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Research Article

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Firm Efficiency and Returns-to-Scale in the Honey Bee Pollination Services Industry

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Abstract

While the demand for pollination services have been increasing, continued declines in honey bee, *Apis mellifera* L. (Hymenoptera: Apidae), colonies have put the cropping sector and the broader health of agro-ecosystems at risk. Economic factors may play a role in dwindling honey bee colony supply in the United States, but have not been extensively studied. Using data envelopment analysis (DEA), we measure technical efficiency, returns to scale, and factors influencing the efficiency of those apiaries in the northern Rocky Mountain region participating in the pollination services market. We find that, although over 25% of apiaries are technically efficient, many experience either increasing or decreasing returns to scale. Smaller apiaries (under 80 colonies) experience increasing returns to scale, but a lack of available financing may hinder them from achieving economically sustainable colony levels. Larger apiaries (over 1,000 colonies) experience decreasing returns to scale.Those beekeepers may have economic incentivizes to decrease colony numbers. Using a double bootstrap method, we find that apiary location and off-farm employment influence apiary technical efficiency. Apiaries in Wyoming are found to be more efficient than those in Utah or Montana. Further, engagement in off-farm employment increases an apiary's technical efficiency. The combined effects of efficiency gains through off-farm employment and diseconomies of scale may explain, in part, the historical decline in honey bee numbers.

Key words: pollination, technical efficiency, returns to scale, data envelopment analysis

Honey bees, *Apis mellifera* L. (Hymenoptera: Apidae), are well-known for producing honey, but they also provide critical ecosystem services through pollination (Goulson 2003, Potts et al. 2010, Ványi et al. 2012). Globally, wild and managed insect pollinators contribute approximately $244.7 (USD) billion to the value of world agricultural export (Gallai et al. 2009). While 70% of crops are dependent on animal pollinators, the estimated dependency of global agricultural production on these pollinators has increased by 56% from 1961 to 2006 (Klein et al. 2007, Aizen and Harder 2009).

Pollination services in the United States are valued at $16 billion annually, with approximately $12 billion attributable to managed honey bees (Calderone 2012) [Estimates of the global and national economic value of pollinators are based on past estimates by Gallai et al. (2009) and Calderone (2012). These past estimates have been updated to 2017 values using the CPI Inflation information from the United States Bureau of Labor and Statistics (BLS 2017, Marthison 2015). For additional estimates see Southwick and Southwick (1992).]. Honey bees are responsible for pollinating over 100 commercially grown crops in North America (Kearns et al. 1998, NRC 2007). Their vital pollination role in U.S. agriculture is highlighted by the revenue attributable to pollination contracts. At the industry level, pollination contracts have displaced honey production as the main revenue source for the apiary industry (Suryanarayanan 2012). This has occurred despite increasing honey consumption and value—national honey prices were at an all-time high in 2015 (NASS 2015).

While demand for pollination services and honey have both been increasing (Aizen and Harder 2009, NASS 2015), the number of managed honey bee colonies in the United States has declined (van Engelsdorp and Meixner 2010, USDA 2016). Beekeepers continue to be affected by colony loss, with a 40.5% annual loss between 2015 and 2016 (Kulhanek et al. 2017). National colony numbers reached a historic low of 2.39 million in 2006 with a slight rebound in 2015 to 2.59 million colonies (NASS 2007, USDA 2016). While domestic honey supply shortfalls may be compensated for with imports, the pollination services gap is more challenging to address. As the acreage of pollination-dependent crops increases, continued declines in honey bee colonies may have lasting effects on the cropping sector, its economic bottom-line, and the broader health of agro-ecosystems (van Engelsdrop et al. 2009).

Existing research on honey bee colony loss has focused primarily on anthropogenic, environmental, agrochemical, and biological drivers (e.g., Potts et al. 2010, Vanbergen 2013, Smith et al. 2013). Yet economic factors also play a role in managed honey bee colony decline (Smith et al. 2013). Beekeepers who experience colony loss often replenish them by purchasing packaged bees or splitting existing colonies. These replacement costs can be high relative to income, leading some beekeepers to not replace lost colonies or to exit the industry (vanEngelsdorp and Meixner 2010). For example, although 17% of colonies were lost in 2015, only 9% of colonies were replaced, leading to a net decline from 2.82 million in 2014 to 2.59 million in 2015 (USDA 2016). When beekeepers replenish lost colonies, they must determine the economically optimal colony level. From 1982 to 2002, the number of U.S. farms reporting apiculture activity decreased by nearly 70%. Among farms maintaining honey bee colonies, their colony inventory declined over the same period, particularly for those with fewer than 5,000 colonies (Daberkow et al. 2009).

In 2012, there were 115,000 to 125,000 North American beekeepers. Ninety-four percent of these were hobbyists (having fewer than 25 colonies) who did not offer pollination services to cultivated crops (NRC 2007, NHB 2017). In fact, Daberkow et al. (2009) report that approximately 50% of beekeepers have only one to four colonies. This leaves much of the commercial honey production and pollination work to larger apiary firms. Only 10% of beekeepers are classified as commercial, i.e., having 300 to 60,000 colonies (Daberkow, et al. 2009). Yet most of these commercial apiaries primarily produce honey, leaving only 1,600 commercial beekeepers that migrate (i.e., truck their colonies between agricultural regions) to pollinate crops throughout the United States (Horn 2006, Jabr 2013, Mairson 1993, Bond et al. 2014).

The biggest pollination market in the world is for California almonds. California almond growers provide 80% of the world's almond supply, and 100% of domestic supply (Ward et al. 2010). California almond production has doubled in the last 10 yr, from 915 million pounds in 2005 to 1,850 million pounds in 2015 (USDA 2015). Over the last 20 yr, the number of managed honey bees required to pollinate California's almond crop has risen exponentially, requiring more than half of all pollinating honey bee colonies in the United States (Champetier de Ribes 2010, Souza 2011, Project Apis m. 2012, Rucker, Thurman and Burgett 2012). Most varieties of almonds are 100% reliant on honey bee pollination (Klein et al. 2007). Two-thirds of almond pollinating colonies come from out-of-state. This amounts to the vast majority of the 1,600 beekeepers who migrate to California each year, pollinating additional crops as they travel to and from the almond bloom (Jabr 2013, Bond et al. 2014). Roughly 900,000 acres of almonds are pollinated by at least 1.6 million honey bee colonies (Johnson and Corn 2015).

Almond pollination revenue is essential to the apiary industry. Almond growers pay the highest average pollination fees to beekeepers, making the crop a top priority for almost all beekeepers that participate in the pollination market (Burgett 2011, Sagili and Caron 2017). Pollination fees for almonds have been steadily increasing since 2005, due in part to increasing acres planted to almonds (Ward et al. 2010). Because of this trend, income from almond pollination exceeds income from honey production in the United States beekeeping industry (Traynor 2017). Many commercial pollinators in the United States cover a large portion of their annual colony maintenance cost by pollinating almonds (Sumner and Boriss 2006).

Despite the potentially serious consequences of dwindling honey bee stocks in the United States, in-depth analyses of the pollination services market are largely missing from the literature (Rucker et al. 2012). Enhanced economic understanding of this market could benefit existing and future beekeepers (Burgett 2011). More specifically, a better understanding of the economic behavior and performance of beekeepers is essential to explaining and forecasting the scarce supply of colonies for pollination services (Champetier 2010). This is especially true in the northern Rocky Mountain region, where economic information on the beekeeping industry is lacking compared to information available for California and the Pacific Northwest, where ongoing surveys provide critical market insights (Caron et al. 2012, CSBA 2017). Given that commercial beekeepers in the northern Rocky Mountain region have the largest share of colonies in the United States—as well as larger operations, on average, than those in other regions (Daberkow et al. 2009)—this lack of information is surprising.

To better understand the potential economic causes of declining honey bee stocks, using the northern Rocky Mountain region as a case-study, we use data envelopment analysis (DEA) to measure the technical efficiency, returns to scale, and factors influencing efficiency of beekeepers who participate in the pollination services market. Rucker et al. (2012) hypothesized large economies of scale available to beekeepers providing pollination services, but this assertion has not yet been empirically tested. The existence of either production inefficiencies or decreasing returns to scale could discourage beekeepers from expanding their pollination services to meet the demands of an expanding almond industry; likewise, increasing returns to scale may create market-entry barriers for new beekeepers. Therefore, an in-depth analysis of beekeepers' technical efficiency at producing outputs from inputs is necessary. To our knowledge, no study has previously attempted to measure the efficiency of beekeepers engaged in the pollination market.

Material and Methods

In 2014, we mailed a survey to a random sample of 585 beekeepers, including 120, 323, and 142 beekeepers from Montana, Utah, and Wyoming, respectively, using the Dillman (1978) method. We received 257 completed surveys, with 41 from Montana, 140 from Utah, and 76 from Wyoming, resulting in an overall response rate of nearly 44%. This is above the median response rate for surveys mailed to business managers (Anseel et al. 2010).

The survey was six pages long, assembled as a booklet. Beekeepers were asked about their beekeeping business location, number of honey bee colonies managed, pollination contract status and colony rental fees, pollination service destinations, crops pollinated, cooperative transport arrangements, years of business operation, and income earned from off-farm employment. Specific costs, such as queen bee replacement and amount spent on hive repairs in 2013 were also gathered along with demographic information such as education, age, gender, race, and ethnicity. Hive repair, though not explicitly defined in the survey, encompasses tasks such as repairing or replacing damaged wood and wire in a hive.

Two methods are commonly used to assess a firm's technical efficiency (i.e., a firm's ability to produce maximum output from a given set of inputs): stochastic frontier analysis and DEA. Stochastic frontier analysis uses a parametric approach to estimate a production frontier and resulting efficiency measures (Jondrow et al. 1982).

The method requires the production technology to be specified a priori, which can be problematic. In many cases, the production technology's functional form is unknown, as is the case with beekeeping operations that provide pollination services. Alternative functional forms can lead to divergent conclusions, so an incorrectly assumed specification can be problematic (Giannikas et al. 2003).

A second method to measure efficiency is DEA. Unlike stochastic frontier analysis, DEA is a nonparametric approach that measures technical, scale, and economic efficiencies (Charnes et al. 1978, Banker et al. 1984, Charnes et al. 1994). Linear programming is employed in DEA to generate an efficiency frontier and then measure, for each firm or decision-making unit (DMU), its Euclidian distance to the frontier, which is based on the DMU's quantity of output achieved from their chosen inputs. We measure output technical efficiency of the Farrell (1957) type as described in more detail below (Färe et al. 1985).

The concept of technical efficiency was first shared by Galenson and Leibenstien (1955), with the first empirical application conducted by Farrell (1957). Technical efficiency measures the ability of a DMU to produce maximum output given a set of inputs (Farrell 1957). Farrell's measure of output technical efficiency for a DMU is defined as the amount by which the DMU's quantity of output is less than the potential quantity of maximum output given a certain combination of inputs. The maximum output, a point on the non-parametric frontier, is jointly determined by the output of similar, yet technically efficient DMUs.

Technical efficiency has been estimated for a wide variety of economic sectors, such as banking (Miller and Noulas 1996, Färe et al. 2004), hospitals (Varabyova and Schreyögg 2013), and swine production (Sharma et al. 1999). It has also been used to explore research questions about drivers of efficiency, such as gender in agriculture (Seymour 2017) and farm size (Helfand and Levine 2004). Relatively few studies have measured technical efficiency in the beekeeping industry. These previous studies have focused only on honey production in developing countries, and without consideration of the pollination services market (Habibullah and Ismail 1994, Aburime et al. 2006, Olarinde et al. 2008, Abdul-Malik and Mohammed 2012). These studies have also primarily used stochastic frontier analysis to measure honey production efficiency, an approach that requires them to assume in advance a shape for the production function (e.g., a Cobb-Douglas function), even though the true production function is rarely known. Given the limitations of stochastic frontier analysis when the true production relationship is unknown, we use DEA to measure the technical efficiency of beekeeping operations in the northern Rocky Mountain region that produce not only honey but also pollination services, specifically for almonds.

The DEA framework considers n DMUs, each producing k outputs from r inputs. For DMU i, the value of output technical efficiency, $\hat{\theta}_i$, is determined by the following linear program, which is calculated for each of the n DMUs separately:

$$\hat{\theta}_i = \max_{\theta_i, \lambda} \theta_i \tag{1}$$

$$\text{s.t.}\, \theta_i Y_i \leq Y\lambda$$

$$X_i \geq X\lambda$$

$$\lambda_i \geq 0$$

$$N1'\lambda = 1$$

Where Y_i is a $(k \times 1)$ vector of outputs produced by the i^{th} DMU using X_i, an $(r \times 1)$ vector of inputs. Y is the $(k \times n)$ matrix of the outputs and X is the $(r \times n)$ vector of inputs for all n DMUs in the sample. λ is the $(n \times 1)$ vector of weights attached to each of the n DMUs (λ_i). $N1$ is an $(n \times 1)$ vector of unit values. The value, $1 - \hat{\theta}_i$, represents the proportional increase in the amount of outputs that the i^{th} DMU could produce from the same level of inputs if it were technically efficient. If $\hat{\theta}_i = 1$ then the i^{th} DMU is on the frontier and is technically efficient. If $\hat{\theta}_i > 1$ then the i^{th} DMU is technically inefficient (note that the Farrell measure is the reciprocal of the Shepard output distance function).

In our study, multiple outputs can be generated from the single input of honey bee colonies owned. The most economically important outputs to an apiary are pollination contracts and honey production (e.g., Frazier et al. 2012) (Due to DEA's sensitivity to outliers, other outputs such as value-added wax products and selling of bees, which are not common among the beekeepers we surveyed, cannot be included in the analysis.). Although the quantity of honey production is straightforward to measure (e.g., pounds per colony), the quantity of pollination services is not. Pollination contracts explicitly define the number of colonies that will be delivered to a customer's field or orchard, so we use the number of colonies devoted to pollination as a proxy for pollination output (Champetier 2010). Because the almond industry is the top employer of pollination services from managed honey bees in the United States (Sagili and Caron 2017), we focus on the number of colonies devoted to almond pollination, in accordance with survey results (Five beekeepers in our sample reported pollinating other crops in addition to almonds. When we attempted to include these other crops in the analysis as additional outputs, these five observations were identified as outliers and thus recommended for omission from the DEA analysis. As a result, we excluded pollination of other crops from our analysis. Although this only affected five apiaries, the omission of their pollination of other crops could artificially reduce our estimates of these apiaries' efficiency.).

A variable returns to scale specification allows the DEA model to also estimate each DMU's returns to scale (Färe et al. 1985). By measuring the ratio of $\hat{\theta}_i$ estimated under the assumption of variable returns to the $\hat{\theta}_i$ estimated under the assumption of constant returns to scale, a scale efficiency measure is generated. Scale efficiency measures the impact of scale on the productivity of a DMU. When the scale efficiency is equal to one, then constant returns to scale prevails for that DMU. If the scale efficiency measure is less than one, then either increasing or decreasing returns to scale exists. Which of these two a DMU experiences cannot be inferred from the magnitude of the scale efficiency measure itself, but instead depends on the DMU's location on the variable returns to scale frontier.

DEA analysis tends to be sensitive to outliers, so we use the *FEAR* package in *R* to conduct an outlier analysis (following Wilson 2008). Results of this analysis influence which DMUs are included in the final DEA analysis, and hence the regression analysis described next.

To account for exogenous factors that may influence the DEA measure of technical efficiency, we conduct a two-stage regression analysis. In the first stage, we regress the $\hat{\theta}_i$ for each DMU on covariates of interest. In the second stage, to ensure statistical efficiency, we use a double-bootstrap procedure to correct for serial correlation between the n $\hat{\theta}_i$ (Simar and Wilson 2007). This procedure uses truncated regression and bootstrapping to overcome unknown serial correlation in the following equation:

$$\hat{\theta}_i = z_i\beta + \varepsilon_i \quad (2)$$

where z_i is a $(1 \times q)$ vector of covariates or environmental variables exogenous to the DMUs, β is a $(q \times 1)$ vector of parameters, and ε_i is an error term assumed to be normally distributed with left-truncation at $(1 - z_i\beta)$ and variance σ^2.

The DEA literature suggests that, for agricultural applications, a DMU's chosen inputs, resulting outputs, and associated technical efficiency may be influenced or correlated with factors such as location, income, years in farming, non-farm income, purchasing power, and capital-sharing arrangements (e.g., Hansson 2007, Afonso 2008, Olson 2009, Larsén 2010). Particular to the beekeeping industry, we hypothesize that location, years of operation, hive repair costs, use of a transportation cooperative, revenue from pollination services, potential revenue from unsold honey, and off-farm employment may influence a DMU's technical efficiency.

Hansson (2007) showed that location significantly influences technical efficiency for dairy farms in Sweden. We include the United States state in which a beekeeping operation is located as a covariate. The hypothesis is that beekeepers located in states with closer proximity to California will be more efficient due to easier access (i.e., lower transportation costs) to almond orchards and thus a stronger position for securing pollination contracts.

The length of time a beekeeper has been in operation may influence technical efficiency in two ways. As tenure increases, a DMU may learn from past experiences and become more efficient. Yet, newer DMUs may bring with them new technology that increases technical efficiency. Olson (2009) found empirical evidence that an increase in years of farming moderately decreases technical efficiency. To determine in which direction the tenure of a beekeeping business affects technical efficiency, we include the number of years in operation in the second-stage analysis.

Hive maintenance and repair are necessary activities to sustain a beekeeping operation's honey production and pollination services (Walker et al. 2014). An example hive-maintenance activity is replacing frames every 5 yr in an effort to control brood diseases (Walker et al. 2014). We therefore include per-colony expenditure on hive repairs in our model and hypothesize that it increases DMU efficiency.

Larsén (2010) found that farmers involved in machinery-sharing arrangements also enjoyed higher farm efficiency. Parallels in the beekeeping industry, which we include in our model, are being a member of a colony-transportation cooperative during the pollination season.

Olson (2009) found that on-farm income is negatively related to the technical efficiency of farms, suggesting that higher-income farms are actually less technically efficient than lower-income farms. We are interested to see if income generated from a beekeeping operation has the same relationship to efficiency. Since some beekeepers involved in the pollination industry only generate revenue from pollination services (meaning no revenue is generated from selling honey), the metric we use in the regression analysis is revenue generated from pollination service per colony. Revenue from pollination services per colony-squared was also used as a covariate in the second-stage analysis.

Many beekeepers in our survey noted that they produce honey but do not sell it. Although we did not explicitly ask survey respondents how they use this unsold honey, many beekeepers voluntarily indicated that they use the honey for personal use or gifts. This lack of marketing may be a symptom or an indicator of general inefficiencies within an apiary operation. We therefore included the value of unsold honey in our regression model, calculated by multiplying average price received for honey through a cooperative by the number of pounds not sold (The price from a honey cooperative was used since it cannot be assumed that a beekeeper would be able to sell honey through other, more lucrative channels. Selling honey through a cooperative may be the most reliable option for selling honey. The price of a pound of a honey was obtained through personal communication with the Sue Bee Corporation's Honey Marketing Division.).

Regarding off-farm income, Larsén (2010) found that farmer participation in off-farm employment was associated with a weak increase in technical efficiency of farms in Sweden. We therefore included off-farm income as a binary variable. Equation 3 represents the final specification used in our regression analysis of technical efficiency.

$$\hat{\theta} = \beta_0 + location\beta_1 + tenure\beta_2 + repair\beta_3 + transcoop\beta_4 + rev\beta_5 + rev^2\beta_6 + unsoldhoney\beta_7 + offfarm\beta_8 + \varepsilon \quad (3)$$

Where *location* is the beekeeper's business home state, *tenure* is the years of continual operation, *repair* is the annual average amount spent on repairing hives, *transcroop* is a dummy variable indicating the use of a transportation cooperative agreement (1 = transport cooperative agreement, 0 = otherwise), *rev* is the revenue per colony from pollination services, rev^2 is the square of per-colony revenue from pollination services, *unsoldhoney* is the value of honey produced but not sold, *offfarm* is a dummy variable indicating whether a beekeeper earns income from off-farm employment (1 = off-farm employment, 0 = otherwise), and ε is an error term.

Results

Survey Results

A summary of survey responses for all respondents, irrespective of their participation (or lack thereof) in the provision of pollination services, is provided in Table 1.

Beekeepers in our survey manage over 180 colonies, on average, and produce almost 13,000 pounds of honey per year. Their apiaries have been in operation, on average, for nearly 14 yr with half of beekeepers reporting income earned from off-farm employment. Regarding hive maintenance, beekeepers in the sample reported spending nearly $33 per colony per year on hive repairs (Table 1).

Also from Table 1, only 12% of beekeepers in the sample are involved in the pollination market. This finding is in line with previous research (e.g., NRC 2007), and suggests the potential for more beekeepers to supply honey bee colonies for crop pollination, if economic conditions allowed.

The same honey bee colony can be hired to pollinate multiple crops throughout the year, each with different pollination needs, timing, location, and market value. Almonds are the most commonly contracted crop for pollination among beekeepers in our sample, with beekeepers sending an average of 1,084 colonies to pollinate almonds (only five beekeepers in our sample send their colonies to pollinate other crops) (Table 2). This finding is consistent with other literature that highlights the almond industry's strong influence on the pollination market (e.g., Champetier de Ribes 2010, Bond et al. 2014). We therefore focus attention from this point forward, including in the DEA analysis, on pollination contracts with almond orchards. This provides a consistent measure of output productivity across otherwise diverse beekeeping operations. Table 2 provides summary statistics of inputs and outputs for the 30 beekeepers in our sample that have pollination contracts.

Table 1. Survey-response summary statistics for entire sample, irrespective of pollination contract participation (in USD)

Variable	No of observations	Average	SD	Min	Max
Apiary location					
Montana	41	0.16		0	1
Utah	139	0.54		0	1
Wyoming	77	0.30		0	1
Number of colonies in 2014	257	187	783	0	8,000
Total pounds of honey production in 2013[a]	251	12,238	58,056	0	500,000
Years in operation	241	13.7	17	0	98
Receive wages from off-farm employment	128	0.50		0	1
Hive repair cost per colony in 2014		$33	62	$0	$500
Pollination contract in place in 2014	30	0.12		0	1

[a]The survey was sent to respondents in the fall of 2014. Therefore, the total number of pounds of honey was not known for 2014.

Table 2. Survey response summary statistics for beekeepers with pollination contracts—inputs, outputs, and other variables of interest (in USD)

Variable	No of observations	Percentage of Sample	Average	SD	Min	Max
Crop pollination						
Almonds	30	100%	1,084	1,535	20	8,000
Apples	5	17%	2,160	3,293	300	8,000
Cherries	4	13%	430	591	54	1,300
Other	4	13%	57	10	50	64
Total honey production per year (lbs)	30		83,502	123,112	125	500,000
Apiary location						
Montana	6	20%				
Utah	10	33%				
Wyoming	14	47%				
Total number of colonies owned	30		1,304	1,583	26	8,000
Years in operation	30		35	28	4	96
Receive wages from off-farm employment	7		23%			
Hive repair cost per colony	30		$10	$14	$0	$63
Pollination fees collected per colony	30		$116	$43	$36	$212

The average number of colonies managed by beekeepers who enter pollination contracts is 1,304 (Table 2), which is seven times larger than the average of 184 colonies among all beekeepers in our sample (Table 1). This suggests that a large number of colonies may be necessary to achieve economic viability in the pollination market. Similarly, the amount of honey produced, on average, by beekeepers with pollination contracts is over 83,000 pounds per year (Table 2), which is also nearly seven-times higher than the 12,000 pounds produced on average among all beekeepers in our sample (Table 1). This difference in total honey production seems to be due primarily to the total number of colonies, since the average amount of honey produced per colony is not notably different for beekeepers with pollination contracts versus all beekeepers in our sample (64 versus 65 pounds per colony, respectively).

Our survey results also provide information about socioeconomic and geographic variables that may influence or reflect the efficiency of our 30 beekeepers' pollination and honey enterprises. Among the 77 Wyoming beekeepers who responded to the survey, 14 (i.e., 18%) have pollination contracts, a larger proportion than respondents in either Montana (14%) or Utah (7%) (Tables 1 and 2). In addition, the average length of time that an apiary has been in business is drastically longer for those participating in the pollination market than for the overall sample, 35 yr versus 13 yr, respectively.

Among beekeepers that have pollination contracts, less than a quarter receive income from off-farm employment, as compared to half of all beekeepers (Tables 1 and 2). Thus, most beekeepers who participate in the pollination market rely upon their apiary business as their only form of income. Lastly, the amount that beekeepers with pollination contracts report spending on hive repair (per colony) is much smaller than that reported for the entire sample—$10 versus $33 (Table 2 versus Table 1). This suggests that a beekeeper's per-colony repair cost might decrease as the number of colonies in their apiary increases, perhaps due to size efficiencies (e.g., spreading any fixed-costs of repair over more colonies, or being able to buy repair materials in bulk). Next, we report measures of technical and scale efficiencies for our sample of 30 beekeepers engaged in pollination contracts.

DEA Efficiency Measures

Recall that the outputs of interest are honey production and almond pollination. A small number of beekeepers also pollinate other crops (e.g., apples and cherries), but attempts to include this characteristic caused the *FEAR* analysis to identify them as outliers. Therefore, pollination of other (non-almond) crops is not included as an output in the DEA analysis. Non-almond crops typically demand pollination at different times of the year than almonds, so our exclusion of these outputs should not influence an engaged DMU's efficiency measures relative to those that engage strictly in almond pollination.

Based on a *FEAR* outlier analysis of the 30 DMUs engaged in almond pollination, four of the DMUs were deemed outliers and omitted from the analysis. The two-stage DEA analysis was then conducted on the remaining 26 DMUs. Technical efficiency results, along with scale and returns-to-scale measures, are shown in Table 3.

Table 3. DEA results for technical efficiency and returns to scale

Observation	Input	Outputs		Efficiency scores		
DMU_i	Number of colonies	Honey production (lbs)	No. colonies in almond pollination	Technical	Scale	Returns-to-scale
1	26	1,060	20	1.000	0.769	Increasing
2	40	1,400	23	1.546	0.889	Increasing
3	80	8,000	80	1.000	1.000	Constant
4	120	5,000	64	1.876	1.000	Constant
5	140	5,700	96	1.458	1.000	Constant
6	150	3,800	50	3.003	1.000	Constant
7	200	12,000	200	1.000	1.000	Constant
8	300	9,900	125	2.400	1.000	Constant
9	400	20,000	300	1.333	1.000	Constant
10	450	6,000	400	1.125	1.000	Constant
11	500	15,000	350	1.429	1.000	Constant
12	600	15,600	500	1.200	1.000	Constant
13	700	12,300	500	1.401	1.000	Constant
14	1,000	4,500	350	2.857	1.000	Constant
15	1,000	78,000	900	1.085	0.976	Decreasing
16	1,000	44,000	800	1.250	1.000	Constant
17	1,000	24,000	700	1.429	1.000	Constant
18	1,100	97,000	900	1.027	0.906	Decreasing
19	1,200	100,000	1,200	1.000	1.000	Constant
20	1,200	95,000	850	1.152	0.912	Decreasing
21	1,500	95,000	1,200	1.209	0.968	Decreasing
22	1,600	77,000	1,000	1.541	0.963	Decreasing
23	1,700	91,000	1,700	1.000	1.000	Constant
24	2,200	120,726	1,800	1.155	0.945	Decreasing
25	2,200	200,000	1,800	1.000	0.909	Decreasing
26	3,500	200,000	3,200	1.000	0.914	Decreasing

Technical Efficiency

Technical efficiency scores for the 26 DMUs (Table 3) range from fully efficient (1.00) to the least efficient DMU (3.03). Twenty-seven percent of all DMUs are fully efficient, and another 46% are nearly efficient with technical efficiency scores between 1.00 and 1.50. Only 12% of the DMUs have a technical efficiency score exceeding 2.00, indicating greater levels of inefficiency. Recall that technical efficiency indicates the extent to which a firm should be able to increase outputs (proportionally) given their chosen input level (i.e., size).

These results suggest that many of the sampled beekeepers in the northern Rocky Mountain region are relatively efficient in using their colonies for honey production and almond pollination. Both the smallest beekeeper (26 colonies) and largest beekeeper (3,500 colonies) are efficient. Based on a univariate regression, there is no significant relationship between the size of a DMU and their level of technical efficiency.

Scale Efficiency

The scale efficiency and returns-to-scale scores in Table 3 show that many DMUs, especially those with 80 to 1,000 colonies, have a scale efficiency of 1.00 and thus enjoy constant returns to scale. Beekeepers with constant returns to scale could double their inputs with a concomitant doubling of their outputs. This implies they are located on the horizontal portion of their long-run average cost curve, with no immediate incentive to adjust their scale of operation (Pindyck and Rubinfeld 2001, p. 228). Table 3 also reveals that DMUs with fewer than 80 colonies experience increasing returns to scale. These beekeepers operate on the downward sloping portion of their long-run average cost curve, where they can reduce long-run average cost by increasing their scale of operation. Finally, Table 3 reveals that, with only a few exceptions, DMUs with more than 1,000 colonies tend to experience decreasing returns to scale and are located on the upward-sloping portion of their long-run average cost curve. These beekeepers could reduce long-run average cost by decreasing their scale of operation. In the long run, we would expect these larger apiaries to reduce their colony stock (and all other inputs) in order to move from decreasing to constant returns-to-scale, which may help explain the United States trend of decreasing colony numbers (Daberkow et al. 2009). In turn, we would expect smaller apiaries to either increase their colony stock (and other inputs) to move from increasing to constant returns-to-scale or exit the industry.

The scale efficiency results provide empirical evidence to inform Rucker et al.'s (2012) hypothesis that 'large economies of scale are available to beekeepers'. Our results suggest large economies of scale are available primarily to beekeepers with fewer than 80 colonies, but not for larger operations with more than 1,000 colonies, limiting the hypothesis to a small range of apiaries.

To determine factors correlated with or influencing technical efficiency in beekeeping, we look next at the results of the two-stage regression approach introduced earlier (Simar and Wilson 2007).

Regression Results

Results for the two-stage model specified in equation 3 are reported in Table 4.

Results from the two-stage regression indicate that location of a beekeeping operation has a significant impact on its technical efficiency. Specifically, beekeepers with apiaries located in Wyoming are more efficient than similar operations located in either Utah or Montana. This is not fully consistent with our initial hypothesis, given Utah is located closer to California than Wyoming. We will therefore explore potential reasons for this finding in the next section. Lastly, beekeepers that report receiving income from off-farm employment

Table 4. Regression results for technical efficiency

Variable	Coefficient
Utah	3.164882*
Montana	4.067009†
Years in operation	−0.000763
Hive repair expenditure per colony	−0.025163
Uses transportation cooperative	0.798703
Pollination revenue per colony	−0.154470
Pollination revenue per colony squared	0.000368
Potential revenue from unsold honey	−0.000082
Off-farm employment	−2.546698*
Constant	12.85779*
Sigma	0.143365

An increase in the efficiency score indicates increasing inefficiency.
*Significant at the 0.05 level. †Significant at the 0.01 level.

are more technically efficient than those that report no off-farm employment. No other covariates were statistically significant at the 0.05 or 0.01 level, despite this being the best-performing model.

Although the remaining covariates are statistically insignificant, their signs are generally as expected. For example, the negative sign on years in operation implies that, as years in operation increases, the magnitude of an apiary's technical efficiency score decreases, which means their technical efficiency increases. Hive repair expenditure per colony also has a negative sign, implying increased technical efficiency with increased expenditure. Similarly, pollination revenue per colony has a negative sign. One of the few covariates with a positive sign is the use of a transportation cooperative, which suggests that participation increases the technical efficiency score, or decreases efficiency. Again, however, none of these covariates are statistically significant at the 0.01 or 0.05 level. Other factors, such as apiary revenue and hours of hired labor, appear to be correlated with technical efficiency measures. Unfortunately, such factors are endogenous (i.e., they are determined simultaneously with technical efficiency) and therefore cannot be included in the analysis (Antonakis et al. 2010). For example, technical efficiency may influence a firm's decision to hire labor, but hired labor may in turn influence a firm's technical efficiency. The direction of causality cannot be teased apart, so this factor cannot be used in our regression model. Even a simple correlation coefficient between these factors and technical efficiency should not be trusted (Antonakis et al. 2010).

Discussion

Our results show that, although there is no statistically significant relationship between technical efficiency and apiary size (Table 3), larger operations (more than 1,000 colonies) experience decreasing returns to scale, and should decrease their colony stock (and other inputs) in order to minimize long-run average cost and thus maximize profit (Pindyck and Rubinfeld 2001, p. 198). The long-term decrease in honey bee colonies might therefore be due in part to beekeepers moving increasingly towards more optimal scales of production. One potential cause of decreasing returns to scale for larger apiaries may relate to be the managerial challenges of preventing pests, pathogens, and other stressors at larger scales of operation. Hive inspection is considered a best practice for preventing disease and increasing bee health (Formate and Smulders 2011). As an apiary's colony numbers grow, a beekeeper's ability to implement best practices, such as frequently inspecting colonies, may be hindered. This and other costs of becoming 'too big' may incentive a beekeeper to maintain lower colony numbers.

Technical efficiency of beekeepers in this region is also affected by off-farm employment and location. Income from off-farm employment may increase the purchasing power of an apiary, which has been shown to affect technical efficiency (e.g., Afonso 2008). An alternative or additional hypothesis is that, by working off farm, a beekeeper is at less risk of over-investing their time in the apiary. Yet, they must not be so distracted by off-farm employment that they neglect their hives. Since off-farm employment most likely distracts from apiary management, these beekeepers may be constrained by time to keep a smaller operation. This smaller colony stock may help avoid decreasing returns to scale, resulting in lower average cost and higher profit. Overall, however, off-farm employment may be contributing to smaller honey bee stocks in the region.

Our results indicate that Wyoming's apiaries are more technically efficient than those in either Montana or Utah. This could be due to greater efficiency in honey production or pollination services. Wyoming's average honey yield per colony is higher than Utah's (77 versus 42 pounds per colony, respectively), and similar to Montana's (83 pounds) (USDA 2016). Regarding pollination, Wyoming apiaries contracted, on average, over 750 colonies (per apiary) to pollinate almonds, while those in Montana contracted, on average, 616 colonies. This is despite Wyoming apiaries being smaller, on average, than Montana (1,445 versus 1,674). Beekeepers in Utah contracted the most colonies to pollinate almonds, nearly 1,010 colonies per apiary, on average (out of the 1,122 colonies owned per apiary). Yet Wyoming produces enough additional honey per colony compared to Utah (77 compared to 42 pounds per colony per year, respectively) to make the former more efficient overall. Together, these factors may explain why technical efficiency levels are higher in Wyoming—more honey production per colony and more colonies under almond pollination contracts per apiary.

Additional location-related factors that should be explored in future research include the relative health of bees in different states, the availability of higher quality pollen or nectar, and the extent or strength of social networking among beekeepers (as well as with potential clientele). These factors would require more-in-depth data collection, beyond a traditional survey, but could provide additional insights about why a beekeeper's location in Wyoming versus Montana or Utah is correlated with their technical efficiency.

The results of our study suggest that economic factors—most notably diseconomies of scale–may be incentivizing beekeepers with more than 1,000 colonies to decrease their scale of operation. At the same time, beekeepers with fewer than 80 colonies should be experiencing economic incentives to expand their operation due to increasing returns to scale, but may be limited by available funds (a hypothesis that remains to be tested), and could potentially leave the industry as a result.

Current and future policies aimed at increasing the supply of honey bee colonies should be sensitive to the potential for apiary expansion to eventually encounter decreasing returns to scale. The smallest of commercial apiaries, though, are consistently experiencing increasing returns to scale, signaling an opportunity to gain additional honey bee colonies through carefully planned growth and available agricultural loans. Daberkow et al. (2009) found that the declining stock of honey bee colonies is driven by apiaries with fewer than 5,000 colonies. Our analysis focused entirely on apiaries with fewer than 5,000 colonies, and yet still found diversity in returns-to-scale. Targeting beekeepers with fewer than 80 colonies for incentives to increase their colony numbers shows some potential for raising the honey bee stock while also increasing their scale efficiency.

Although this study uses well-established methods for calculating DEA efficiency scores and a robust regression approach, the small sample of apiaries on which it relies (n = 30) likely limited our ability to identify more statistically significant covariates. Studies have also shown that, with smaller sample sizes, DEA tends to overestimate efficiency (Alirezaee et al. 1998, Zhang and Bartels 1998). Thus, our analysis likely overestimates the technical efficiency of beekeeping operations in the Rocky Mountain region. However, the relative ranking of DMUs to each other is still valid (Zhang and Bartels 1998). Furthermore, the tendency to overestimate efficiency can be partially mitigated by analyzing fewer inputs and outputs, i.e., aggregating them into fewer categories (Alirezaee et al. 1998), as we have done in this study. Future research should nonetheless focus on obtaining larger samples of apiaries that are involved in pollination services, not only within the Rocky Mountain region, but also for other regions, to better understand the role of economic factors in the long-term decline of honey bee stocks in the United States.

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