Online Appendix for:

To (Rent) Bees or Not to (Rent) Bees? An Examination of the Farmer's Question

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A Theory Model

A.1 Pollination Choice

Farmers of pollination-dependent crops grow much of the world's nutritious and high-value fruits, nuts, and vegetables. They face very complex production decisions, which in many cases involve long-term investments – especially for long-lived tree fruits and nuts – and production is often labor intensive and dependent on migrant farmworkers (Ridley and Devadoss, 2021). Agronomic trends are also evolving away from traditional, low-density, very long-lived plants to high intensity, university-driven plant materials that are selected to tolerate greater density of fruit into smaller area on smaller trees, which are easier to harvest (Robinson et al., 2013).

Pollination choice, and general production strategies that affect pollination resource demand (e.g., planting density), are very important. Although insect pollination is not necessary for all crops, many crops require or benefit greatly from pollination from insects or other organisms.[1] In addition to decisions about general production strategies and other input choices, producers of pollination-dependent crops make decisions about whether and how much to use managed pollination services (e.g., renting honey bees); and whether and how much to invest in wild pollination (e.g., setting aside land for planting wildflower strips, or other natural cover (Cohen, 2022)).[2] Available research suggests that farmer pollination choices are critical as they impact farm-level outcomes like yield and fruit quality (Roubik, 2002; Garibaldi et al., 2013; Park et al., 2016; Russo et al., 2017; Danforth, Minckley, and Neff, 2019), local pollination resources within and beyond the

[1] In many cases crops are sufficiently self-pollinating (e.g., grasses), and in some special cases pollination is carried out with a combination of human labor and motorized or non-motorized farm implements (e.g., paint brushes, compressed air, and possibly drone-based technology in the future). Researchers are also developing self-pollinating plant varieties (Lee, Sumner, and Champetier, 2019). Widely consumed crops that require or greatly benefit from insect pollination include almonds, coffee, apples, avocados, cherries, peaches, blueberries, among many others.

[2] Although reliable global data on variation in pollination practices is not known to exist, available information suggests that farmers of pollination-dependent crops vary widely in the form of pollination they depend upon and in how critical pollination is viewed and valued as a resource. For example, contrast the well-trodden tail of US almond growers' seeming absolute dependence on imported honey bee colonies with reports that for many Northeast US apple growers pollination is almost an afterthought compared to concerns surrounding labor and traditional farm capital (Biltonen, 2020; Kahlke, 2019). Other qualitative variation is documented by Narjes and Lippert (2019) and Narjes and Lippert (2021) who document relationships between beekeepers and longan fruit farmers in Thailand. There are also special cases like vanilla in Madagascar, which is entirely dependent on labor for pollination (Kaila and Boone, 2020).

farm-gate (Kennedy et al., 2013; Park et al., 2015; Grab et al., 2018), and market-level outcomes through shifts in the supply and demand of both pollination resources and agricultural commodities (Rucker, Thurman, and Burgett, 2012; Goodrich, Williams, and Goodhue, 2019).

A.2 Proofs of Propositions 1 through 5

We take our start from the optimal control theory model in the main text:

$$
\begin{aligned}
\max_{\{I_k(t),\, L(t),\, M(t),\, I_w(t)\}} \ & \int_0^\infty \pi(K(t),L(t),M(t),W(t))e^{-rt}dt \\
\text{s.t.} \ \ & \dot{K}(t) = \delta_k K(t) + I_k(t) \ \ : \ \lambda_k(t) \\
& \dot{O}_w(t) = F(W(t)) + I_w(t) - \delta_{mw}M(t) - \delta_{kw}I_k(t) \ \ : \ \lambda_w(t) \\
& K(t),\, L(t),\, M(t),\, W(t) \geq 0 \\
& K(0) = K_o,\, W(0) = W_o,
\end{aligned}
\tag{A.1}
$$

and its current-value Hamiltonian:

$$
\begin{aligned}
H_c &= \pi(K,\, L,\, M,\, W) \ + \ \lambda_k\left[\delta_k K + I_K\right] + \lambda_w\left[F(W) + I_w - \delta_{mw}M - \delta_{kw}I_k\right] \\
&= p_c\Big(A\big[\gamma_o(\alpha_m M^{-\rho_o} + \alpha_w W^{-\rho_o})^{\frac{\rho}{\rho_o}} + \gamma_{kl}(\alpha_k K^{-\rho_{kl}} + \alpha_l L^{-\rho_{kl}})^{\frac{\rho}{\rho_{kl}}}\big]^{\frac{-1}{\rho}}\Big) - \\
&\quad \Big(p_k I_k + p_l L + p_m M + p_w I_w\Big) + \\
&\quad \lambda_k\left[\delta_k K + I_K\right] + \lambda_w\left[F(W) + I_w - \delta_{mw}M - \delta_{kw}I_k\right].
\end{aligned}
\tag{A.2}
$$

After applying the Maximum Principle and simplifying expressions we arrive at the following optimality conditions:

[#1L]: $p_c(t)\frac{\partial Q}{\partial L} = p_l(t)$

[#1M]: $p_c(t)\frac{\partial Q}{\partial M} = p_m(t) + p_w(t)\delta_{mw}$

[#1w]: $p_w(t) = \lambda_w(t)$

[#1k]: $p_k(t) = \lambda_k(t) - p_w(t)\delta_{kw}$

[#2w]: $\dot{p}_w = p_w(t)[r - \frac{\partial F(W)}{\partial W}] - p_c(t)\frac{\partial Q}{\partial W}$

[#2k]: $\dot{p}_k = p_k(t)(r - \delta_k) + p_w(t)\delta_{kw}(\frac{\partial F(W)}{\partial W} - \delta_k) + p_c(t)(\delta_{kw}\frac{\partial Q}{\partial W} - \frac{\partial Q}{\partial k})$

[#3w]: $\lim_{t\to\infty} p_w(t)W(t)e^{-rt} = 0$

[#3k]: $\lim_{t\to\infty}(p_k(t) + p_w(t)\delta_{kw})K(t)e^{-rt} = 0$

Per our assumptions stated in the main text, we focus on the respective first-order condition for M, denoted [#1M].

We start with the following Lemma:

Lemma 1:

First, we show that, for most reasonable values of the parameters, the production function is weakly concave in M: $\frac{\partial^2 Q}{\partial M^2} \leq 0$. Since a more explicit expression for this derivative is useful for our results of interest, we can also establish the negativity result analytically.

Given the stated structure of output Q as given by a 2-level CES production (Sato, 1967), we use the following expressions to simplify notation:

$$\text{Let } B = \alpha_m M^{-\rho_o} + \alpha_w W^{-\rho_o}$$

$$\text{Let } C = \alpha_k K^{-\rho_{kl}} + \alpha_l L^{-\rho_{kl}}$$

$$\text{Let } D = \gamma_o(\alpha_m M^{-\rho_o} + \alpha_w W^{-\rho_o})^{\frac{\rho}{\rho_o}} + \gamma_{kl}(\alpha_k K^{-\rho_{kl}} + \alpha_l L^{-\rho_{kl}})^{\frac{\rho}{\rho_{kl}}}$$

$$\Rightarrow Q = A[\gamma_o(B)^{\frac{\rho}{\rho_o}} + \gamma_{kl}(C)^{\frac{\rho}{\rho_{kl}}}]^{\frac{-1}{\rho}} = A[D]^{\frac{-1}{\rho}}$$

Taking this simplified notation as our starting point we see the marginal product with respect to M is as below and that the sign is positive.

$$\frac{\partial Q}{\partial M} = \frac{Q\,(B(M,W))^{\frac{\rho-\rho_o}{\rho_o}}\,\alpha_m\,\gamma_o}{D\,M^{(\rho_o+1)}}$$

$$\Rightarrow\ \text{sign}\left[\frac{\partial Q}{\partial M}\right] \geq 0\ \text{ since all terms are} \geq 0.$$

Taking the above equation as the starting point for the second derivative we have the following expression for the second derivative with respect to M, with many simplifying steps omitted.

$$\frac{\partial^2 Q}{\partial M^2} = \frac{\partial}{\partial M}\left(\frac{QB(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m\gamma_o}{DM^{\rho_o+1}}\right)$$

$$= \frac{\alpha_m\gamma_o QB(M,W)^{\frac{\rho-\rho_o}{\rho_o}}}{\left(DM^{\rho_o+1}\right)^2}\left[\alpha_m\gamma_o B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}(1+\rho) - \left(\gamma_o(B(M,W))^{\frac{\rho-\rho_o}{\rho_o}} + \frac{\gamma_{kl}(C(K,L))^{\frac{\rho}{\rho_{kl}}}}{B(M,W)}\right)\left(\alpha_m(\rho-\rho_o)\right) - D(1+\rho_o)M^{\rho_o}\right]$$

Since we know for sure that $\frac{\alpha_m\gamma_o B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}Q}{\left(DM^{\rho_o+1}\right)^2} > 0$, we can resolve the sign of $\frac{\partial^2 Q}{\partial M^2}$ analytically as shown below:

$$\text{sign}\left[\frac{\partial^2 Q}{\partial M^2}\right] =$$
$$\text{sign}\left[\alpha_m\gamma_o B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}(1+\rho) - \left(\gamma_o(B(M,W))^{\frac{\rho-\rho_o}{\rho_o}} + \frac{\gamma_{kl}(C(K,L))^{\frac{\rho}{\rho_{kl}}}}{B(M,W)}\right)\left(\alpha_m(\rho-\rho_o)\right) - D(1+\rho_o)M^{\rho_o}\right]$$

$$\Rightarrow \frac{\partial^2 Q}{\partial M^2} \leq 0 \iff$$
$$\left(\gamma_o(B(M,W))^{\frac{\rho-\rho_o}{\rho_o}} + \frac{\gamma_{kl}(C(K,L))^{\frac{\rho}{\rho_{kl}}}}{B(M,W)}\right)\left(\alpha_m(\rho-\rho_o)\right) + D(1+\rho_o)M^{\rho_o} \geq \alpha_m\gamma_o B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}(1+\rho)$$

From the above we can see that a negative sign is likely analytically. This is because under realistic assumptions, the above inequality is likely to hold given that D, for example, is the majority of what comprises Q. Hence it should hold that $D \geq B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}$.

By this additional work, we assume for the remaining expressions that $\frac{\partial Q}{\partial M} \geq 0$ and $\frac{\partial^2 Q}{\partial M^2} \leq 0$.

Proof of Proposition 1:

Taking [#1M] as the starting point, the respective total derivative and expression for $\frac{dM}{dp_m}$ are as follows:

$$-dp_m + p_c \frac{\partial^2 Q}{\partial M^2} dM = 0$$

$$\Rightarrow \frac{dM}{dp_m} = \frac{1}{p_c \frac{\partial^2 Q}{\partial M^2}}$$

The elasticity η_{M,p_m} of M with respect to managed pollination price p_m is then given by:

$$\eta_{M,p_m} = (\frac{p_m}{M}) \frac{dM}{dp_m} = \frac{p_m}{M p_c \frac{\partial^2 Q}{\partial M^2}}$$

With the intermediate results from Lemma 1, we obtain:

$$\text{sign}\left[\frac{dM}{dp_m}\right] = \text{sign}\left[\frac{1}{p_c \frac{\partial^2 Q}{\partial M^2}}\right] = \frac{(+)}{(+)(-)} \leq 0$$

The remainder of our claims under Proposition 1 follow immediately from the preceding work. Specifically, we see that, *ceteris paribus*, managed pollination use M is decreasing in managed pollination price p_m (since $\frac{dM}{dp_m} \leq 0$), and the own-price elasticity η_{M,p_m} declines in magnitude with with managed pollination use M and with output price p_c.

Under the assumptions from Lemma 1 that Q is concave in M, output Q will exhibit diminishing returns to M. The more production is curved with respect to M (i.e., the greater the diminishing returns to M), the less elastic M will be with respect to managed pollination price (i.e., the less responsive M will be to increases in price).

If production is linear with respect to M (no diminishing returns, hence $\frac{\partial^2 Q}{\partial M^2} = 0$), then demand will be perfectly elastic.

QED.

Proof of Proposition 2:

Taking [#1M] as the starting point, the respective total derivative and expression for $\frac{dM}{dp_c}$ are as follows:

$$\frac{\partial Q}{\partial M} dp_c + p_c \frac{\partial^2 Q}{\partial M^2} dM = 0$$

$$\Rightarrow \frac{dM}{dp_c} = \frac{\frac{-\partial Q}{\partial M}}{p_c \frac{\partial^2 Q}{\partial M^2}}$$

The elasticity η_{M,p_c} of M with respect to output price p_c is then given by:

$$\eta_{M,p_c} = (\frac{p_c}{M}) \frac{dM}{dp_c} = \frac{\frac{-\partial Q}{\partial M}}{M \frac{\partial^2 Q}{\partial M^2}}$$

With the intermediate results in Lemma 1, we obtain:

$$\text{sign}\left[\frac{dM}{dp_c}\right] = \text{sign}\left[\frac{\frac{-\partial Q}{\partial M}}{p_c \frac{\partial^2 Q}{\partial M^2}}\right] = \frac{(-)(+)}{(+)(-)} \geq 0$$

The remainder of our claims under Proposition 2 follow immediately from the preceding work. Specifically, we see that, *ceteris paribus*, managed pollination use M is increasing in output price

p_c (since $\frac{dM}{dp_c} \geq 0$), while the elasticity of M with respect to output price p_c does not depend on p_c.

QED.

Proof of Proposition 3:

We establish Proposition 3 in a few steps. First, we establish conditions where $\frac{dM}{dA} > 0$ is likely to hold. Second, we show conditions where $\frac{dM}{dA}$ is likely to be small in magnitude. Third, we show conditions where $\frac{d^2M}{dA^2} < 0$. Finally, we show when all three conditions hold.

Using [#1M] as our starting point, we arrive at the following expression for $\frac{dM}{dA}$,

$$p_c \frac{\partial^2 Q}{\partial A \partial M} dA + p_c \frac{\partial^2 Q}{\partial M^2} dM$$

$$\Rightarrow \frac{dM}{dA} = \frac{-\frac{\partial^2 Q}{\partial A \partial M}}{\frac{\partial^2 Q}{\partial M^2}}$$

By Lemma 1, we established the claim that $\frac{\partial^2 Q}{\partial M^2} \leq 0$. Therefore, we must show that $\frac{\partial^2 Q}{\partial A \partial M} > 0$. Using the earlier expression for $\frac{\partial Q}{\partial M}$ as our starting point we have the following expression, which is positive assuming it is always optimal to use some amount of inputs:

$$\frac{\partial^2 Q}{\partial A \partial M} = \frac{\alpha_m \ \gamma_o (B)^{\frac{\rho - \rho_o}{\rho_o}}}{D^{\frac{\rho+1}{\rho}} \ M^{(\rho_o + 1)}} > 0$$

Thus, $\frac{dM}{dA} > 0$: the use of managed pollination M is increasing in total factor productivity and/or size of farms A.

Moreover, the more production is curved with respect to M (i.e., the greater the diminishing returns to M), the less responsive M is to increases in total factor productivity.

After putting the full result together and simplifying we get the next expression:

$$\frac{dM}{dA} = \frac{-DM^{\rho_o+1}}{A\left[B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m\gamma_o(1+\rho) - D\left(\frac{\alpha_m(\rho-\rho_o)+(\rho_o+1)M^{\rho_o}B(M,W)}{B(M,W)}\right)\right]}.$$

By inspection of the last expression, we can establish conditions where $\frac{dM}{dA}$ is likely to be small in magnitude. We see the denominator term in square brackets is the same term that was used to establish Lemma 1; we showed in our proof of Lemma 1 that this term is likely to be negative.

Combined with conditions such that $\rho > 0$ (i.e., input groups complements) and $-1 < \rho_o < 0$ (i.e., pollination inputs substitutes), or $\rho > \rho_o > 0$ (i.e., input groups being strong complements and pollination inputs being weak complements), the above inequalities ensure the term in square brackets will be negative. These conditions also suggest that the entire term in square brackets may be a comparatively small magnitude.

If the term in square brackets is small in magnitude, then A and M^{ρ_o+1} are likely to play important roles in the magnitude of the effect. This further suggests that for farmers with high total factor productivity A, the change in M with respect to A will be small in magnitude, particularly if $A \geq M^{\rho_o+1}$.

The line of logic above suggests that, although we expect use of managed pollination M to be increasing in farm size, the magnitude of the effect may be comparatively small. This means that other factors may be playing a larger role in determining a farmers' managed pollination use.

Now we need to establish conditions where $\frac{d^2M}{dA^2} < 0$. Using the preceding expression as a starting point, we arrive the following result for this second derivative.

$$\frac{d^2M}{dA^2} = \quad = \frac{DM^{\rho_o+1}}{A^2\left[B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m\gamma_o(1+\rho) - D\left(\frac{\alpha_m(\rho-\rho_o)+(\rho_o+1)M^{\rho_o}B(M,W)}{B(M,W)}\right)\right]} \leq 0$$

The last inequality will hold because, once again, we see in the denominator term in square brackets is the same term that was used to establish Lemma 1; we showed in our proof of Lemma

1 that this term is likely to be negative. The relationship between A and M^{ρ_o+1} is also similar to that found for $\frac{dM}{dA}$, but now the rate of diminishing returns in M will increase with unit increases in A because A^2 is present.

From the preceding results and Lemma 1, it is apparent that when the conditions below hold, use of M will increase with A; $\frac{dM}{dA}$ will be small in magnitude; and M will be concave in A.

(1) Positive amounts of all inputs are used, especially capital and labor (this will ensure that $D > B^{\frac{\rho-\rho_o}{\rho_o}}$).

(2) Total factor productivity exceeds use of managed pollination: $A > M$.

(3) Input groups are strong complements (i.e., $\rho \geq 1$) and pollination inputs are on the spectrum of substitutes (i.e., $-1 < \rho_o < 0$); or, $\rho > \rho_o > 0$ (i.e. input groups are strong complements and pollination inputs are weak complements). (Either condition will ensure that $\rho - \rho_o > 0$ and $\rho_o + 1 > 0$, which ensures that the term in square brackets will be negative.)

QED.

Proof of Proposition 4:

We establish that $\frac{dM}{dK} > 0$.

Starting again from condition [#1M], we arrive at the following expression for $\frac{dM}{dK}$.

$$p_c \frac{\partial^2 Q}{\partial K \partial M} dK + p_c \frac{\partial^2 Q}{\partial M^2} = 0$$

$$\Rightarrow \frac{dM}{dK} = \frac{-\frac{\partial^2 Q}{\partial K \partial M}}{\frac{\partial^2 Q}{\partial M^2}}$$

Given Lemma 1, it suffices to show $\frac{\partial^2 Q}{\partial K \partial M} > 0$.

Using the same expression for the marginal product with respect to M as the starting point, we find the following expression for the second order derivative in the numerator of $\frac{dM}{dK}$.

$$\begin{aligned}
\frac{\partial^2 Q}{\partial K \partial M} &= \frac{\partial}{\partial K}\left(\frac{QB(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m \gamma_o}{DM^{\rho_o+1}}\right) \\
&= \frac{\partial Q}{\partial M}\left(\frac{C(K,L)^{\frac{\rho-\rho_{kl}}{\rho_{kl}}}\gamma_{kl}\alpha_k(\rho+1)}{DK^{\rho_{kl}+1}}\right) > 0
\end{aligned}$$

All the terms in this expression are positive, regardless of the sign of the ρ parameters. Therefore, we can conclude that $\frac{dM}{dK} > 0$.

QED.

Proof of Proposition 5:

Finally, we derive the expression for $\frac{dM}{dW}$ and establish plausible scenarios where $\frac{dM}{dW} < 0$.

$$p_c \frac{\partial^2 Q}{\partial W \partial M} dW + p_c \frac{\partial^2 Q}{\partial M^2} dM$$

$$\Rightarrow \frac{dM}{dW} = \frac{-\frac{\partial^2 Q}{\partial W \partial M}}{\frac{\partial^2 Q}{\partial M^2}}$$

To identify possible signing regimes, we solve and simplify the expression for $\frac{\partial^2 Q}{\partial W \partial M}$.

$$\frac{\partial^2 Q}{\partial W \partial M} = \frac{\partial}{\partial W}\left(\frac{QB(M,W)^{\frac{\rho-\rho_o}{\rho}}\alpha_m\gamma_o}{DM^{\rho_o+1}}\right)$$

$$= \left[\frac{-A\alpha_m\alpha_w\gamma_o B(M,W)^{\frac{\rho-2\rho_o}{\rho_o}}}{O_w^{\rho_o+1}\, D^{\frac{2\rho+1}{\rho}}\, M^{\rho_o+1}}\right]\left[(\rho-\rho_o)D \;-\; \gamma_o(\rho+1)B(M,W)^{\frac{\rho}{\rho_o}}\right]$$

Now putting the pieces together, we arrive at a signable expression for $\frac{dM}{dW}$.

$$\frac{dM}{dW} = \frac{-\left(\frac{\partial^2 Q}{\partial W \partial M}\right)}{\frac{\partial^2 Q}{\partial M^2}} = -\frac{\left[\frac{-A\alpha_m\alpha_w\gamma_o B(M,W)^{\frac{\rho-2\rho_o}{\rho_o}}}{O_w^{\rho_o+1}\, D^{\frac{2\rho+1}{\rho}}\, M^{\rho_o+1}}\right]\left[(\rho-\rho_o)D \;-\; \gamma_o(\rho+1)B(M,W)^{\frac{\rho}{\rho_o}}\right]}{\frac{\alpha_m\gamma_o B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}Q}{\left(DM^{\rho_o+1}\right)^2}\left[B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m\gamma_o(1+\rho) - D\left(\frac{\alpha_m(\rho-\rho_o)+(\rho_o+1)M^{\rho_o}B(M,W)}{B(M,W)}\right)\right]}$$

$$= \left[\frac{\alpha_w M^{\rho_o+1}}{B(M,W)O_w^{\rho_o+1}}\right]\frac{\left[(\rho-\rho_o)D \;-\; \gamma_o(\rho+1)B(M,W)^{\frac{\rho}{\rho_o}}\right]}{\left[B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m\gamma_o(1+\rho) - D\left(\frac{\alpha_m(\rho-\rho_o)+(\rho_o+1)I_m^{\rho_o}B(M,W)}{B(M,W)}\right)\right]}$$

$$\Rightarrow\ \text{sign}\left[\frac{dM}{dW}\right] = \text{sign}\left[\left[\frac{\alpha_w M^{\rho_o+1}}{B(M,W)O_w^{\rho_o+1}}\right]\frac{\left[(\rho-\rho_o)D \;-\; \gamma_o(\rho+1)B(M,W)^{\frac{\rho}{\rho_o}}\right]}{\left[B(M,W)^{\frac{\rho-\rho_o}{\rho_o}}\alpha_m\gamma_o(1+\rho) - D\left(\frac{\alpha_m(\rho-\rho_o)+(\rho_o+1)M^{\rho_o}B(M,W)}{B(M,W)}\right)\right]}\right]$$

$$= (+)\frac{(?)}{(-)} \quad \text{...by observation, Lemma 1, and preceding work.}$$

$$\begin{aligned}
\Rightarrow\ \frac{dM}{dW} \leq 0 \ &\iff\ (\rho-\rho_o)D \;-\; \gamma_o(\rho+1)B(M,W)^{\frac{\rho}{\rho_o}} \geq 0 \\
&\iff\ (\rho-\rho_o)D \geq \gamma_o(\rho+1)B(M,W)^{\frac{\rho}{\rho_o}}
\end{aligned}$$

These conditions are likely to hold when:

- $-1 < \rho_o < 0$ and $\rho > 0$ (pollination inputs are substitutes and input groups are complements); or
- $\rho > \rho_o$ (input groups being strong complements and pollination inputs being weak complements).

QED.

B Data

B.1 Background on Apple Production

Apples are a useful crop to study farmer pollination behavior. Apples are a widely produced and consumed commodity around the world[3] with high cultural value. From a pollination perspective, apples are also unique in the sense that wild pollinators have been shown to be much more effective at inducing fruit set[4] than honey bees are (Blitzer et al., 2016; Russo et al., 2017), with important implications for fruit quality and price received. This may be particularly important for farmers as high quality fruit receives a much better price on average compared to lower quality fruit which is often sold for processing (e.g., apple sauce and other products). A complexity in mapping pollination efficacy to yield, at least with modern approaches to apple production, is that farmers commonly engage in thinning (typically with a chemical agent) immediately after fruit set to encourage the plant to drop poorly pollinated fruit early and thus increase investment in remaining fruit. Another interesting aspect of pollination with apples is that apples are not considered to be a "honey crop" as nector from apples does not produce palatable honey, and this translates into higher pollination rental fees for apple farmers to mitigate against the fact that beekeepers do not gain forage resources to produce palatable honey from pollinating apples (Rucker, Thurman, and Burgett, 2012).

From a production perspective, apples have traditionally been grown in orchards with tall (6-8 meters), widely spaced (80-100 trees per hectare), and very long-lived trees (30-50 years or more). In recent decades, production strategies have started shifting towards more modern approaches where apples are grown in high density plantings on trellis systems, with shorter trees and very small spacings between rows and individual trees (Robinson et al., 2007, 2013). These high density systems bear little resemblance to the orchards of the past, with hopes of increasing yields and

[3]Today, China leads the world in global apple production with the US a fairly distant second (authors' calculations, FAOSTAT). Among states in the US, apple production is highest in Washington followed by New York.

[4]Fruit set is the biological process in which flowers become fruit and potential fruit size is determined (Mid Valley Agricultural Services, 2006). When seed formation is complete and well-distributed, the fruit is considered to be more appealing (e.g., consistent shape and fruit quantity/quality), which generally means a higher price is received by the farmer.

lowering labor costs. Some recommendations put optimal tree height at around 3-4 meters, orchard rows at 3-4 meters apart, and trees spaced within rows at as little as 0.7 meters, resulting in tree densities of 2-3,000 trees per hectare or more at the high end (Robinson et al., 2013).

B.2 Data and Data Sources

For our empirical analysis, we leverage rich, farm-level microdata from the 2007 USDA Agricultural Resource Management Survey (USDA-ARMS), which is designed to be nationally representative as well as representative at the level of a state. The USDA National Agricultural Statistics Service (USDA-NASS) imposes stringent conditions and restrictions on the use of its USDA-ARMS data, including strict security measures, data confidentiality, and the required use of provided replication weights. Qualified researchers at US universities or Government agencies can submit a formal request to the USDA Economic Research Service (ERS) and USDA-NASS to have access granted to USDA-ARMS data for specific research projects (USDA Economic Research Service (ERS), 2022). We access the USDA-ARMS data via the NORC Data Enclave.

The 2007 USDA-ARMS provides rich farm-level data from apple farmers in seven US states: California (CA), Michigan (MI), New York (NY), North Carolina (NC), Oregon (OR), Pennsylvania (PA), and Washington (WA). Useful data comes from the Phase III and Phase II surveys. Phase III covers operation-level data on land, production, and financial information. Phase II provides rich production data for a random operation and a random block of apples within the selected operation. Data at the random apple block level covers all the main aspects of production, including input use, costs and yield, for the 2007 production year, as well as honey bee rental data for the years 2006-2007. Although data on costs and on the binary choice to rent bees are available for 2006-2007, the quantity of honey bee colonies rented is only available for 2007. There are 1057 farmers who have sufficient responses for our research, which comprises the vast majority of the farmers sampled. In Figure B.1, we provide a barplot showing the distribution by state for the responses that comprise our base sample. Our observations span 7 states, 207 counties, and 466 zip codes.

To operationalize and enhance our research objectives, we also merge a variety of other data with the 2007 ARMS. We use data on almond production in California from USDA-NASS.

The 2007 USDA-ARMS did not request information on output prices. Thus, for apple output price, we use the state-level total utilized production price from USDA-NASS, which is a weighted average of fresh market and processed prices. We use the state-level apple price to derive revenue estimates and approximate profits at the random apple block level.

For distance measures, we compute Euclidean distances using R and we also employ the Google Distance Matrix API to derive road distances as alternative "share" variables in our instrument construction.

To derive relevant data on weather covariates that might affect yield, and collect credible proxy measures for landscape influence and local pollinator habitat (the closest proxy available for wild pollinator stocks), we use the closest[5] and most reliable coverage year from the USDA Cropland Data Layer (CDL) (Boryan et al. (2011)) for each state to construct a county-level mask of apple and tree-crop producing regions within each county. Using the resulting boundaries within each county for apple-specific and/or tree-crop-specific regions, as well as the county boundaries themselves, we further use the CDL to construct a variety of variables to characterize land cover heterogeneity, and also credible measures of pollinator habitat quality (Martins, Gonzalez, and Lechowicz, 2015; Park et al., 2015), including the proportion of land area in natural forest cover and the the proportion of land area in natural open cover. We define natural open cover as the proportion of apple-specific and/or tree-crop-specific areas within a county in any of the following cover

[5]Apples are difficult to identify with high accuracy, as are tree crops, therefore classification error in annual CDL layers induce potential for measurement error. Since tree crops are long-lived, there are unlikely to be large year-to-year changes in cover. Therefore we adopted the following rule to construct apple- and tree-crop specific spatial masks and gather other land cover information within county domains, and county-specific apple and tree-crop spatial domains: use the CDL crop mask data for the timepoint closest to 2007 as possible, but if the closest year to 2007 had low cover for apples and tree-crops, use the next closest year of the CDL that had substantially higher cover for apples and/or tree crops. The logic here is that if ARMS data imply that apple growers are present within a county, yet the CDL does not pick up apples or tree-crops, the closest year to 2007 that shows at least some spatial footprint for these crops is likely a more accurate spatial mapping of this agricultural activity than another year that might be closer to 2007. Since we cannot resolve sampled farm locations in space, these boundaries are designed to reflect that average conditions that apple growers face in their respective counties. Crops that are included in our tree crop definition include: apples, cherries, peaches, other tree crops, pears, prunes, plums, nectarines, and apricots; citrus and nut crops were excluded.

types: clover, wildflowers, shrubland, herbaceous wetlands, developed open space, and wetlands. We also employ the tree-crop-specific regions and county boundaries to gather monthly precipitation and temperature data from PRISM spanning January-November of the 2007 production (Daly et al., 2008).

The West Coast states in our data set are California (CA), Oregon (OR), and Washington (WA). The Midwest and East Coast states in our data set (which we refer to collectively as the 'Eastern' states) are Michigan (MI), New York (NY), North Carolina (NC), and Pennsylvania (PA).

B.3 Supplementary Tables and Figures

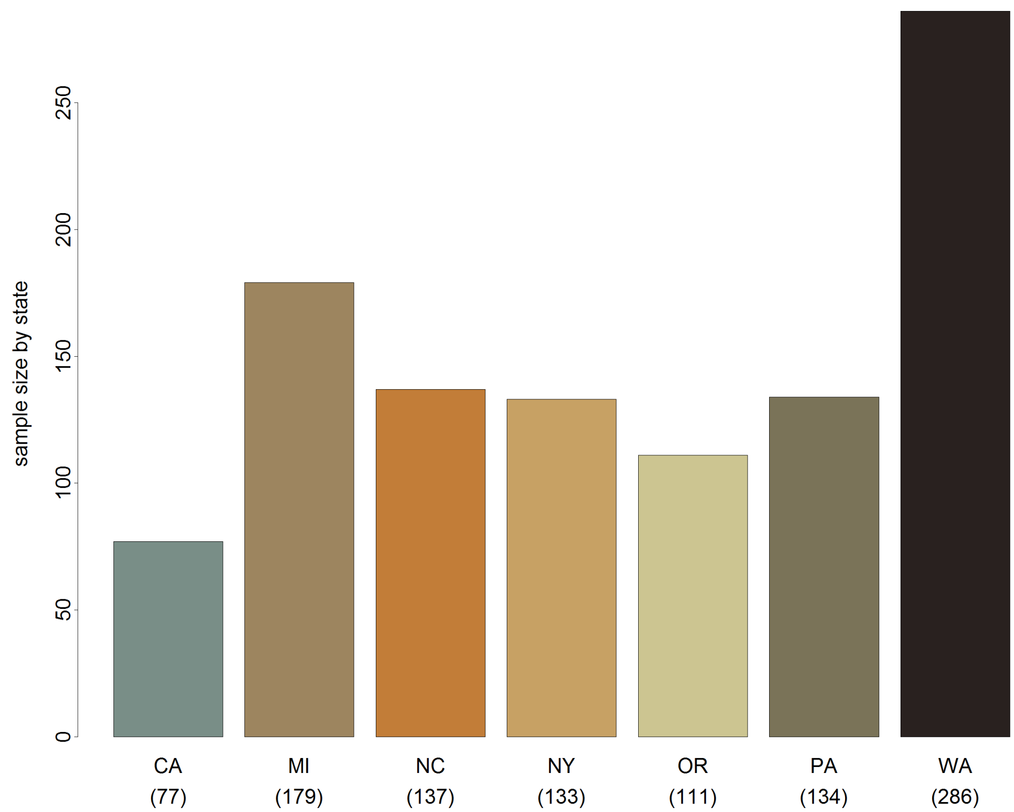

Figure B.1: Distribution of the sample apple farmers from 2007 USDA-ARMS that we employ in our analysis.

Table B.1: Weighted operation-level summary statistics.

Variable	Weighted Means All	West	East	Difference in Mean (West - East)
year apple operation was established	1981.46	1983.88	1978.39	5.49***
	(14.61)	(14.46)	(14.25)	(0.9)
	[1057]	[474]	[583]	
operator has some college (dummy)	0.72	0.76	0.67	0.1***
	(0.45)	(0.43)	(0.47)	(0.03)
	[779]	[337]	[442]	
total cropland acres	330.44	351.34	303.95	47.39
	(777.08)	(832.99)	(699.94)	(50.42)
	[1057]	[474]	[583]	
total apple acres	156.91	177.01	131.44	45.57*
	(397.39)	(511.24)	(161.48)	(24.37)
	[1057]	[474]	[583]	
total bearing apple acres	148.43	169.42	121.84	47.57**
	(393.78)	(509.13)	(149.06)	(24.18)
	[1057]	[474]	[583]	
total non-bearing apple acres	8.47	7.59	9.59	-2
	(19.6)	(19.52)	(19.67)	(1.22)
	[1057]	[474]	[583]	
total organic apple acres	1.01	1.79	0.01	1.79**
	(14.88)	(19.87)	(0.15)	(0.87)
	[1057]	[474]	[583]	
total number apple blocks	15.08	12.13	18.83	-6.7***
	(20.55)	(18.72)	(22.11)	(1.27)
	[1057]	[474]	[583]	
number of farm vehicles and implements	11.62	10.57	12.85	-2.28***
	(10.87)	(11.13)	(10.45)	(0.77)
	[772]	[333]	[439]	
difficulty with pollination (dummy)	0.2	0.2	0.19	0.01
	(0.4)	(0.4)	(0.39)	(0.03)
	[778]	[336]	[442]	
difficulty with labor (dummy)	0.65	0.68	0.61	0.08**
	(0.48)	(0.47)	(0.49)	(0.03)
	[778]	[336]	[442]	
own honey bees (dummy)	0.03	0.01	0.04	-0.03**
	(0.17)	(0.12)	(0.21)	(0.01)
	[779]	[337]	[442]	

Notes: Summary statistics are at the operation level for the selected apple operation. From left to right, columns are as follows: variable; mean for observations from all states ('All'); mean for West Coast states ('West'); mean for Midwest and East Coast states ('East'); mean for West Coast minus mean for Midwest and East Coast states ('West - East'). Below the means for each variable, standard deviations are in parentheses and sample sizes are in square brackets. Sample sizes may differ from respective full sample sizes because a farmer did not answer the question, or the question was not applicable. Below the differences in mean between West and East, bootstrapped standard errors from two-sample t-tests for the mean of the West Coast minus the mean for East Coast and Midwest states are in parentheses. Significance codes for two-sample t-tests: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.2: Weighted random block-level summary statistics focused on pollination.

Variable	Weighted Means All	Weighted Means West	Weighted Means East	Difference in Mean (West - East)
rented bees in 2007 (dummy)	0.74	0.81	0.64	0.17***
	(0.44)	(0.39)	(0.48)	(0.03)
	[1057]	[474]	[583]	
rented bees in 2006 (dummy)	0.74	0.8	0.66	0.14***
	(0.44)	(0.4)	(0.48)	(0.03)
	[1057]	[474]	[583]	
did not rent bees in 2006-2007 (dummy)	0.25	0.18	0.33	-0.14***
	(0.43)	(0.39)	(0.47)	(0.03)
	[1057]	[474]	[583]	
number of bee colonies rented in 2007	17.36	18.39	15.72	2.67
	(30.13)	(30.24)	(29.94)	(2.43)
	[601]	[313]	[288]	
number of bee colonies per acre in 2007	1.91	1.68	2.28	-0.6***
	(2.25)	(1.79)	(2.80)	(0.18)
	[601]	[313]	[288]	
bee rental fee in 2007 ($/colony)	40.54	37.58	45.26	-7.67***
	(13.4)	(10.73)	(15.71)	(1.10)
	[601]	[313]	[288]	
bee rental fee in 2006 ($/colony)	37.33	35.47	40.2	-4.73***
	(12.01)	(10.14)	(13.98)	(0.97)
	[627]	[312]	[315]	
bee rental cost in 2007 ($/acre)	76.92	63.63	98.15	-34.52***
	(102)	(85.17)	(121.43)	(8.38)
	[601]	[313]	[288]	
bee rental cost in 2006 ($/acre)	73.14	62.69	89.27	-26.58***
	(100.73)	(91.75)	(111.49)	(8.04)
	[627]	[312]	[315]	
bee rental proportion of total costs 2007	0.07	0.05	0.1	-0.05***
	(0.11)	(0.08)	(0.15)	(0.01)
	[601]	[313]	[288]	
bee rental proportion of total costs 2006	0.07	0.05	0.09	-0.04***
	(0.11)	(0.08)	(0.15)	(0.01)
	[627]	[312]	[315]	

Notes: Summary statistics are at the block level for the selected block. From left to right, columns are as follows: variable; mean for observations from all states ('All'); mean for West Coast states ('West'); mean for Midwest and East Coast states ('East'); mean for West Coast minus mean for Midwest and East Coast states ('West - East'). Below the means for each variable, standard deviations are in parentheses and sample sizes are in square brackets. Sample sizes may differ from respective full sample sizes because a farmer did not answer the question, or the question was not applicable. Below the differences in mean between West and East, bootstrapped standard errors from two-sample t-tests for the mean of the West Coast minus the mean for East Coast and Midwest states are in parentheses. Significance codes for two-sample t-tests: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.3: Weighted random block-level summary statistics focused on production.

Variable	Weighted Means All	West	East	Difference in Mean (West - East)
year block started production	1989.13	1990.72	1987.15	3.57^{***}
	(11.96)	(11.41)	(12.43)	(0.74)
	[1037]	[467]	[570]	
number of apple trees	3512.68	5027.92	1584.66	3443.26^{***}
	(12248.46)	(16008.70)	(2927.93)	(712.03)
	[1039]	[467]	[572]	
average age of trees	18.94	17.21	21.12	-3.92^{***}
	(12.71)	(12.36)	(12.82)	(0.76)
	[1042]	[466]	[576]	
for fresh market (dummy)	0.84	0.93	0.71	0.22^{***}
	(0.37)	(0.25)	(0.45)	(0.02)
	[1057]	[474]	[582]	
has federal crop insurance in 2007 (dummy)	0.62	0.58	0.68	-0.11^{***}
	(0.48)	(0.49)	(0.47)	(0.03)
	[1057]	[474]	[583]	
yield (bushels/acre)	589.78	650.47	512.87	137.59^{***}
	(422.30)	(455.71)	(361.90)	(26.69)
	[1057]	[474]	[583]	
approximate apple revenue ($) per acre	7225.63	9090.93	4861.83	4229.10^{***}
	(6130.79)	(6845.39)	(3988.85)	(360.30)
	[1057]	[474]	[583]	
approximate apple revenue ($) per tree	56.40	69.86	39.28	30.58^{**}
	(239.54)	(316.04)	(54.08)	(14.44)
	[1039]	[467]	[572]	
approximate apple cost ($) per acre	2285.37	2890.75	1518.19	1372.56^{***}
	(3072.22)	(3893.56)	(1075.89)	(184.08)
	[1057]	[477]	[583]	
approximate apple cost ($) per tree	22	29.03	13.06	15.97^{*}
	(148.10)	(197.31)	(14.89)	(8.98)
	[1039]	[467]	[572]	
approximate profit ($) per acre	4940.26	6200.18	3343.63	2856.54^{***}
	(6416.43)	(7582.36)	(4002.39)	(383.93)
	1057	474	583	
approximate profit ($) per tree	34.40	40.83	26.22	14.61^{**}
	(104.75)	(131.47)	(53.38)	(6.32)
	[1039]	[467]	[572]	

Notes: Summary statistics are at the block level for the selected block. From left to right, columns are as follows: variable; mean for observations from all states ('All'); mean for West Coast states ('West'); mean for Midwest and East Coast states ('East'); mean for West Coast minus mean for Midwest and East Coast states ('West - East'). Below the means for each variable, standard deviations are in parentheses and sample sizes are in square brackets. Sample sizes may differ from respective full sample sizes because a farmer did not answer the question, or the question was not applicable. Below the differences in mean between West and East, bootstrapped standard errors from two-sample t-tests for the mean of the West Coast minus the mean for East Coast and Midwest states are in parentheses. Revenues and profits are approximate and employ state-level average output prices obtained from USDA-NASS. Significance codes for two-sample t-tests: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.4: Summary statistics for apple prices, instruments, and land cover variables.

Variable	Weighted Means All	Weighted Means West	Weighted Means East	Difference in Mean (West - East)
Apple output prices				
total utilized production price ($/lb) in 2007	0.23	0.30	0.16	0.14**
	(0.09)	(0.04)	(0.05)	(0.034)
	[7]	[3]	[4]	
total utilized production price ($/lb) in 2006-2007	0.20	0.26	0.16	0.10***
	(0.07)	(0.05)	(0.04)	(0.025)
	[14]	[6]	[8]	
Instrumental variables				
zip code distance (Euclidean) to Fresno County, CA (km)	2490.48	876.92	3478.72	-2601.80***
	(1313.74)	(383.12)	(341.78)	(35.121)
	[466]	[177]	[289]	
zip code distance (Euclidean) to Fresno County, CA (km) X	1.893E9	0.666E9	2.644E9	-1.977E9***
total almond acres in CA	(0.998E9)	(0.291E9)	(0.260E9)	(0.189E9)
	[932]	[354]	[578]	
Land cover variables				
natural forest cover (county proportion)	0.50	0.44	0.53	-0.09**
	(0.22)	(0.26)	(0.19)	(0.035)
	[207]	[71]	[136]	
natural open cover (county proportion)	0.17	0.31	0.10	0.21***
	(0.16)	(0.19)	(0.06)	(0.023)
	[207]	[71]	[136]	

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Notes: From left to right, columns are as follows: variable; mean for observations from all states ('All'); mean for West Coast states ('West'); mean for Midwest and East Coast states ('East'); mean for West Coast minus mean for Midwest and East Coast states ('West - East'). Below the means for each variable, standard deviations are in parentheses and sample sizes are in square brackets. Below the differences in mean between West and East are standard errors in parentheses from two-sample t-tests for the mean of the West Coast minus the mean for East Coast and Midwest states. Apple prices are at the state level, instrumental variables are at the zip code level, and land cover variables are at the county level. There are 7 states, 207 counties, and 466 zip codes. Significance codes for two-sample t-tests: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table B.5: Summary statistics for weather variables.

Variable	Weighted Means All	Weighted Means West	Weighted Means East	Difference in Mean (West - East)
mean temperature (C), winter 2006-2007	1.86	5.37	0.04	5.33***
	(4.64)	(3.27)	(4.18)	(0.374)
	[414]	[142]	[272]	
mean precipitation (mm), winter 2006-2007	2.84	3.62	2.44	1.18***
	(1.98)	(3.14)	(0.62)	(0.266)
	[414]	[142]	[272]	
mean temperature (C), spring 2006-2007	13.47	13.10	13.66	-0.56***
	(2.51)	(2.84)	(2.31)	(0.276)
	[414]	[142]	[272]	
mean precipitation (mm), spring 2006-2007	2.31	1.62	2.67	-1.05***
	(0.97)	(1.09)	(0.67)	(0.10)
	[414]	[142]	[272]	
mean temperature (C), summer 2006-2007	20.83	20.05	21.23	-1.18***
	(2.59)	(3.20)	(2.09)	(0.297)
	[414]	[142]	[272]	
mean precipitation (mm), summer 2006-2007	2.41	0.36	3.48	-3.12***
	(1.81)	(0.43)	(1.23)	(0.083)
	[414]	[142]	[272]	
mean temperature (C), fall 2006-2007	10.07	10.01	10.10	-0.09
	(2.77)	(3.31)	(2.45)	(0.315)
	[414]	[142]	[272]	
mean precipitation (mm), fall 2006-2007	3.10	2.87	3.23	-0.36
	(1.89)	(2.95)	(0.94)	(0.254)
	[414]	[142]	[272]	

Notes: From left to right, columns are as follows: variable; mean for observations from all states ('All'); mean for West Coast states ('West'); mean for Midwest and East Coast states ('East'); mean for West Coast minus mean for Midwest and East Coast states ('West - East'). Below the means for each variable, standard deviations are in parentheses and sample sizes are in square brackets. Below the differences in mean between West and East are standard errors in parentheses from two-sample t-tests for the mean of the West Coast minus the mean for East Coast and Midwest states. Weather variables are at the county level. There are 207 unique counties observed. Significance codes for two-sample t-tests: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

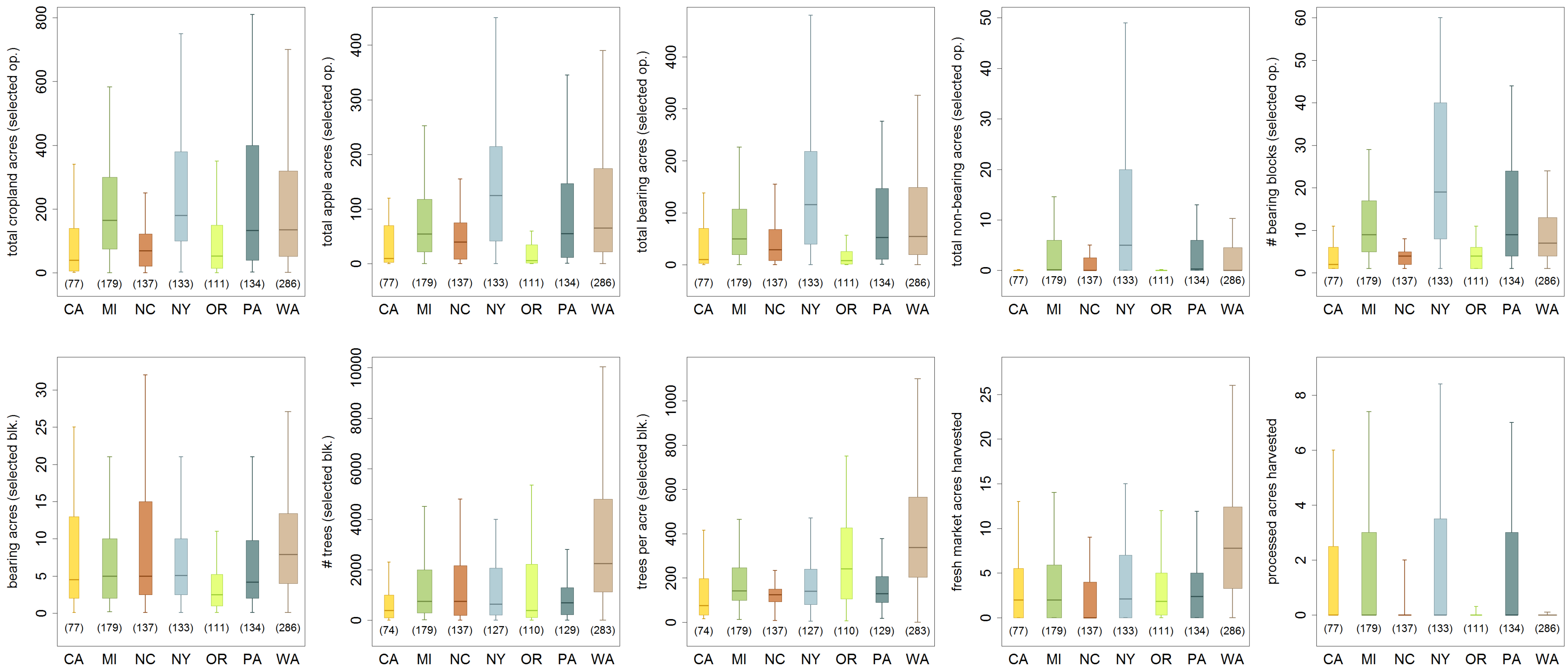

Figure B.2: Weighted boxplots by state for a suite of farm and orchard characteristics. Numbers in parentheses next to state abbreviations indicate the respective sample size per boxplot.

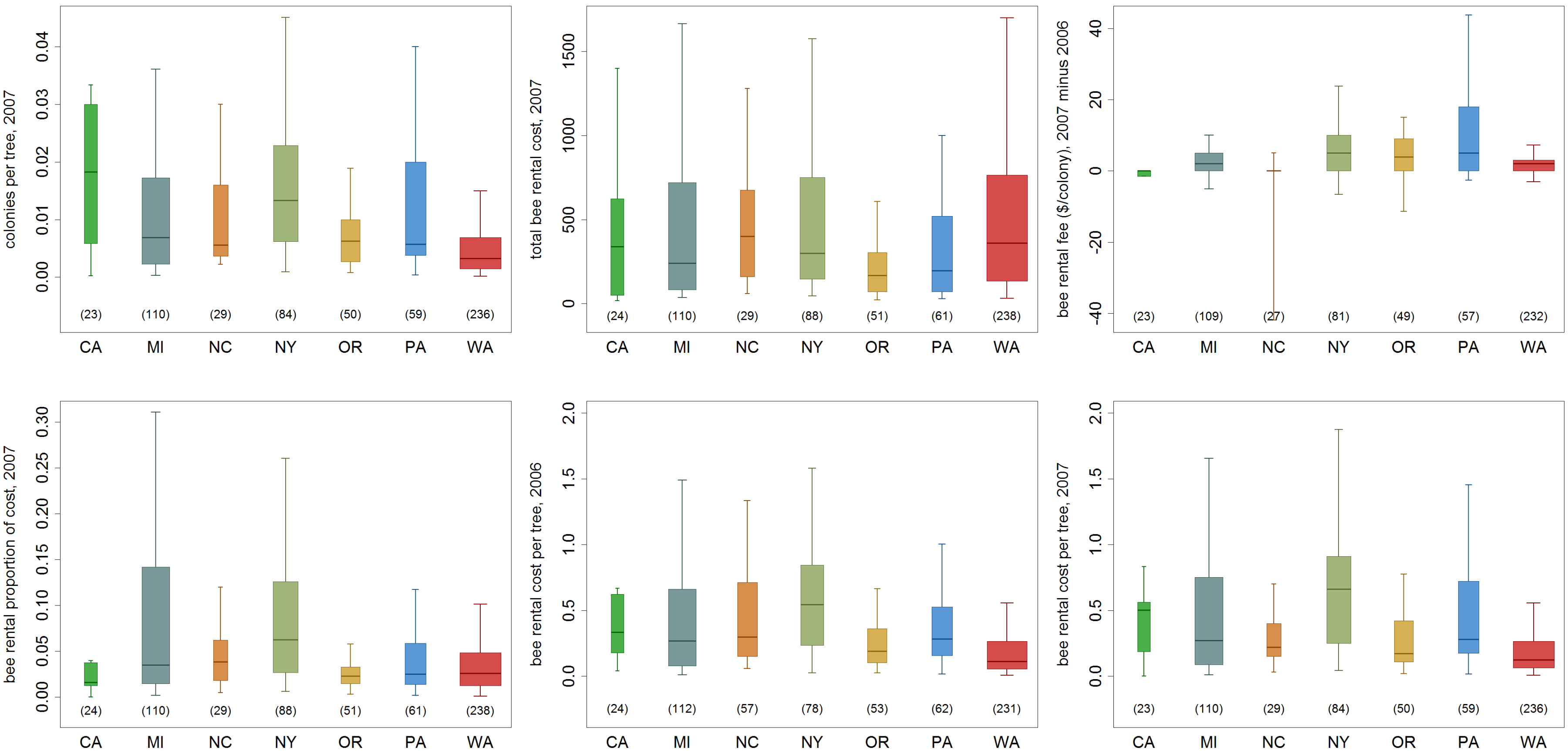

Figure B.3: Weighted boxplots by state capturing: the number of colonies rented per tree in 2007; total honey bee colonies rented per tree; total bee rental costs in 2007; dollars per colony rental fee in 2007 minus dollars per colony rental fee in 2006; bee rental proportion of block level costs in 2007; bee rental costs per tree in 2006; bee rental costs per tree in 2007. All variables comprised random block-level variation. Numbers in parentheses indicate the sample size per state.

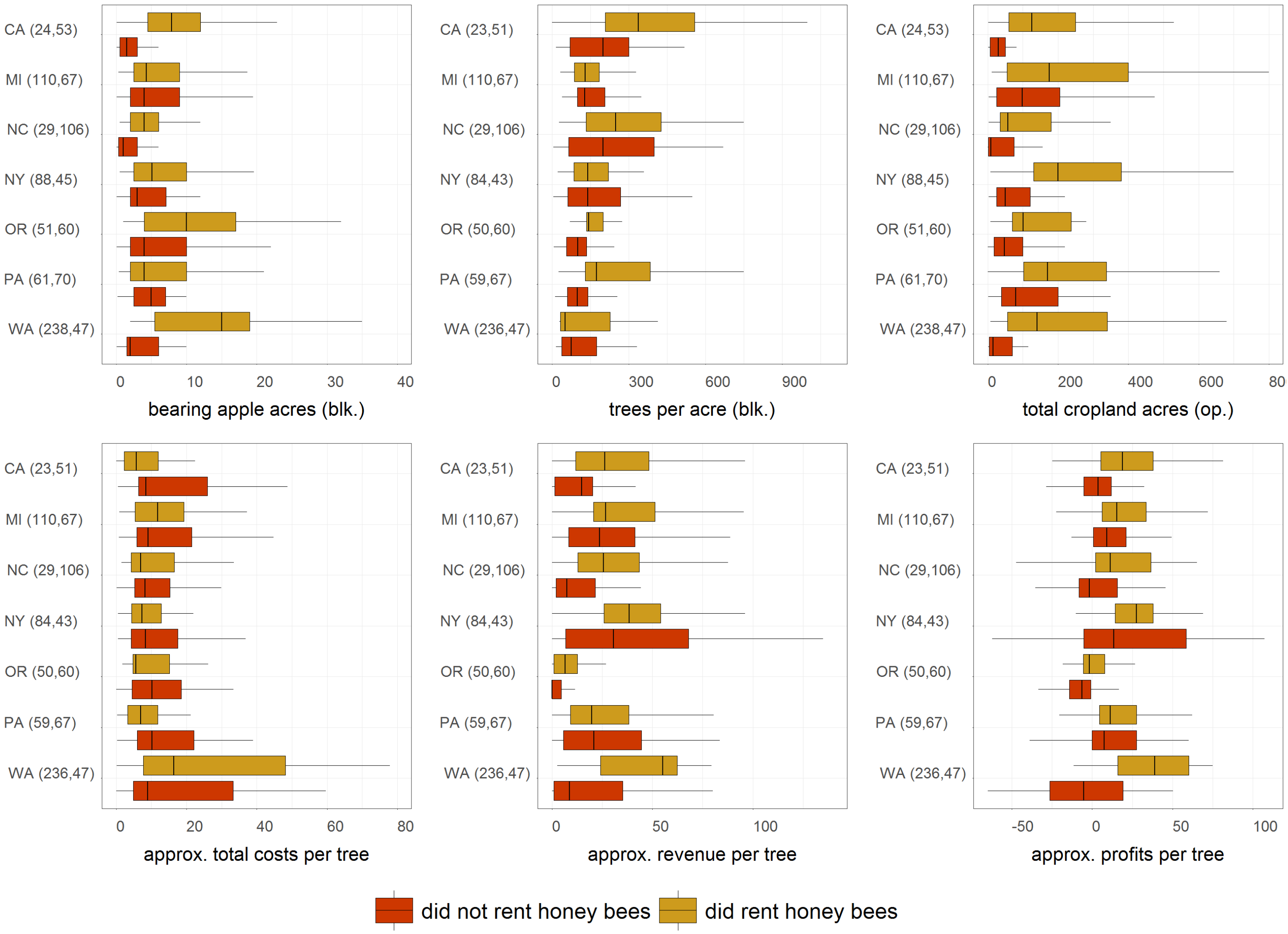

Figure B.4: Weighted boxplots by state and if an apple farmer rented honey bees for: bearing apple acres (block-level); trees per acre (block level); total cropland acreage (operation level); and approximate block level production costs per tree; revenue per tree; and profits per tree. Numbers in parentheses indicate the sample size per state, and the choice to rent honey bees or not. For example, in the top left plot the notation for the bottom rows, WA (238, 47), indicates of the 286 apple farmers sampled in Washington State, 238 reported renting honey bees, while 47 reported not renting honey bees.

C Empirical Analysis of the Choice to Rent Bees

C.1 Econometric Model

For the binary choice to use pollination service markets (in our case, renting honey bees), we seek to study associations between the discrete choice to use managed pollination and important farm characteristics, state variables, and parameters, each of which addresses particular elements of Propositions 2-5. To explore these associations, we estimate the following logit fixed effects regression using methods developed by Bergé (2018) for efficiently estimating maximum likelihood models with large numbers of fixed effects:

$$\Pr(y_{isct} = 1) = \mathbf{x}'_{\mathbf{isct}}\beta + \lambda_s + \sigma_t + \varepsilon_{it}, \tag{C.1}$$

where y_{isct} is a dummy variable for farmer i in state s and county c renting honey bees in year t; $\mathbf{x}'_{\mathbf{isct}}$ is a vector of covariates, including measures of farm production scale (to proxy for total factor productivity), output price, and remotely sensed measures of natural open cover and natural forest cover (to proxy for wild pollinator stocks and landscape heterogeneity); λ_s and σ_t are state and time fixed effects; and ε_{it} is the error term.

Bergé (2018) employs fixed-point algorithms in combination with the concentrated likelihood function to efficiently estimate maximum likelihood models with large numbers of fixed effects. The concentrated log-likelihood function, $g(\beta) = l(y_{isct}, \mathbf{x}'_{\mathbf{isct}}\beta + \lambda_s(\beta) + \sigma_t(\beta))$, treats fixed effects as functions of the parameters of interest and leverages the observation that each fixed effect represents a partition of the data to improve efficiency.[6]

To address Propositions 2-5, we employ several strategies. For Proposition 2, we use state-level total utilized production price (a weighted average of the fresh market and processed prices). For

[6] We also tried using the bias-corrected discrete choice estimator from Stammann, Heiss, and McFadden (2016) and Czarnowske and Stammann (2019), which corrects for the incidental parameter bias in discrete choice fixed effects estimation. Unfortunately, the available code for these bias-corrected discrete choice estimators currently does not permit the use of sampling weights, and USDA-NASS does not permit us to retrieve results from the NORC Data Enclave unless their provided replication weights are applied. We therefore cannot make use of these estimators. Nevertheless, our qualitative results using the bias-corrected discrete choice estimator without sampling weights are similar to the results we report using the fixed effects discrete choice estimator from Bergé (2018) with the provided replication weights.

Proposition 3, we study second-degree polynomials in the apple bearing acreage of the selected block, the total number of bearing apple blocks (in the selected operation), as well as trees per acre and age of apple trees for the selected apple block. For Proposition 4, we use the number of farm vehicles and farm implements available for use on the selected block. For Proposition 5, we study second-degree polynomials in county-level remotely sensed measures of natural open cover and natural forest cover to proxy for wild pollinator stocks and landscape heterogeneity.[7] We also include measures of management (including pest training and scouting effort), state level fixed effects, and a dummy for 2007 (equivalent to year fixed effects in this two-period panel).

In all specifications, we use multi-way clustered standard errors that are clustered at both the state and county levels. Clustering at the county level alone is problematic as there are counties with only one farmer sampled, and this will not address potential spatial correlation within states. Clustering at the state level alone is also problematic as there are too few clusters with only seven states (Cameron and Miller, 2015). Clustering at both the state and county levels therefore offers a conservative approach to standard error estimation.

We also estimate analogous logit fixed effects regressions of the binary choice to *never* rent honey bees during 2006-2007. For these regressions, output price (which is at the state level) and the dummy for 2007 are omitted as there is no temporal variation in our dependent variable.

[7] In our exploration of CDL-based land cover measures, we study measures summarized at different buffer sizes of 500 meters, 1000 meters, 3000 meters, and at the county level. We apply buffers to apple-specific polygons and tree-crop-specific polygons within counties where apple farmers are sampled, and also summarize these cover types at the county level (without buffers). Similar qualitative results are generally apparent using these alternative measures.

C.2 Supplementary Tables and Figures

Table C.1: Point estimates from weighted logit regression of the binary choice to rent honey bees.

	Dependent variable is probability of renting honey bees					
	(1)	(2)	(3)	(4)	(5)	(6)
apple bearing acres	0.040**	0.049**	0.009	0.009	0.086***	0.101***
	(0.0176)	(0.0193)	(0.0162)	(0.0208)	(0.0123)	(0.0131)
apple bearing acres, squared	−0.00008**	−0.00010***	0.000124685	0.00020	−0.00017***	−0.00020***
	(0.000037)	(0.000038)	(0.000155)	(0.000333)	(0.0000297)	(0.000030)
total bearing apple blocks	0.12***	0.12***	0.09***	0.07***	0.27***	0.36***
	(0.027)	(0.040)	(0.020)	(0.025)	(0.021)	(0.043)
total bearing apple blocks, squared	−0.0010***	−0.0008***	−0.0008***	−0.0004***	−0.0021***	−0.0031***
	(0.00020)	(0.00032)	(0.00011)	(0.00012)	(0.00031)	(0.00031)
trees per acre	0.00006	0.00106	0.00317	0.00805***	0.00074	−0.00137
	(0.001922)	(0.002263)	(0.003391)	(0.002013)	(0.001588)	(0.001608)
trees per acre, squared	0.000003	0.000003	−0.000002	−0.000006*	0.000002	0.000004
	(0.0000023)	(0.0000030)	(0.0000044)	(0.0000031)	(0.0000026)	(0.0000039)
average age of trees	0.02	0.07	0.05	0.10	0.06	0.13
	(0.041)	(0.050)	(0.060)	(0.090)	(0.064)	(0.122)
average age of trees, squared	−0.0006	−0.0016**	−0.0009	−0.0018*	−0.0017	−0.0031
	(0.00054)	(0.00071)	(0.00074)	(0.00111)	(0.00200)	(0.00332)
total utilized production price ($/pound)	6.22***	6.70**	13.72***	18.61***	6.38**	4.35
	(2.394)	(3.400)	(2.113)	(2.969)	(2.751)	(2.706)
natural forest cover	−0.50	2.77	−0.07	−2.03	0.01	1.20
	(3.865)	(3.328)	(4.147)	(8.538)	(5.078)	(2.854)
natural forest cover, squared	1.03	−2.07	0.10	0.26	1.20	3.19
	(3.388)	(3.463)	(3.168)	(6.869)	(5.2817)	(4.656)
natural open cover	8.62*	11.27*	21.74*	17.83	11.72	245.0***
	(4.532)	(6.006)	(12.448)	(17.126)	(7.449)	(7.901)
natural open cover, squared	−7.37**	−9.01*	−64.26	−60.0	−9.96**	−20.61***
	(3.139)	(5.029)	(40.250)	(55.187)	(3.985)	(4.228)
number farm vehicles and implements		0.01		0.03		−0.01
		(0.02)		(0.03)		(0.02)
deliberate pest scouting (dummy)	0.76**	0.70*	0.01	−0.31	1.43***	1.27***
	(0.339)	(0.373)	(0.226)	(0.680)	(0.057)	(0.135)
recent pest training (dummy)	0.55	0.60**	1.06***	1.07***	−0.39	−0.20
	(0.335)	(0.306)	(0.179)	(0.204)	(0.427)	(0.526)
year 2007 (dummy)	−0.23*	−0.27	−0.32***	−0.41***	−0.26***	−0.14
	(0.119)	(0.193)	(0.079)	(0.113)	(0.078)	(0.084)
State FE	Y	Y	Y	Y	Y	Y
Sample	All	All	East	East	West	West
Standard Errors	C,S	C,S	C,S	C,S	C,S	C,S
Pseudo R^2	0.33	0.37	0.20	0.30	0.50	0.54
# Observations	2056	1514	1136	858	920	656

Notes: Table presents point estimates from weighted logit regression of the binary choice to rent honey bees on block- and operation-level characteristics, output prices, physical capital, and land cover measures. For land cover measures, we use remotely sensed measures of natural open cover and natural forest cover proportions at the county level. Standard errors are clustered at both the state (S) and county (C) levels, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table C.2: Average partial effects from weighted logit regression of the binary choice to never rent honey bees.

	Dependent variable is probability of never renting honey bees					
	(1)	(2)	(3)	(4)	(5)	(6)
apple bearing acres	-0.007^{***}	-0.008^{***}	-0.003^{*}	-0.004^{*}	-0.008^{*}	-0.008^{**}
	(0.0024)	(0.0027)	(0.0018)	(0.0020)	(0.0042)	(0.0033)
total bearing apple blocks	-0.02^{***}	-0.02^{***}	-0.02^{***}	-0.01	-0.03^{***}	-0.05^{***}
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.009)
trees per acre	-0.0001	-0.0002	-0.0004	-0.0010^{***}	-0.0002	-0.0001
	(0.00029)	(0.00030)	(0.00063)	(0.00024)	(0.00020)	(0.00016)
average age of trees	0.001	0.001	-0.002	-0.002	0.003	0.0002
	(0.0035)	(0.0040)	(0.0058)	(0.0081)	(0.0016)	(0.0036)
natural forest cover	-0.13	-0.16	-0.09	0.19	-0.18	-0.47^{*}
	(0.175)	(0.206)	(0.163)	(0.285)	(0.260)	(0.246)
natural open cover	-1.11^{**}	-1.19^{*}	-1.79^{***}	-1.00	-0.74	-1.20^{**}
	(0.563)	(0.623)	(0.623)	(1.008)	(0.587)	(0.530)
number farm vehicles and implements		-0.006^{*}		-0.012^{*}		-0.001
		(0.0038)		(0.0056)		(0.0044)
deliberate pest scouting (dummy)	-0.12^{***}	-0.10^{**}	-0.01	0.05	-0.15^{***}	-0.12^{***}
	(0.037)	(0.045)	(0.033)	(0.122)	(0.042)	(0.046)
recent pest training (dummy)	-0.10^{*}	-0.10^{**}	-0.22^{***}	-0.19^{***}	0.02	0.01
	(0.055)	(0.041)	(0.048)	(0.029)	(0.035)	(0.045)
State FE	Y	Y	Y	Y	Y	Y
Sample	All	All	East	East	West	West
Standard Errors	C,S	C,S	C,S	C,S	C,S	C,S
Pseudo R^2	0.35	0.41	0.21	0.32	0.57	0.62
# Observations	1028	757	1136	858	920	656

Notes: Table presents average partial effects from weighted logit regression of the binary choice to never rent honey bees on block- and operation-level characteristics, physical capital, and land cover measures. For land cover measures, we use remotely sensed measures of natural open cover and natural forest cover proportions at the county level. Standard errors are clustered at both the state (S) and county (C) levels, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table C.3: Point estimates from weighted logit regression of the binary choice to never rent honey bees.

	Dependent variable is probability of never renting honey bees					
	(1)	(2)	(3)	(4)	(5)	(6)
apple bearing acres	-0.05^{**}	-0.06^{***}	-0.02	-0.02	-0.09^{***}	-0.09^{***}
	(0.019)	(0.023)	(0.012)	(0.016)	(0.021)	(0.021)
apple bearing acres, squared	0.0001^{***}	0.0001^{***}	-0.0001	-0.0003	0.0002^{***}	0.0002^{***}
	(0.00004)	(0.00004)	(0.00013)	(0.00024)	(0.00005)	(0.00005)
total bearing apple blocks	-0.13^{***}	-0.14^{**}	-0.10^{***}	-0.05	-0.53	-0.53
	(0.032)	(0.056)	(0.020)	(0.043)	(0.337)	(0.337)
total bearing apple blocks, squared	0.0011^{***}	0.0008^{*}	0.0009^{***}	-0.0005	0.0019	0.0019
	(0.00024)	(0.00050)	(0.00013)	(0.00091)	(0.02175)	(0.02175)
trees per acre	0.0003	-0.0003	-0.0020	-0.0069^{***}	0.0009	0.0009
	(0.00227)	(0.00236)	(0.00425)	(0.00152)	(0.00195)	(0.00195)
trees per acre, squared	-0.000003	-0.000004	0.000001	0.000004^{*}	-0.000003	-0.000003
	(0.0000028)	(0.0000031)	(0.0000055)	(0.0000024)	(0.0000041)	(0.0000041)
average age of trees	-0.006	-0.040	-0.045	-0.081	-0.059	-0.059
	(0.0465)	(0.0525)	(0.0572)	(0.0870)	(0.1746)	(0.1746)
average age of trees, squared	0.0004	0.0013^{*}	0.0008	0.0017	0.0018	0.0018
	(0.00064)	(0.00077)	(0.00075)	(0.00113)	(0.00449)	(0.00449)
natural forest cover	3.57	-0.06	0.84	2.58	2.78	2.78
	(3.406)	(3.100)	(4.821)	(10.110)	(2.153)	(2.153)
natural forest cover, squared	-4.43	-1.08	-1.32	-1.48	-8.04^{**}	-8.04^{**}
	(3.048)	(3.131)	(3.884)	(8.731)	(3.401)	(3.401)
natural open cover	-10.52^{**}	-12.19^{**}	-22.91^{**}	-17.42	-32.23^{***}	-32.23^{***}
	(5.210)	(6.175)	(11.068)	(14.939)	(9.867)	(9.867)
natural open cover, squared	9.50^{**}	10.29^{*}	68.48^{*}	57.43	28.92^{***}	28.92^{***}
	(4.022)	(5.464)	(35.324)	(47.673)	(8.126)	(8.126)
number farm vehicles and implements		-0.05^{**}		-0.06^{**}	-0.01	-0.01
		(0.022)		(0.031)	(0.046)	(0.046)
deliberate pest scouting (dummy)	-0.79^{**}	-0.69^{*}	-0.06	0.32	-1.33^{***}	-1.33^{***}
	(0.353)	(0.409)	(0.172)	(0.692)	(0.331)	(0.331)
recent pest training (dummy)	-0.66^{**}	-0.72^{***}	-1.14^{***}	-1.11^{***}	0.09	0.09
	(0.281)	(0.276)	(0.096)	(0.189)	(0.484)	(0.484)
State FE	Y	Y	Y	Y	Y	Y
Sample	All	All	East	East	West	West
Standard Errors	C,S	C,S	C,S	C,S	C,S	C,S
Pseudo R^2	0.35	0.41	0.21	0.32	0.62	0.62
# Observations	1028	757	1136	858	656	656

Notes: Table presents point estimates from weighted logit regression of the binary choice to never rent honey bees on block- and operation-level characteristics, physical capital, and land cover measures. For land cover measures, we use remotely sensed measures of natural open cover and natural forest cover proportions at the county level. Standard errors are clustered at both the state (S) and county (C) levels, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

D Elasticity of Demand for Managed Pollination

D.1 Econometric Model of Honey Bee Demand

To estimate the own-price demand elasticity for managed pollination use, we estimate the honey bee demand function for apple farmers using an instrumental variables strategy to address the endogeneity problem that arises because observed equilibrium prices and quantities are simultaneously determined in the supply-and-demand system (Manski, 1995; Goldberger, 1991; Angrist, Graddy, and Imbens, 2000; Lin, 2011). Our first-stage equation is given by:

$$p_{m,isct} = \delta_1 Z_{sct} + \mathbf{X'_{isct}}\alpha + \mathscr{D}_l + \gamma_t + \nu_{isct}, \tag{D.1}$$

where $p_{m,isct}$ is the price of managed pollination services (here the honey bee rental fee per colony) faced by farm i, in state s, county c, and year t; Z_{sct} is our shift-share instrument for price (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022), which interacts almond acreage in California with distance measures to California; $\mathbf{X'_{isct}}$ is comprised of farm and orchard characteristics; $\mathscr{D}_l$ and γ_t are dummies for location and time, respectively; and ν_{isct} is the first-stage error term.

Our second-stage managed pollination demand equation is given by:

$$M_{isct} = \beta_1 \widehat{p}_{m,isct} + \mathbf{X'_{isct}}\theta + \mathscr{D}_l + \gamma_t + \varepsilon_{isct}, \tag{D.2}$$

where M_{isct} is the number of bee colonies demanded by farm i in state s, county c, and time t; $\widehat{p}_{m,isct}$ is the predicted price from the first stage; and ε_{isct} is the second-stage error term.

We use a linear demand specification (e.g., rather than a log-log specification) for several reasons. First, since we find in Proposition 1 that elasticity η_{p_m} is not constant, but instead depends on managed pollination price p_m and managed pollination M, we do not want a functional form (such as a log-log specification) that would assume that the elasticity is constant. Second, we expect the demand function to intersect the price axis and therefore that there is a price above which farmers will not rent bees. Indeed, we observe farmer-years in the data for which quantity rented is zero, which is only possible if the demand function intersects the price axis.[8] Third, we also expect the demand function to intersect the quantity axis and therefore that farmers would rent a finite number of bee colonies even if renting bees were free.

To identify β_1, the coefficient on managed pollination price in the second-stage managed pollination demand equation (D.2), we use a shift-share instrument Z_{sct} for price.[9] As a shift-share instrument, Z_{sct} is an interaction term, $Z_{sct} = d_{sc} * s_t$, of something that is ideally an exogenous, time-invariant "share" d_{sc} with an exogenous, time-varying "shift" s_t, which in combination predict the endogenous variable of interest while not violating the exclusion restriction (Goldsmith-Pinkham, Sorkin, and Swift, 2020; Borusyak, Hull, and Jaravel, 2022). In particular, our shift-share instrument Z_{sct} for price interacts distance from the zip codes where apple farms are located to the approximate center of almond production in Fresno County, California (our share d_{sc}) with the total almond acreage in California (our shift s_t). As explained in detail in Section 6.1 of the paper, this instrument accounts for demand for honey bees from almond growers in California (where most of US almond production takes place) and its well-documented effects on the availability and distribution of honey bees (e.g., see Ward, Whyte, and James (2010); Rucker, Thurman, and Burgett (2012); Goodrich, Williams, and Goodhue (2019)).

Although the 2007 USDA-ARMS collected data on the binary choice to rent honey bees, and the costs to rent honey bees per colony over 2006-2007, data on the quantity of honey bees demanded in 2006 is not available except in the instance a farmer reported not renting bees (in which case we know quantity rented is zero). We therefore use three different subsamples of data to estimate honey bee demand.

The first subsample uses data from 2007 only. For growers who rented honey bees in 2007, we use the grower's rental fee for the price. If a grower reported not renting bees in 2007 (i.e., quantity rented is zero), they did not report a bee rental fee; to deal with this we use the state average rental

[8] The inverse hyperbolic sine transformation was also studied as an alternative approach that permits observations of zero in price or quantity, but this is not our preferred approach as model diagnostics (e.g., lower adjusted R^2) were worse than the linear specifications and respective elasticity point estimates are implausibly large (ranging between -4 and -2).

[9] The indices reflect that we cannot resolve farm locations precisely and are restricted to zip code, county, and state level locations

fee in 2007 for the price. For specifications that use data from 2007 only, the instrument Z_{sct} is the Euclidean distance from the centroids of zip code units of farm locations to the centroid of Fresno, County California. As a consequence, the variation in the instrument Z_{sct} in specifications (1) and (2) comes from variation in the Euclidean distance from the centroids of zip codes where farms are located to the centroid of almond production in Fresno, County California.

The second subsample uses an unbalanced panel over 2006-2007 that includes all observations from 2007, as well as growers who reported not renting bees in 2006, for whom we know the number of colonies rented in 2006 is zero (thereby eliminating the need for quantity imputation), and for whom we use the state average rental fee in 2006 as the price in 2006. For this second subsample, the instrument is the full shift-share version of Z_{sct}, and is therefore the interaction between the distance from zip code centroids where farms are located to the centroid of Fresno, County California and the total almond acres in California in year t.

The third subsample uses a balanced panel that includes all growers in the data for both 2006 and 2007. If a grower rented in both years, we impute the number of colonies rented in 2007 to be the number of colonies rented in 2006. If a grower rented bees in 2006 but not in 2007, we impute the quantity rented in 2006 by multiplying the acreage of the selected apple block with the state level average honey bee stocking density in 2007. We use the state average rental fee in 2006 as the price in 2006. For farmers who never rented bees over 2006-2007, their quantity rented is zero in both years and we use the state average rental fee in the respective year for the price. For this subsample, the instrument is once again the full shift-share version of Z_{sct}, and is therefore the interaction between the distance from zip code centroids where farms are located to the centroid of Fresno, County California and the total almond acres in California in year t.

There are several challenges to estimating demand elasticities in this setting, which stem primarily from having limited temporal and cross-sectional variation (particularly for the number of honey bee colonies rented) and aggregate-level variation in our distance measures (the share in our instrument). Particular limitations come with state and county fixed effects, which eliminate too much information to provide a useful model, as well as high sensitivity to even including a moderate number of covariates. We can, however, effectively use time fixed effects in our specifications that use data from both 2006 and 2007 (in this two-period panel, including a dummy for 2007 is equivalent to including year fixed effects). The issue with state fixed effects is that they remove too much variation and effectively eliminate the strength of our instrument; the remaining variation in distance to Fresno, CA (the share in our shift-share instrument) after inclusion of state fixed effects is only weakly correlated with price. Analogous challenges with the limitations of fixed effects in demand estimation have been encountered by Bruno and Jessoe (2021), who find that year fixed effects remove excessive variation when estimating groundwater demand elasticities in California. In Section 6.2 of our paper, we use methods from Petterson, Seim, and Shapiro (2023) to assess the bounds and robustness of our results. Over a longer panel with an ability to resolve farm-specific locations, we anticipate that our instrument would retain sufficient strength to withstand location- and even farm-level fixed effects. For this reason, we focus on specifications with a limited set of covariates and state level dummies that do not overload the model. As such, our specifications limit us to testing Propositions 1 and 3 in our models. On these scores, our findings are consistent with these propositions.

Standard error estimation comes with the same aforementioned challenges as with our binary choice models. For this reason, standard errors are either clustered at the county level, or multi-way clustered at state and county levels.

D.2 Methods for Bounding the Elasticity of Demand

As a further step to study honey bee demand, we employ new methods developed by Petterson, Seim, and Shapiro (2023) for studying bounds on elasticities. Petterson, Seim, and Shapiro (2023) show that economic intuitions about the plausible size of demand shocks can be informative about and help bound the elasticity of demand. In particular, Petterson, Seim, and Shapiro (2023) develop methods for determining demand elasticities that are consistent with a given bound on the plausible size of demand shocks.

Following the approach taken in Figures 3 and 4 of Petterson, Seim, and Shapiro (2023), we determine the range of demand elasticities consistent with a range of demand shocks. In particular, following the approach taken in Figure 3 of Petterson, Seim, and Shapiro (2023), for each given bound B on the plausible size of shocks to demand, we make a plot with first differenced price on the x-axis and first differenced quantity on the y-axis. Around each point, we construct a dotted interval of radius the length of the given demand shock bound B, thus indicating, for each first differenced price, the plausible range of first differenced quantity given positive or negative demand shocks of magnitude up to the given bound B. In first differences, a demand function is a line through the origin with with non-positive slope. A demand function consistent with a bound B on the maximum absolute value of the demand shock is a downward sloping line that passes through the origin as well as through all of the dotted intervals. We determine the set of all demand functions consistent with a bound B, depict the set on the plot with a shaded region, and use the set to calculate the corresponding bound on demand elasticities (when evaluated at mean price and quantity) consistent with the demand shock bound B. We repeat the approach taken in Figure 3 of Petterson, Seim, and Shapiro (2023) for different demand shock bounds B, obtain the range of demand elasticities consistent with each demand shock bound B, and then, following the approach taken in Figure 4 of Petterson, Seim, and Shapiro (2023), we plot the range of demand elasticities consistent with the range of demand shocks.

We use two alternative demand shocks for our demand shock bound B. One demand shock we use are shocks to demand in the year 2007. Estimates of demand shocks from 2007 are obtained from point estimates on the dummy for 2007 in specifications (3), (4), and (5) of our econometric model of honey bee demand in Table 2 of our paper. Shocks in 2007 are potentially informative as this was a year of diesel price shocks and widespread onset of colony collapse disorder (CCD) (vanEngelsdorp and Meixner, 2010). For the second demand shock, following Appendix C of Petterson, Seim, and Shapiro (2023), we use the absolute value of the differenced quantity for observations for which the differenced price is equal to zero.

As the new methods developed by Petterson, Seim, and Shapiro (2023) involve taking first differences in price and quantity, we apply them to subsamples of our data that have observations in both 2006 and 2007. One such subsample is the subset of 430 farmers from the sample used in specifications (3)-(4) in Table 2 of our paper who have data in both 2006 and 2007. The advantage of this sample is that it does not require any quantity imputation; the disadvantage is that this sample does not have much variation in the absolute value of the differenced quantity for observations for which the differenced price is equal to zero, and therefore is not amenable to using our second demand shock. Another subsample of our data that has observations in both 2006 and 2007 is the balanced panel of all 1057 farmers that we use in specification (5) in Table 2 of our paper.

Large magnitude changes in quantity among those who rent bees in one year but not the other in our data, and the lack of changes in quantity for growers who rent in 2006 resulting from our quantity imputation in specification (5), present challenges for cleanly applying results from Petterson, Seim, and Shapiro (2023), however. To address make the effort more informative, and also to comply with USDA NASS conditions and restrictions on data confidentiality, we apply data smoothing methods to the first differenced quantity to average out outliers, and view our respective analysis as a simulation-focused approach on a pseudo-version of the actual data, which can be used to study the plausibility of our findings. To smooth the first differenced quantity, we average the first differenced quantity over observations that share similar values of first differenced price.[10]

D.3 Supplementary Tables and Figures

[10]We smooth the first differenced quantity when calculating the second demand shock, the absolute value of the differenced quantity for observations for which the differenced price is equal to zero, as well. For the results we report, we discretize the first differenced price using the empirical distribution of first differenced price, and then average the first differenced quantity for each bin of first differenced price. Based on the empirical distribution of first differenced price, we use the following bounds for the bins: -61, -40, -25, -20, -15, -10, -7.5, -5, -2.5, -0.5, 0.5, 2.5, 5, 7.5, 10, 12.5, 15, 20, 25, 40, 60. Our results are fairly robust to different smoothing approaches. For example, results are very similar when we apply smoothing approaches that re-assign each grower's first differenced quantity with the mean the first difference quantity over observations whose first difference price is within a given neighborhood of that grower's first difference price.

Table D.1: First-stage results for honey bee demand elasticity estimation (weighted).

Dependent variable is the honey bee rental fee per colony	(1)	(2)	(3)	(4)	(5)
IV: zip code distance to Fresno County, CA (km)	0.000003***	0.000004***			
	(0.000001)	(0.0000003)			
IV: zip code distance to Fresno County, CA (km) X total almond acres in CA			0.000000004***	0.000000005***	0.000000004***
			(0.0000000008)	(0.0000000005)	(0.0000000004)
apple bearing acres	0.002	-0.009	-0.02	-0.02	0.008
	(0.0290)	(0.0326)	(0.0289)	(0.0337)	(0.019)
apple bearing acres, squared	0.00004	0.00005	0.00007	0.00008	0.0000097
	(0.00006)	(0.00008)	(0.000064)	(0.000079)	(0.0000463)
deliberate pest scouting (dummy)		2.64***		1.65*	1.98
		(0.470)		(0.532)	(0.5346)
CA (dummy)	-13.03***	-11.76***	-13.46***	-12.54***	-12.93***
	(4.940)	(0.407)	(4.314)	(0.503)	(0.408)
MI (dummy)	-4.09***	-5.07***	-2.86***	-4.26***	-3.83***
	(1.460)	(0.541)	(1.306)	(0.568)	(0.396)
PA (dummy)		-4.11***		-5.01***	-5.54***
		(0.813)		(0.828)	(0.610)
year 2007 (dummy)			4.89***	4.31**	3.59***
			(0.880)	(1.069)	(0.854)
Constant	35.15***	32.31***	31.01***	29.44***	30.27***
	(1.533)	(0.601)	(1.393)	(0.759)	(0.678)
Data included in sample:					
All observations from 2007	Y	Y	Y	Y	Y
Growers who did not rent in 2006	N	N	Y	Y	Y
Growers who rented bees in 2006	N	N	N	N	Y
Standard Errors	C	C,S	C	C,S	C,S
First-stage F-statistic, F_{kp}	22.42	118.03	21.41	87.04	128.39
DWH	1.80	2.08	2.24	3.16	3.19
Adjusted R^2	0.25	0.27	0.30	0.31	0.27
# Observations	1057	1057	1487	1487	2114

Notes: Table presents the first-stage results for the honey bee demand IV estimation. Specifications (1) and (2) use data from 2007 only. For growers who rented honey bees in 2007, we use the grower's rental fee for the price. If a grower reported not renting bees in 2007, they did not report a bee rental fee; to deal with this we use the state average rental fee in 2007 for the price. Specifications (3) and (4) employ an unbalanced panel over 2006-2007 that includes all observations from 2007, as well as growers who reported not renting bees in 2006, for whom we use the state average rental fee in 2006 as the price in 2006. For specification (5), which is a balanced panel that includes all growers in the data for both 2006 and 2007, we use the state average rental fee in 2006 as the price in 2006. For specifications (1) and (2), the instrument Z_{sct} is the Euclidean distance from the centroids of zip code units of farm locations to the centroid of Fresno, County California. For specifications (3), (4), and (5) the instrument Z_{sct} is the interaction between the distance from zip code centroids where farms are located to the centroid of Fresno, County California and the total almond acres in California in year t. Standard errors are clustered at the county (C) and/or state (S) level, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table D.2: Honey bee demand own-price elasticity estimation, OLS results (weighted).

	Dependent variable is the number of honey bee colonies rented				
	(1')	(2')	(3')	(4')	(5')
honey bee rental fee ($/colony)	-0.009	-0.008	-0.007	-0.007	-0.009
	(0.0652)	(0.0697)	(0.060)	(0.071)	(0.074)
apple bearing acres	1.15***	1.13***	1.00***	0.99***	1.15***
	(0.153)	(0.202)	(0.170)	(0.235)	(0.199)
apple bearing acres, squared	-0.0009**	-0.0008	-0.0005	-0.0005	-0.0009*
	(0.00035)	(0.00044)	(0.00039)	(0.00052)	(0.00043)
deliberate pest scouting (dummy)		2.97***		1.48**	2.63***
		(0.807)		(0.632)	(0.679)
CA (dummy)	-4.14	-3.92**	-2.61	-3.01**	-3.84**
	(2.961)	(1.199)	(2.372)	(1.002)	(1.320)
MI (dummy)	2.03	1.31**	1.35	0.57	1.47**
	(2.616)	(0.537)	(2.137)	(0.725)	(0.479)
PA (dummy)		-5.41***		-4.23***	-5.09***
		(0.457)		(0.702)	(0.295)
year 2007 (dummy)			9.58***	7.87***	0.018
			(0.992)	(1.681)	(0.445)
Constant	1.58	-0.23	-5.83	-5.70	-0.12
	(3.600)	(4.140)	(2.878)	(3.303)	(3.954)
Elasticity at mean	-0.03	-0.03	-0.027	-0.027	-0.10
	Data included in sample:				
All observations from 2007	Y	Y	Y	Y	Y
Growers who did not rent in 2006	N	N	Y	Y	Y
Growers who rented bees in 2006	N	N	N	N	Y
Standard Errors	C	C,S	C	C,S	C,S
Adjusted R^2	0.53	0.54	0.52	0.52	0.54
# Observations	1057	1057	1487	1487	2114

Notes: Table presents OLS results for honey bee demand (weighted). Although the 2007 USDA-ARMS collected data on the binary choice to rent honey bees, and the costs to rent honey bees per colony over 2006-2007, data on the quantity of honey bees demanded in 2006 is not available except in the instance a farmer reported not renting bees (in which case we know quantity rented is zero). Specifications (1) and (2) use data from 2007 only. For growers who rented honey bees in 2007, we use the grower's rental fee for the price. If a grower reported not renting bees in 2007, they did not report a bee rental fee; to deal with this we use the state average rental fee in 2007 for the price in 2007. Specifications (3) and (4) employ an unbalanced panel over 2006-2007 that includes all observations from 2007, as well as growers who reported not renting bees in 2006, for whom we know the number of colonies rented in 2006 is zero (thereby eliminating the need for quantity imputation), and for whom we use the state average rental fee in 2006 as the price in 2006. Specification (5) is a balanced panel that includes all growers in the data for both 2006 and 2007: if the grower rented bees in 2007 and 2006, we impute the number of colonies rented in 2007 to be the number of colonies rented in 2006; if the grower rented bees in 2006 but not in 2007, we impute the quantity rented in 2006 by multiplying the acreage of the selected apple block with the state level average honey bee stocking density in 2007. We use the state average rental fee in 2006 as the price in 2006. Elasticity is evaluated at the mean price and quantity in the data for the respective sample of data. Standard errors are clustered at the county (C) and/or state (S) level, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

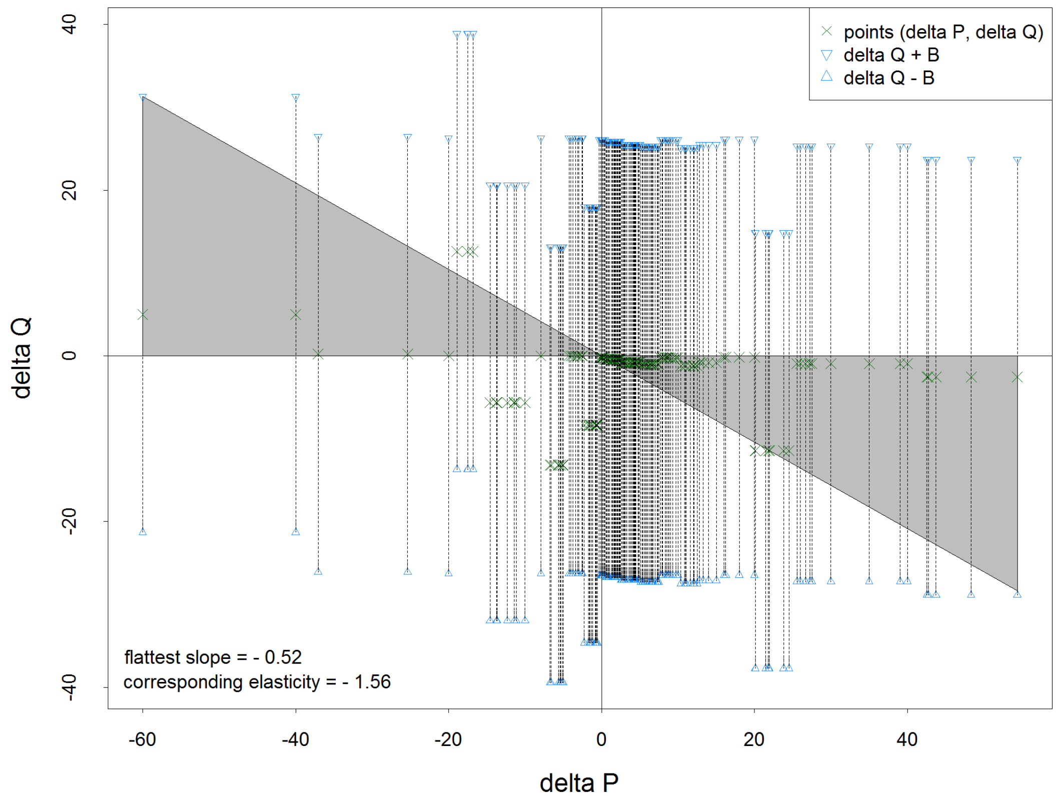

Figure D.1: Figure illustrates the construction of bounds on the honey bee demand elasticity from using the absolute value of the smoothed differenced quantity for observations for which the differenced price is equal to zero as our demand shock and a demand shock bound B of 26.3, which is twice the maximum absolute value of the smoothed differenced quantity for observations for which the differenced price is equal to zero. The subsample is the balanced panel of all 1057 farmers that we use in specification (5) in Table 2. The cross-hatches depict a scatterplot of the first differenced price on the x-axis and smoothed first differenced quantity on the y-axis. The dotted interval around each cross-hatch as radius of $B = 26.3$. The shaded region depicts all demand functions consistent with an upper bound of $B = 26.3$ on the maximum absolute value of the demand shock. These are the downward-sloping lines that pass through the origin and through all of the dotted intervals. The implied bound on the slope is -0.52 and the corresponding bound on demand elasticity (when evaluated at mean price and quantity) is -1.56.

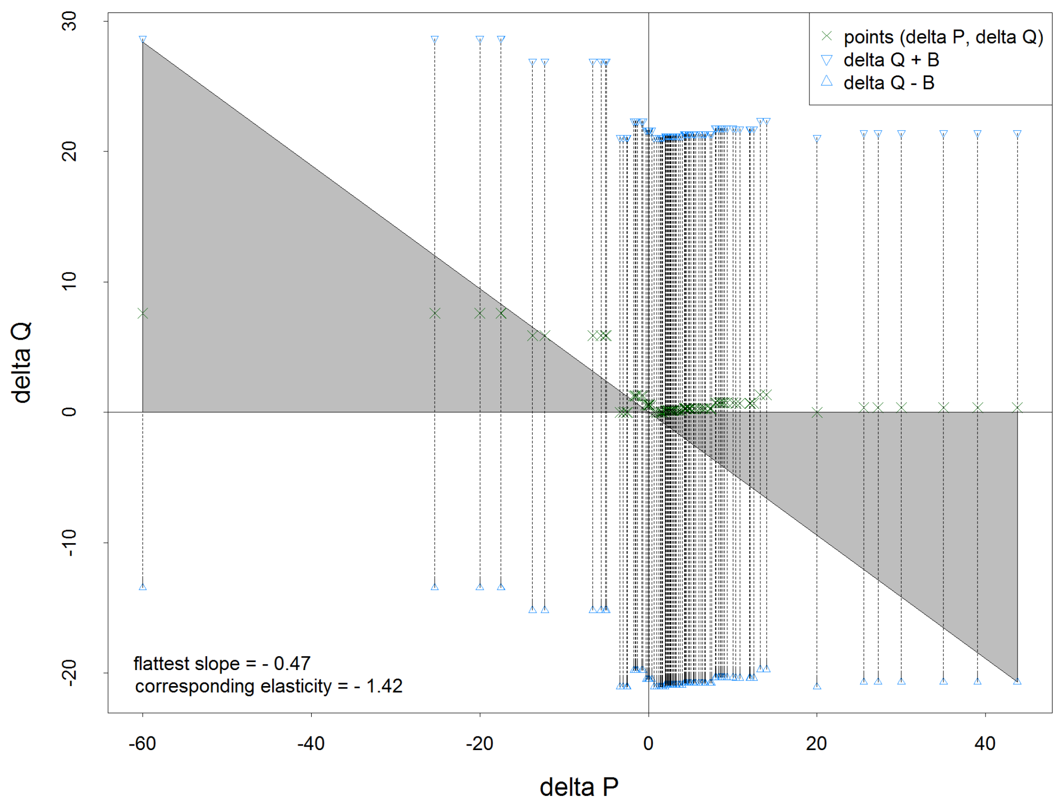

Figure D.2: Figure illustrates the construction of bounds on the honey bee demand elasticity (when evaluated at mean price and quantity) from using shocks to demand in the year 2007 as our demand shock and a demand shock bound B of 21.05, which is twice the maximum estimated shock in 2007. The subsample is the the subset of 430 farmers from the sample used in specifications (3)-(4) in Table 2 who have data in both 2006 and 2007. The cross-hatches depict a scatterplot of the first differenced price on the x-axis and smoothed first differenced quantity on the y-axis. The dotted interval around each cross-hatch as radius of $B = 21.05$. The shaded region depicts all demand functions consistent with an upper bound of $B = 21.05$ on the maximum absolute value of the demand shock. These are the downward-sloping lines that pass through the origin and through all of the dotted intervals. The implied bound on the slope is -0.47 and the corresponding bound on demand elasticity (when evaluated at mean price and quantity) is -1.42.

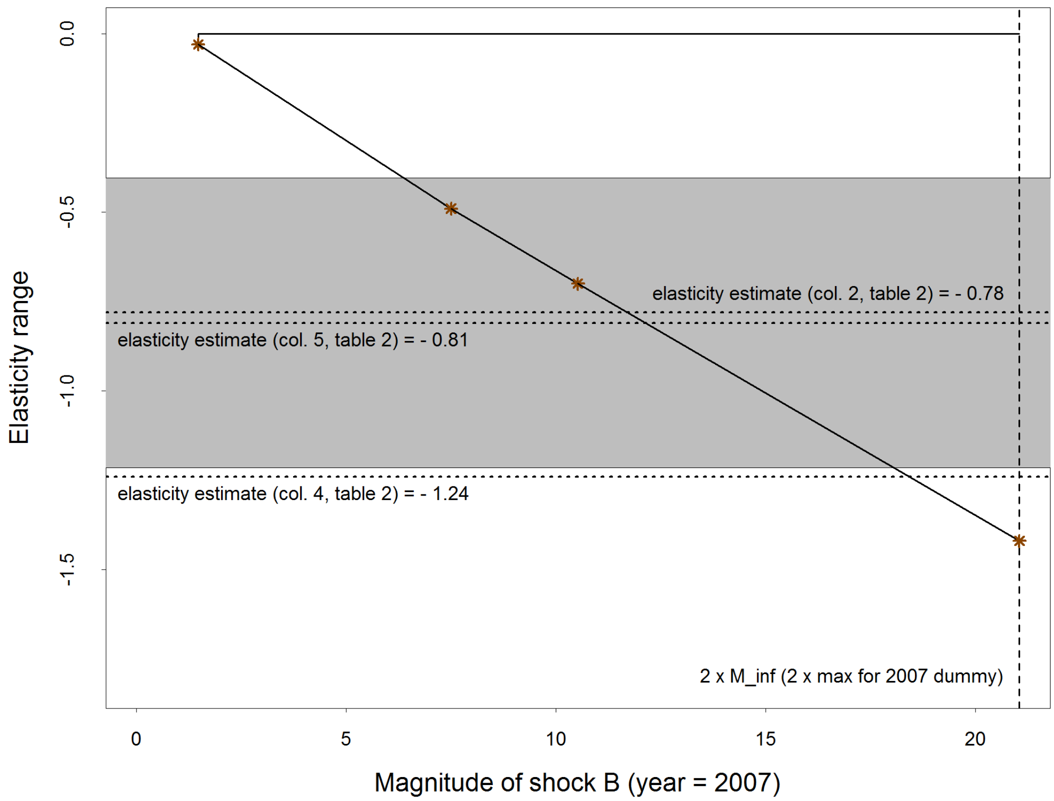

Figure D.3: Figure plots the range of honey bee demand elasticities (when evaluated at mean price and quantity) that are consistent with bounds on the plausible size of shocks to demand in the year 2007 ranging from the minimum estimated shock in 2007 to twice the maximum estimated shock in 2007. The subsample is the subset of 430 farmers from the sample used in specifications (3)-(4) in Table 2 who have data in both 2006 and 2007. Estimates of shocks from 2007 are obtained from point estimates on the dummy for 2007 included in specifications (3), (4), and (5) in Table 2. The dashed vertical line is at twice the maximum estimated shock in 2007. The horizontal dotted lines depict the point estimates for the demand elasticity from specifications (2), (4), and (5) in Table 2, and the shaded region depicts the associated 95% confidence interval for the estimated demand elasticity from specification (5) in Table 2.

E Relationship Between Yield, Profits, and Honey Bee Use

E.1 Econometric Model

To study how yield and profits vary with managed pollination use, we rely on optimal binscatter estimators from Cattaneo et al. (2021) to estimate the following semi-parametric function:

$$y_{isct} = \mu(x_{isct}) + \mathbf{w}'_{\mathbf{isct}}\gamma + \varepsilon_{isct}, \tag{E.1}$$

using the following p-th order polynomial, q-times continuously differentiable, covariate-adjusted least-squares extended binscatter estimator:

$$\hat{\mu}^{(v)}(x_{isct}) = \hat{\mathbf{b}}_q^{(v)}(x_{isct})'\hat{\beta}, \quad \begin{bmatrix} \hat{\beta} \\ \hat{\gamma} \end{bmatrix} = \arg\min_{\beta,\gamma} \sum_{i=1}^{n} (y_{isct} - \hat{\mathbf{b}}_q^{(v)}(x_{isct})'\beta - \mathbf{w_{isct}}'\gamma)^2, \;\; 0 \leq v, \;\; q \leq p, \tag{E.2}$$

where y_{isct} is either block-level profits or yield per acre for farmer i in state s, county c in year t; x_{isct} is the number of honey bee colonies per acre employed for pollination at the random apple block level for farmer i in state s, county c in year t; $\mu(x_{isct})$ is some unknown function of x_{isct}; p is the polynomial order used; v is the desired derivative to be approximated; q is the level of smoothness imposed across bins; $\mathbf{w_{isct}}$ is a vector of covariates; and where the model can be expanded to include dummies for fixed effects. The condition $q \leq p$ requires that a least squares p-th order polynomial is constructed in each bin, v refers to the derivative of interest, and $\hat{\mathbf{b}}_q^{(v)}$ reflects a spline basis to approximate $\mu^{(v)}(\cdot)$ (B-splines are employed). The goal is to recover the unknown function $\mu(x_{isct})$, which in our case is the functional relationship between outcome (profits or yield) y_{isct} and honey bee colonies per acre x_{isct}.

We use the optimal binscatter estimators from Cattaneo et al. (2021). Cattaneo et al. (2021) are the first to formalize the ad-hoc binscatter approaches that have long been in use and they offer a number of innovations to improve upon prior practice,[11] including: formalization within the frame-

[11] Common approaches have involved binning the regressor of interest to some ad-hoc number of bins, and then plotting the mean of the response variable of interest within bins, while also applying residualization in the Frisch-Waugh sense.

work of semi-linear least squares approximations (since $\mu(x)$ is non-linear, Frisch-Waugh logic is not applicable); data-driven selection of the number and placement of bins (using a data-driven rule of thumb approach, or integrated mean squared error (IMSE) criteria); smoothness restrictions using splines (between bins); smooth confidence bands; estimation of response function derivatives; and parametric (e.g., concavity) and shape restriction (e.g., monotonicity) t-tests.[12]

We use data-driven rule of thumb bin selection and provide results for both quantile-spaced and equally spaced bins. Compelling arguments can be made for quantile-spaced bins perhaps being preferable. In our setting, equally spaced bins produced more distinct value per bin, and therefore have some appealing properties, as one element of the methods of Cattaneo et al. (2021) that drives the data-driven approach is having sufficient degrees of freedom in regards to the number of distinct values within bins. Integrated mean squared error (IMSE)-based bin selection rules also have appealing properties over rule of thumb data-driven selection as potentially being more adaptable, but they also have a higher bar for the number of distinct values within bins. For these reasons, we opt for the data-driven rule of thumb approach and provide results for both quantile- and equally spaced bins for robustness.

At present, these methods are not adapted to address endogeneity beyond controlling for fixed effects and covariate adjustment. Hence estimation of $\mu(\cdot)$ remains vulnerable to endogeneity concerns. In our setting, while honey bees are an input, and hence potentially endogenous, honey bee colonies rented per acre is arguably exogenous to yield and profit, since honey bees are rented during the bloom period, several months before yield and profits are realized. Honey bee colonies per acre is also likely exogenous to yield and profits because farmers are unable to precisely control insect pollination. Beyond placement of pallets of colonies around orchards, little can be done to ensure honey bees pollinate crops as desired. Indeed, any effort to directly engage with bees can result in significant harm from bee stings (a reality clearly demonstrated by beekeepers' extensive use of protective clothing and implements to prevent injury when working with their colonies). Moreover, rented honey bees may end up foraging outside of the locations they are brought to

[12]Implementation software for R is known as *bingsreg*.

pollinate crops. For example, findings from McArt et al. (2017) suggest that honey bees utilized for apple pollination in New York may conduct a significant amount of foraging in non-crop areas. Since farmers have limited control over these potentially dangerous insects with minds of their own, they are unable to precisely control insect pollination. There are therefore good reasons to view insect pollination as an exogenous process on some level, hence omitted variable bias may be the larger issue and we employ a highly relevant set of controls in $\mathbf{w_{isct}}$ to mitigate this concern (including monthly weather variation, farm labor, landscape cover measures, and farm scale measures). Although some amount of bias may be present in our estimations, in our view, the novelty of the opportunity to make *any* estimation of the functional relationship between realized farm-level production outcomes and managed pollination outweighs concerns of bias – particularly given the innovative tools provided by Cattaneo et al. (2021). To assess the stability of the relationships between colonies per acre and production outcomes, we also assess these relationships using standard linear fixed effects models to assess the stability of parametric point estimates.[13]

For further robustness checks, we estimate linear fixed effects models and employ second-order polynomials in honey bee colonies per acre and other covariates. For the linear fixed effects regressions, standard error estimation comes with the same aforementioned challenges as with our binary choice models. For this reason, we use either Huber-White heteroskedasticity-robust standard errors, or standard errors that are multi-way clustered at the county and state levels.

E.2 Supplementary Tables and Figures

[13]We have explored a two-stage least squares set-up, using prior year pollination prices and/or the aforementioned shift-share instrument, as plausible instruments for honey bee colonies per acre. Unfortunately, none of these instruments predict colonies per acre with sufficient strength to make associated tests useful.

Table E.1: Weighted linear fixed effects regressions of yield.

	Dependent variable is block-level apple yield (bushels/acre)			
	(1)	(2)	(3)	(4)
Honey bee colonies per acre				
honey bee colonies per acre	110.031***	110.031***	157.534**	67.836*
	(19.494)	(23.817)	(36.068)	(22.308)
honey bee colonies per acre, squared	-10.996***	-10.996**	-15.143	-5.787
	(3.136)	(3.365)	(8.264)	(3.818)
Measures of production scale				
apple bearing acres	-1.037	-1.037	-1.818**	-1.377
	(1.024)	(0.744)	(0.199)	(3.434)
apple bearing acres, squared	0.0003	0.0003	0.003*	-0.005
	(0.003)	(0.002)	(0.001)	(0.052)
trees per acre	0.158	0.158	-0.169	0.682
	(0.143)	(0.313)	(0.280)	(0.307)
trees per acre, squared	-0.0002**	-0.0002	-0.00002	-0.001
	(0.0001)	(0.0002)	(0.0002)	(0.0004)
average age of trees	10.219***	10.219***	8.658**	15.724*
	(2.279)	(2.726)	(1.380)	(6.451)
average age of trees, squared	-0.117***	-0.117***	-0.084*	-0.154*
	(0.033)	(0.021)	(0.022)	(0.057)
Labor input variables				
pruning/thinning hours	-0.059***	-0.059***	-0.039	-0.116
	(0.018)	(0.012)	(0.016)	(0.050)
harvesting hours	0.073***	0.073***	0.044**	0.117*
	(0.015)	(0.010)	(0.010)	(0.043)
land prep and machine hours	0.283**	0.283***	0.287**	0.645**
	(0.110)	(0.053)	(0.037)	(0.166)
pest scouting hours	0.127***	0.127***	0.137**	0.651*
	(0.043)	(0.014)	(0.022)	(0.215)
part time and seasonal hours	0.007	0.007*	0.0003	0.006
	(0.012)	(0.003)	(0.003)	(0.027)
full time hours	0.075***	0.075**	0.066	0.065**
	(0.024)	(0.028)	(0.036)	(0.014)
Land cover variables				
natural forest cover	-219.613	-219.613	-281.935**	759.463***
	(186.591)	(220.246)	(62.627)	(112.357)
natural forest cover, squared	185.792	185.792	300.656	-1,020.779***
	(249.471)	(403.285)	(142.217)	(22.319)
natural open cover	-160.877	-160.877	-1,258.030	-3,550.023*
	(525.951)	(683.298)	(1,141.463)	(1,280.448)
natural open cover, squared	-567.918	-567.918	408.736	8,171.569
	(595.006)	(759.403)	(1,298.848)	(4,152.272)
Weather variables				
Jan. average precipitation (mm)	-42.780	-42.780	6.025	-33.643
	(29.738)	(36.270)	(77.009)	(38.332)
Jan. average temperature (C)	-114.840***	-114.840*	-51.497	-217.290

	(33.833)	(50.809)	(62.456)	(101.180)
Feb. average precipitation (mm)	3.904	3.904	-72.013*	171.598***
	(14.490)	(21.730)	(17.522)	(15.796)
Feb. average temperature (C)	61.916	61.916	-138.821	177.358
	(49.780)	(85.217)	(59.304)	(112.731)
Mar. average precipitation (mm)	19.598	19.598	55.934	-198.468*
	(28.516)	(41.088)	(45.298)	(80.035)
Mar. average temperature (C)	21.888	21.888	79.640	104.990
	(51.375)	(86.584)	(148.471)	(56.589)
Apr. average precipitation (mm)	28.696	28.696	176.996**	37.360*
	(29.602)	(35.735)	(20.137)	(11.821)
Apr. average temperature (C)	37.609	37.609	-167.630	-110.854*
	(63.338)	(55.664)	(166.129)	(45.685)
May average precipitation (mm)	-108.142**	-108.142*	-359.718	-73.980*
	(46.097)	(50.813)	(164.899)	(29.323)
May average temperature (C)	-20.035	-20.035	-12.161	159.515
	(59.615)	(71.919)	(24.359)	(94.450)
Jun. average precipitation (mm)	-56.635	-56.635**	283.116	9.808
	(35.165)	(20.462)	(187.178)	(34.478)
Jun. average temperature (C)	-11.240	-11.240	123.762	-27.402
	(55.419)	(60.573)	(187.206)	(91.193)
Jul. average precipitation (mm)	-94.401***	-94.401**	-230.351	-102.319**
	(35.549)	(35.346)	(206.623)	(22.429)
Jul. average temperature (C)	65.610	65.610*	-240.338	65.218
	(54.926)	(32.966)	(96.740)	(56.350)
Aug. average precipitation (mm)	22.829	22.829	-754.282	3.241
	(19.669)	(30.622)	(310.293)	(25.175)
Aug. average temperature (C)	-66.040	-66.040	29.549	-134.824
	(58.443)	(51.631)	(73.414)	(63.034)
Sep. average precipitation (mm)	119.168***	119.168	-55.096	76.542
	(44.303)	(67.851)	(35.449)	(69.675)
Sep. average temperature (C)	24.369	24.369	308.891*	-4.208
	(63.923)	(63.645)	(96.817)	(33.437)
State FE	Y	Y	Y	Y
Sample	All	All	West	East
Standard Errors	HW	S,C	S,C	S,C
Adjusted R^2	0.31	0.31	0.32	0.33
# Observations	1000	1000	449	551

Notes: Table presents results from weighted linear fixed effects regressions of block-level yield in bushels per acre regressed on honey bee colonies per acre, block characteristics, labor inputs, monthly average temperature and precipitation (Jan-Sept), and remotely sensed land cover measures to proxy for wild bee habitat and landscape heterogeneity. Standard errors are either Huber-White robust standard errors (HW), or multi-way clustered at the county (C) and state (S) levels, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.2: Weighted linear fixed effects regressions of yield for Eastern states using alternative measures of land cover.

	Dependent variable is block-level apple yield (bushels/acre)		
	(1)	(2)	(3)
Honey bee colonies per acre			
honey bee colonies per acre	67.836*	67.727*	68.685*
	(22.308)	(23.488)	(22.966)
honey bee colonies per acre, squared	-5.787	-6.275	-6.449
	(3.818)	(3.922)	(3.905)
Land cover variables			
natural forest cover (county)	759.463***		
	(112.357)		
natural forest cover (county), squared	-1,020.779***		
	(22.319)		
natural forest cover (3000 m. buffer)		1,157.634**	
		(317.524)	
natural forest cover (3000 m. buffer), squared		-1,567.622*	
		(545.776)	
natural forest cover (1000 m. buffer)			903.257*
			(308.524)
natural forest cover (1000 m. buffer), squared			-1,123.942
			(502.324)
natural open cover (county)	-3,550.023*		
	(1,280.448)		
natural open cover (county), squared	8,171.569		
	(4,152.272)		
natural open cover (3000 m. buffer)		-1,467.648	
		(1,297.936)	
natural open cover (3000 m. buffer), squared		1,253.466	
		(2,403.695)	
natural open cover (1000 m. buffer)			-1,331.240
			(1,522.495)
natural open cover (1000 m. buffer), squared			900.154
			(2,854.113)
Measures of production scale	Y	Y	Y
Labor input variables	Y	Y	Y
Weather variables	Y	Y	Y
State FE	Y	Y	Y
Sample	East	East	East
Standard Errors	HW	S,C	S,C
Adjusted R^2	0.33	0.34	0.34
# Observations	551	551	551

Notes: Table presents results for weighted linear regressions of block-level yield in bushels per acre regressed on honey bee colonies per acre, block characteristics, labor inputs, monthly average temperature and precipitation (Jan-Sept), and alternative wild bee habitat proxies for the Eastern states. Remotely sensed habitat measures include county-level proportions in specification (1), and the proportion within a buffer of 3000 and 1000 meters around apple producing areas in specifications (2) and (3). A caveat for specifications (2) and (3) is that apple-specific areas are not necessarily identifiable within the USDA-CDL within a given county. To deal with this, we use proportions within buffers around tree crop producing areas, or the county proportion (if tree crop areas are not identifiable). Of the 551 observations in these regressions, 431 farms are in counties where apple specific areas can be identified, 6 farms are in counties where tree crop areas can be identified, and the remaining 114 farms are in counties where natural forest and open cover can only be summarized at the county level. Standard errors are either Huber-White robust standard errors (HW), or multi-way clustered at the county (C) and state (S) levels, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.3: Weighted linear fixed effects regressions of profits.

	Dependent variable is block-level apple profits ($/acre)			
	(1)	(2)	(3)	(4)
Honey bee colonies per acre				
honey bee colonies per acre	1,549.111***	1,549.111**	2,075.516	1,006.975*
	(279.126)	(419.982)	(954.052)	(327.935)
honey bee colonies per acre, squared	-171.891***	-171.891*	-203.250	-117.006
	(44.908)	(71.225)	(200.751)	(54.302)
Measures of production scale				
apple bearing acres	56.507***	56.507***	32.510***	66.840**
	(14.660)	(13.141)	(1.560)	(20.797)
apple bearing acres, squared	-0.028	-0.028	0.019	-0.601**
	(0.041)	(0.034)	(0.007)	(0.145)
trees per acre	0.945	0.945	-2.066	8.091
	(2.041)	(5.724)	(3.433)	(4.684)
trees per acre, squared	-0.003	-0.003	-0.001	-0.004
	(0.002)	(0.004)	(0.003)	(0.003)
average age of trees	79.385**	79.385**	93.205***	42.677
	(32.630)	(24.938)	(8.587)	(26.753)
average age of trees, squared	-1.449***	-1.449***	-0.834**	-0.839**
	(0.474)	(0.382)	(0.131)	(0.145)
Labor input variables				
pruning/thinning hours	-1.427***	-1.427***	-1.647***	-0.804
	(0.257)	(0.073)	(0.111)	(0.557)
harvesting hours	-0.042	-0.042	0.671*	-0.516*
	(0.214)	(0.189)	(0.160)	(0.175)
land prep and machine hours	2.355	2.355	1.910	6.088**
	(1.573)	(1.298)	(1.579)	(1.367)
pest scouting hours	-1.257**	-1.257***	-0.717*	7.222
	(0.616)	(0.291)	(0.189)	(4.059)
part time and seasonal hours	0.096	0.096	0.023	0.345
	(0.175)	(0.111)	(0.073)	(0.189)
full time hours	0.265	0.265***	0.218	0.644
	(0.344)	(0.052)	(0.254)	(0.756)
Land cover variables				
natural forest cover	-5,984.983**	-5,984.983	5,945.144	-514.450
	(2,671.699)	(4,518.220)	(2,644.068)	(6,370.526)
natural forest cover, squared	5,059.542	5,059.542	-12,532.420	-1,758.821
	(3,572.048)	(6,085.677)	(5,807.915)	(3,844.049)
natural open cover	10,508.770	10,508.770	-26,537.320	-46,329.760***
	(7,530.827)	(6,983.854)	(14,737.680)	(5,403.654)
natural open cover, squared	-26,533.220***	-26,533.220***	15,685.780	182,183.100**
	(8,519.587)	(5,901.124)	(19,905.380)	(31,886.730)
Weather variables				
Jan. average precipitation (mm)	-1,145.566***	-1,145.566*	-1,621.610	-1,180.238**
	(425.806)	(473.491)	(1,103.637)	(235.590)
Jan. average temperature (C)	-2,243.378***	-2,243.378**	-2,798.264*	-621.450

	(484.444)	(724.466)	(866.428)	(538.706)
Feb. average precipitation (mm)	807.156***	807.156*	438.406	2,475.269**
	(207.472)	(397.865)	(490.717)	(546.171)
Feb. average temperature (C)	-492.970	-492.970	-7,305.001	702.282
	(712.774)	(1,473.341)	(3,164.172)	(880.198)
Mar. average precipitation (mm)	79.614	79.614	4,784.945**	-2,021.727**
	(408.308)	(625.294)	(710.380)	(488.922)
Mar. average temperature (C)	2,153.403***	2,153.403	7,509.021	760.360
	(735.609)	(1,687.360)	(2,662.791)	(848.077)
Apr. average precipitation (mm)	87.671	87.671	-1,339.856	317.139*
	(423.852)	(686.790)	(3,750.771)	(129.491)
Apr. average temperature (C)	1,283.824	1,283.824	5,123.948	-1,493.162**
	(906.906)	(1,473.880)	(2,539.635)	(290.012)
May average precipitation (mm)	-1,060.300	-1,060.300	-6,940.986*	-155.317
	(660.042)	(1,021.956)	(1,813.886)	(560.079)
May average temperature (C)	1,671.445*	1,671.445*	-2,281.300**	1,108.217
	(853.603)	(700.738)	(453.605)	(632.785)
Jun. average precipitation (mm)	-1,512.475***	-1,512.475*	-2,662.714	539.282
	(503.516)	(744.122)	(1,133.519)	(819.057)
Jun. average temperature (C)	-1,910.459**	-1,910.459	-1,009.436	679.472
	(793.513)	(1,397.355)	(2,575.067)	(1,118.294)
Jul. average precipitation (mm)	192.324	192.324	-4,150.616**	-857.996
	(509.013)	(741.224)	(439.469)	(460.047)
Jul. average temperature (C)	904.911	904.911	-5,751.975	126.626
	(786.463)	(1,246.463)	(2,259.378)	(1,057.315)
Aug. average precipitation (mm)	-638.195**	-638.195	764.923	302.561
	(281.627)	(613.630)	(654.339)	(444.199)
Aug. average temperature (C)	-1,341.222	-1,341.222	5,083.671*	1,113.124
	(836.812)	(1,714.507)	(1,237.662)	(1,148.521)
Sep. average precipitation (mm)	1,281.286**	1,281.286	-2,224.227	665.372
	(634.348)	(825.776)	(1,299.754)	(466.498)
Sep. average temperature (C)	63.660	63.660	-1,098.149	-3,121.417
	(915.286)	(857.229)	(2,596.546)	(1,343.887)
State FE	Y	Y	Y	Y
Sample	All	All	West	East
Standard Errors	HW	S,C	S,C	S,C
Adjusted R^2	0.427	0.427	0.516	0.318
# Observations	1,000	1,000	449	551

Notes: Table presents results from weighted linear fixed effects regressions of block-level profits per acre regressed on honey bee colonies per acre, block characteristics, labor inputs, monthly average temperature and precipitation (Jan-Sept), and remotely sensed land cover measures to proxy for wild bee habitat and landscape heterogeneity. Standard errors are either Huber-White robust standard errors (HW), or multi-way clustered at the county (C) and state (S) levels, and are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

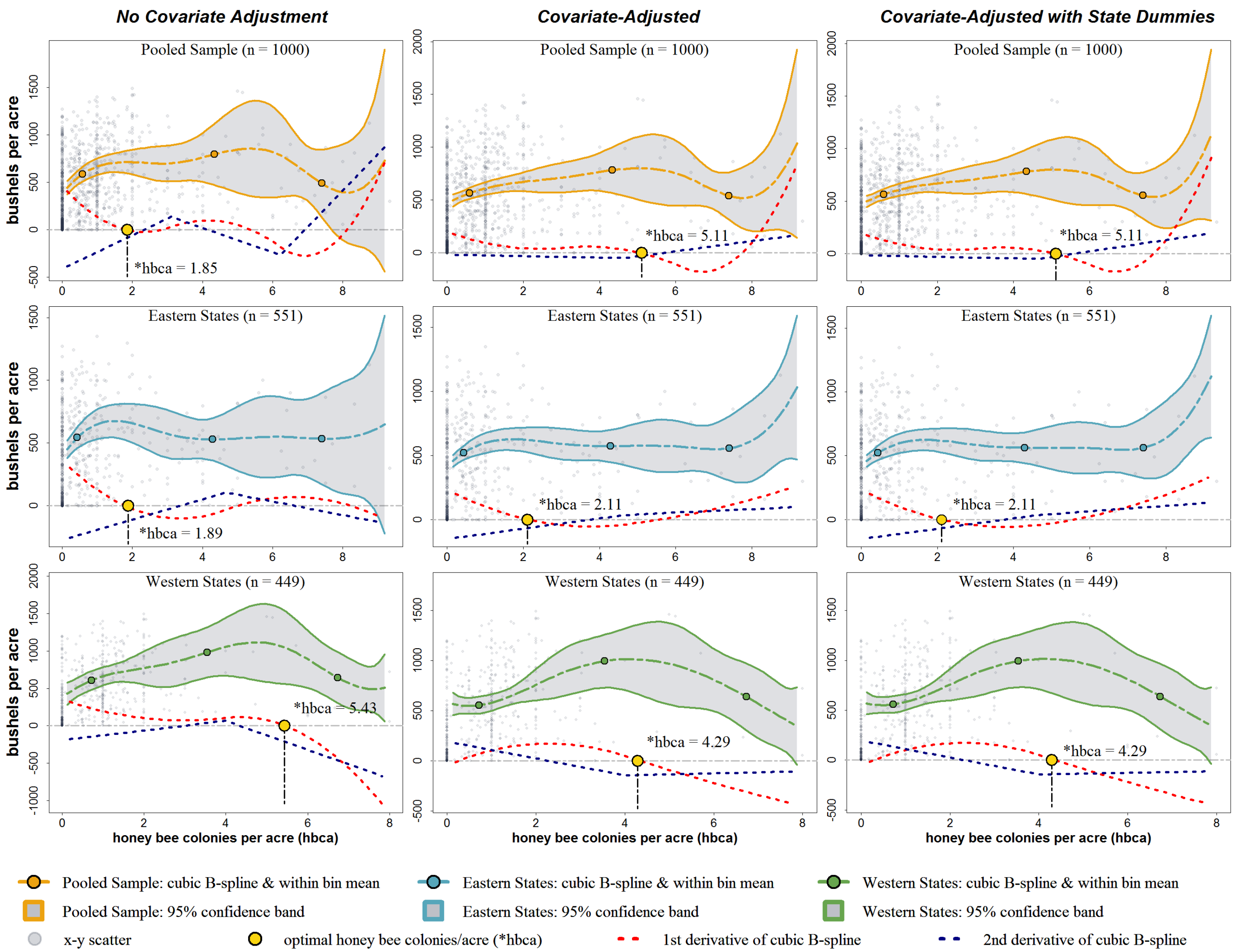

Figure E.1: Optimal binscatter (following Cattaneo et al. (2021)) of *yield* in bushels per acre on the semi-parametric function $\mu(x)$, where x is honey bee colonies per acre, which is defined as the number of honey bee colonies rented divided by selected block size in acres. Each panel trims the 99% centile of the outcome variable and honey bee colonies per acre to reduce the influence of extreme outliers that can dramatically affect the readability of the figure. Column 1 is the optimal binscatter of yield on honey bee colonies per acre. Column 2 includes covariate-adjustment using the same covariates employed in the linear models in Tables E.1-E.5, with the exception of the polynomial versions of some of these variables. Column 3 employs the same model in Column 2 but includes state dummies. These estimations employ *equally spaced*, data-driven rule of thumb bin selection, and cubic B-splines within and between bins. Confidence bands are bootstrapped with n draws. Optimal honey bee colonies per acre are plotted where the estimated first derivative (in red) of the response function equals zero and the response function is at a global (or local) maximum. Second derivatives are also plotted in dark blue.

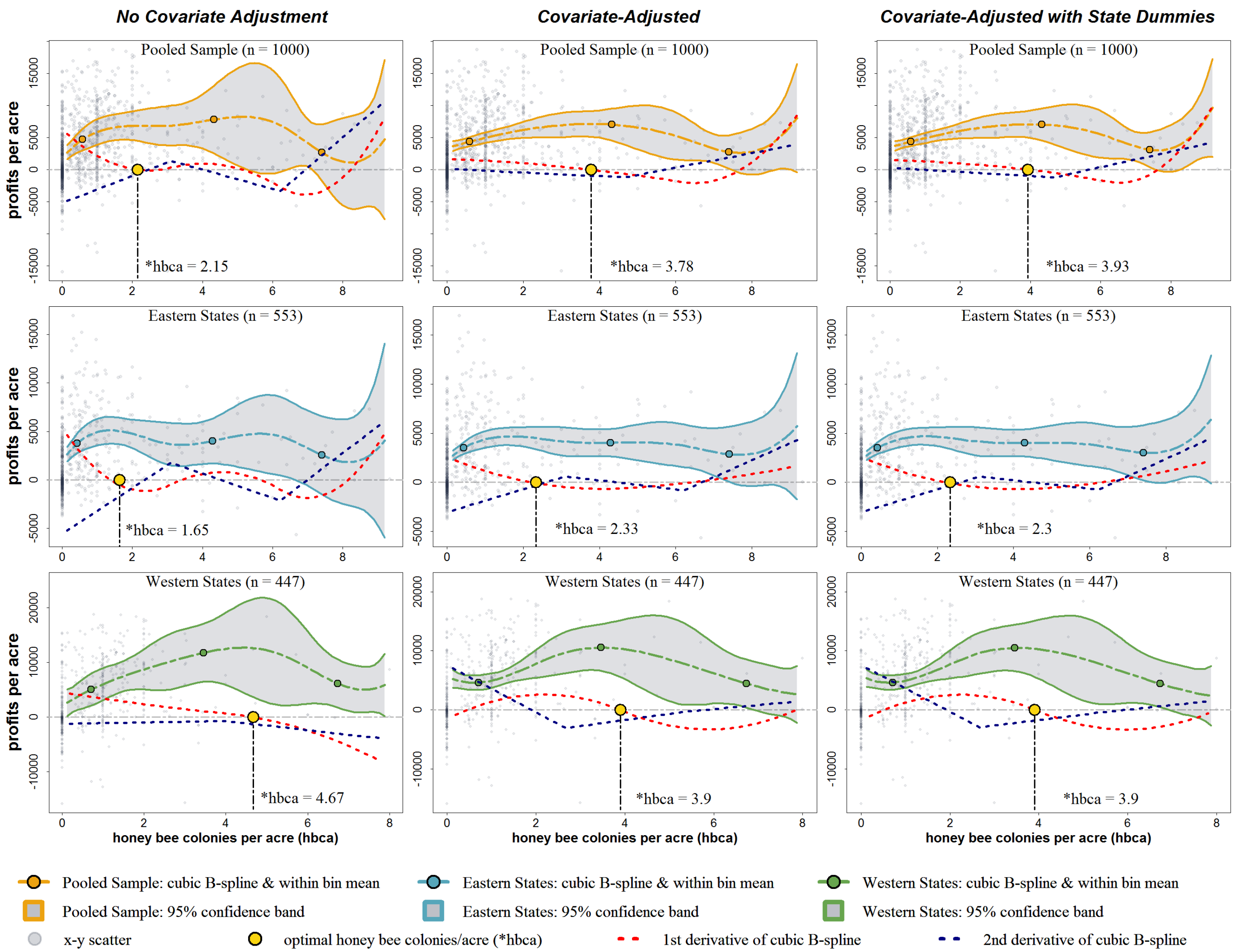

Figure E.2: Optimal binscatter (following Cattaneo et al. (2021)) of *profits* in dollars per acre on the semi-parametric function $\mu(x)$, where x is honey bee colonies per acre, which is defined as the number of honey bee colonies rented divided by selected block size in acres. Each panel trims the 99% centile of the outcome variable and honey bee colonies per acre to reduce the influence of extreme outliers that can dramatically affect the readability of the figure. Column 1 is the optimal binscatter of yield on honey bee colonies per acre. Column 2 includes covariate-adjustment using the same covariates employed in the linear models in Tables E.1-E.5, with the exception of the polynomial versions of some of these variables. Column 3 employs the same model in Column 2 but includes state dummies. These estimations employ *equally spaced*, data-driven rule of thumb bin selection, and cubic B-splines within and between bins. Confidence bands are bootstrapped with n draws. Optimal honey bee colonies per acre are plotted where the estimated first derivative (in red) of the response function equals zero and the response function is at a global (or local) maximum. Second derivatives are also plotted in dark blue.

Table E.4: Parametric tests of response function $\mu(x)$ for yield for Eastern states.

	no covariate adjustment	covariate-adjusted	covariate-adjusted with state dummies
constant	4.509	3.479	3.453
	(0.000)	(0.000)	(0.000)
linear	3.491	2.306	2.374
	(0.004)	(0.029)	(0.019)
quadratic	2.633	1.797	2.281
	(0.071)	(0.086)	(0.029)
cubic	1.635	0.486	0.420
	(0.525)	(0.686)	(0.718)
# Bins	3	3	3
# Observations	551	551	551
# Distinct values	159	159	159

Notes: Table presents t-statistics (p-values in parentheses) from parametric tests of the response function $\mu(x)$ for yield for specifications using the Eastern states subsample. Yield is in bushels per acre; x is honey bee colonies per acre defined as the number of honey bee colonies rented divided by selected block size in acres. Tests employ rule of thumb approach for selection of the number of bins (Cattaneo et al. 2021), quantile-spaced bins, and sample weights. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.5: Parametric tests of response function $\mu(x)$ for yield for Western states.

	no covariate adjustment	covariate-adjusted	covariate-adjusted with state dummies
constant	4.006	3.181	3.130
	(0.000)	(0.003)	(0.003)
linear	4.086	3.586	3.545
	(0.000)	(0.001)	(0.001)
quadratic	1.101	1.987	2.001
	(0.856)	(0.077)	(0.070)
cubic	0.843	0.891	0.891
	(0.938)	(0.526)	(0.526)
# Bins	3	3	3
# Observations	449	449	449
# Distinct values	136	136	136

Notes: Table presents t-statistics (p-values in parentheses) from parametric tests of the response function $\mu(x)$ for yield for specifications using the Western states subsample. Yield is in bushels per acre; x is honey bee colonies per acre defined as the number of honey bee colonies rented divided by selected block size in acres. Tests employ rule of thumb approach for selection of the number of bins (Cattaneo et al. 2021), quantile-spaced bins, and sample weights. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.6: Shape restriction tests of response function $\mu(x)$ for yield for Eastern states.

	no covariate adjustment	covariate-adjusted	covariate-adjusted with state dummies
non-positive	4.970	3.750	3.857
	(0.000)	(0.000)	(0.000)
non-negative	−1.139	−1.190	−1.371
	(0.625)	(0.599)	(0.496)
concave	2.402	2.566	2.983
	(0.033)	(0.020)	(0.003)
convex	−3.758	−3.126	−3.297
	(0.000)	(0.001)	(0.000)
# Bins	2	2	2
# Observations	551	551	551
# Distinct values	159	159	159

Notes: Table presents t-statistics (p-values in parentheses) from shape restriction tests of the response function $\mu(x)$ for yield for specifications using the Eastern states subsample. Yield is in bushels per acre; x is honey bee colonies per acre defined as the number of honey bee colonies rented divided by selected block size in acres. Monotonicity tests are applied to the first derivative of respective optimal binscatter curves for the models represented in each column. Tests for concavity and convexity are applied to the respective second derivatives. Tests employ data-driven rule of thumb approach for selection of the number of bins (Cattaneo et al. 2021), quantile-spaced bins, and sample weights. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.7: Shape restriction tests of response function $\mu(x)$ for yield for Western states.

	no covariate adjustment	covariate-adjusted	covariate-adjusted with state dummies
non-positive	3.464	3.344	3.311
	(0.003)	(0.003)	(0.003)
non-negative	−1.990	−2.282	−2.261
	(0.157)	(0.090)	(0.092)
concave	0.565	1.505	1.534
	(0.834)	(0.306)	(0.290)
convex	−2.614	−2.909	−2.886
	(0.030)	(0.013)	(0.014)
# Bins	2	2	2
# Observations	449	449	449
# Distinct values	136	136	136

Notes: Table presents t-statistics (p-values in parentheses) from shape restriction tests of the response function $\mu(x)$ for yield for specifications using the Western states subsample. Yield is in bushels per acre; x is honey bee colonies per acre defined as the number of honey bee colonies rented divided by selected block size in acres. Monotonicity tests are applied to the first derivative of respective optimal binscatter curves for the models represented in each column. Tests for concavity and convexity are applied to the respective second derivatives. Tests employ data-driven rule of thumb approach for selection of the number of bins (Cattaneo et al. 2021), quantile-spaced bins, and sample weights. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

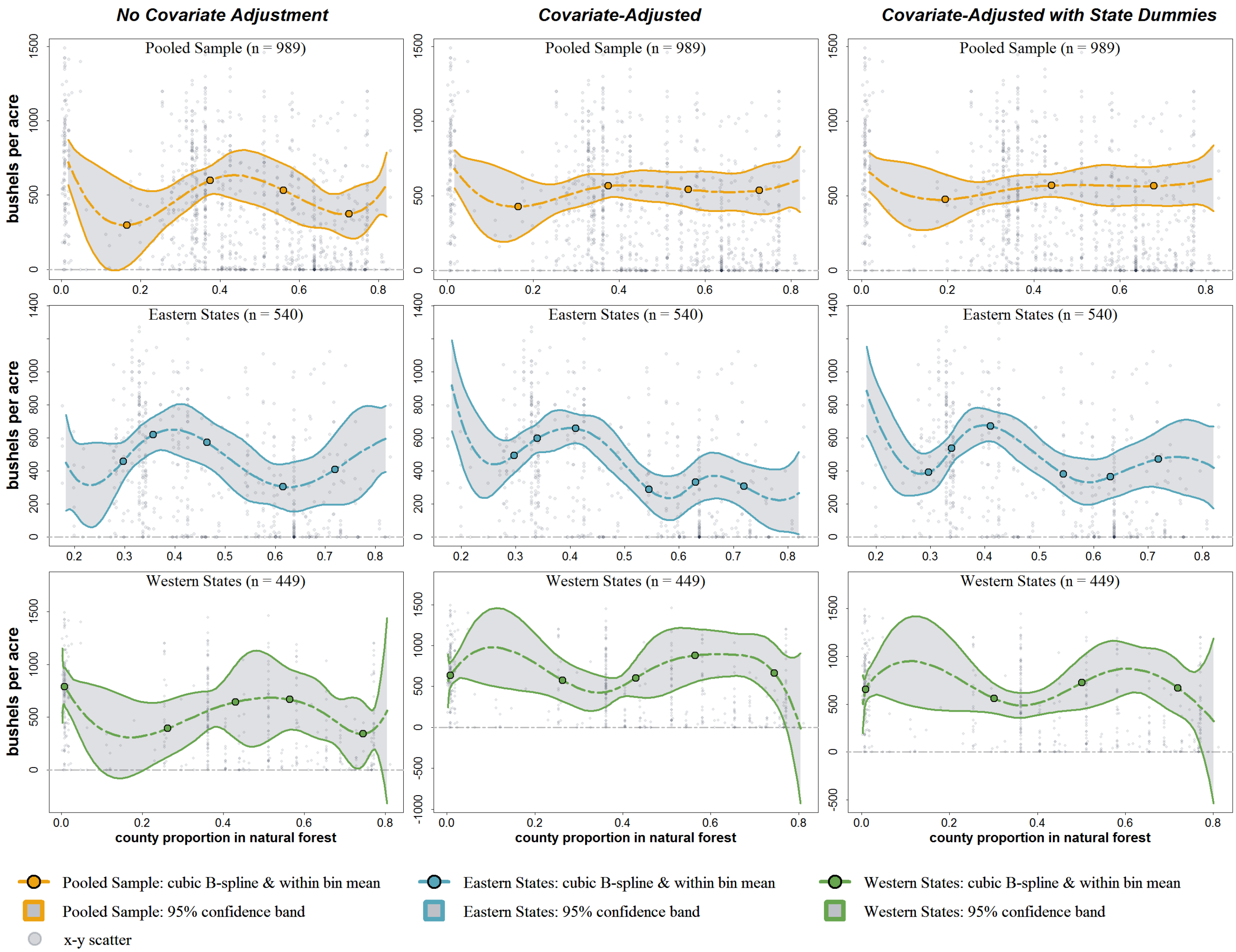

Figure E.3: Optimal binscatter (following Cattaneo et al. (2021)) of *yield* in bushels per acre on the semi-parametric function $\mu(x)$, where x is the county-level proportion in natural forest cover. Each panel trims the 99% centile of the outcome variable and honey bee colonies per acre to reduce the influence of extreme outliers that can dramatically affect the readability of the figure. Column 1 is the optimal binscatter of yield on natural forest cover. Column 2 includes covariate-adjustment using the same covariates employed in the linear models in Tables E.1-E.5, with the exception of the polynomial versions of some of these variables. Column 3 employs the same model in Column 2 but includes state dummies. These estimations employ *quantile-spaced*, data-driven rule of thumb bin selection, and cubic B-splines within and between bins. Confidence bands are bootstrapped with n draws.

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