for a moderate-size farm and 5.23 ha for a large farm. The simulated specialization schemes are: $K = 2$, with z^1 being specialized in rice and z^2 being specialized in other (non-rice) activities. These results are based on data collected in a Farm Household Economy Survey between 2003 and 2007 by the National Statistical Office in Korea

Concluding Remarks

This paper has presented an analysis of the microeconomics of firm specialization. We have proposed a measure of economies of specialization, reflecting the productivity effects of greater firm specialization. We have identified the distinct role played by returns to scale versus non-convexity. Our conceptual analysis showed that diseconomies of firm specialization occur under IRS and a convex technology. Alternatively, economies of firm specialization arise under decreasing returns to scale and a non-convex technology. This indicates a need for a combined empirical assessment of the nature of returns to scale and non-convexity. In this context, we developed measures of economies of scale and non-convexity and proposed methods to evaluate them empirically.

The usefulness of the approach was illustrated in an empirical application to a data set of Korean farms. The analysis documented the presence of non-convexity as well as scale effects. We showed that non-convexity varies across farm types. Non-convexity was found to be more common on larger farms, indicating that specialized operators have a greater ability to improve productivity on larger farms. We also found that non-convexity effects are more important than scale effects on larger farms. This has two implications. First, it means that scale effects are not the major factor affecting farm specialization. Second, the changes in non-convexity effects across farm size can help explain why larger farms tend to be more specialized. Our empirical analysis also evaluates the linkages between management and non-convexity. Most farms being family farms, we find that non-convexity varies with the education and experience of the farm manager. This provides new insights into the role of management and its implications for firm productivity and the economics of specialization.

Our analysis could be extended in several directions. First, the gains of specialization need to be analyzed at the aggregate level. This means examining how the micro effects analyzed in this paper translate into macro effects (e.g., in the analysis of gains from trade). Second, our application has focused on agriculture. There is a need to expand the empirical analysis to other industries. Third, there is a need for further investigations of the linkages between management and specialization gains. Exploring these issues appears to be good topics for future research.

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Appendix

Proof of Proposition 1: Eq. (2) can be alternatively written as $EP(z, z^1, ..., z^K, T) = \sum_{k=1}^{K} D(z^k, T) – K\ D(z/K, T) + K\ D(z/K, T) – D(z, T)$. Given (4) and (5), this gives the decomposition in (3).

For $K > 1$, note that $T \begin{Bmatrix} \supset \\ = \\ \subset \end{Bmatrix} K\ T$ under $\begin{Bmatrix} IRS \\ CRS \\ DRS \end{Bmatrix}$. It follows from (1) that $D(z, T) = \sup_{\beta} \{\beta : (z + \beta\, g) \in T\} \begin{Bmatrix} \geq \\ = \\ \leq \end{Bmatrix} \sup_{\beta} \{\beta : (z + \beta\, g) \in K\ T\}$ under $\{ IRS\ \ CRS\ \ DRS\}$. Letting $b = \beta/K$, we have $\sup_{\beta} \{\beta : (z + \beta\, g) \in K\ T\} = K \sup_{b} \{b : (z/K + b\, g) \in T\} = K\ D(z/K, T)$. Combining these results gives the inequalities in (4).

From (1), we have $D(z^k, T) = \sup_{\beta_k} \{\beta_k : (z^k + \beta_k\, g) \in T\}$ and $\sum_{k=1}^{K} (1/K)\ D(z^k, T) = \sup_{\beta} \{\sum_{k=1}^{K} \beta_k/K : (z^k + \beta_k\, g) \in T, k = 1, \ldots, K\}$. Assume that the set T is convex. Then, $(z^k + \beta_k\ g) \in T$ for all k implies that $\sum_{k=1}^{K} [z^k/K + (\beta_k/K)g] \in T$. Letting $\alpha = \sum_{k=1}^{K} \beta_k/K$, it follows that $\sup_{\beta} \{\sum_{k=1}^{K} \beta_k/K : (z^k + \beta_k\, g) \in T, k = 1, \ldots, K\} \leq \sup_{\alpha} \{\alpha : (\sum_{k=1}^{K} z_k/K + \alpha\, g) \in T\} = D(\sum_{k=1}^{K} z_k/K, T)$. When $z = \sum_{k=1}^{K} z^k$, this yields $\sum_{k=1}^{K} (1/K)\ D(z^k, T) \leq D(z/K, T)$, which gives the first inequality in (5).

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