Pollination, Production, and Profits

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Abstract

The relationship between managed pollination and production outcomes is important in theory and practice. In this paper we estimate semi-parametric response functions between yield and profits and honey bee colonies per acre in the US apple sector. Our results suggest an optimal honey bee stocking density of around 2 and 4 colonies per acre for Eastern and Western states, respectively. Shape restriction tests are consistent with a concave relationship and diminishing returns. We also find that Western apple farmers receive a larger return from the marginal colony, and that yield in Eastern states may be concave in natural forest cover.

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1 Introduction

In economics generally and particularly in applied work, bridging theory and empirical work can be both challenging and important (Hood and Koopmans, 1970; Varian, 1992; Rust, 2010; Timmins and Schlenker, 2009). Take, for example, the importance of the shape of economic relationships, an issue recognized as early as Slutsky (1915). Particular relationships are often posited to exist in theory, but in practice there may be empirical challenges associated with knowing whether the shapes of economic relationships posited by theory exist in practice (Chetverikov, Santos, and Shaikh, 2018; Matzkin, 1994). A better understanding of the empirical shape of economic relationships would provide opportunities to test theory and offer practical guidance to decision-makers.

A tangible setting to consider these fundamental tensions is in production economics, particularly as regards input decisions and their relationships to production and profit outcomes (Cobb and Douglas, 1928; Tintner, 1944; Heady and Dillon, 1961; Just and Pope, 1979; Jorgenson, 1986; Chambers, 1988; Griliches and Mairesse, 1999; Ray, Chambers, and Kumbhakar, 2022; Chavas, 2025). For example, from a theory perspective, diminishing returns, reflected by concavity in production inputs, are a standard economic relationship predicted by theory. Nevertheless, compelling empirical evidence for such relationships can be difficult to present convincingly for a variety of reasons (Mundlak, 1961; Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015). In the absence of empirical support for such relationships, economics research may offer little tangible guidance to practitioners (e.g., optimal input use levels), and therefore have limited applicability and relevance to decision-makers. These tensions have an important history in agricultural economics, where efforts to test theory and offer practical guidance have yielded important advances that help explain behavioral anomalies (Wuepper et al., 2023; Just and Messer, forthcoming).

In this paper, we study these ideas in the important production setting of pollination-dependent agriculture. Pollination, provided mainly by bees, is an essential service that contributes to the yield and quality of most globally produced crops (Klein et al., 2007). Farmers of pollination-dependent crops grow much of the world's nutritious and high-value fruits, nuts, and vegetables; and many use managed pollination services as a strategy for pollination (Wilcox et al., 2025a).[1] The most common market transaction between managed pollination service providers and crop producers in the US is the rental of domesticated honey bee colonies during the bloom period.[2] 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 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).

Given how critical farmer pollination choices are for the production of pollination-dependent crops, knowledge of the shape of the relationship between yields and profits and managed pollination use is of interest to theory and practice. Theoretically, knowing whether and to what extent yields and profits are concave with respect to managed pollination use enables one to ascertain whether there are diminishing returns to managed pollination use, whether there are decreasing returns to scale, the existence of global maxima and local maxima, the steepness of the respective curve, and the magnitude of the implied marginal response. Wilcox et al. (2025b) show that, for most reasonable values of the parameters, the production function for pollination-dependent crops is weakly concave in managed pollination use; and moreover that other relationships, including the price elasticity of managed pollination use and the importance of the scale of production to pollination choices, may depend on how concave production is with respect to managed pollination use. Thus, demonstrating diminishing returns to the use of managed pollination would not only be noteworthy by itself, but would also help elucidate other phenomena including managed pollination demand elasticities and the importance of production scale to managed pollination use.

[1] Crops that require or benefit greatly from insect pollination include almonds, coffee, apples, avocados, cherries, peaches, blueberries, among many others.

[2] Additional market-based options for managed pollination services include: the purchase of so-called "buckets of bees" for the bloom period (e.g. single containers of cultivated bumble bees, which do not live past a single season); as well as bloom season rental of mason bees or blue orchard bees (Ward, Whyte, and James, 2010).

In practice, knowing whether and to what extent yields and profits are concave with respect to managed pollination use enables one to potentially recover optimal stocking densities, determine if there are global or local optima, and assess if crop producers seem to be operating above or below optimal levels. There is very little empirical evidence for what the optimal use of pollination might look like for particular production sectors (Rollin and Garibaldi, 2019; Ramírez-Mejía et al., 2024), and also a dearth of evidence about the extent to which crop production is pollination limited (Reilly et al., 2020). The relationship between agricultural outcomes and pollinator availability is also an important public policy issue given ongoing concerns over colony collapse disorder (CCD) and declines of wild pollinators (Rucker, Thurman, and Burgett, 2019; Grab et al., 2019). These relationships are likely also important for crop insurance policies, which may stipulate a minimum colony count as a condition for payout, despite the fact that such thresholds often lack empirical justification (e.g., see current guidance regarding claim losses related to pollination for almonds in United States Department of AgricultureRisk Management Agency (2008)). In the absence of empirical efforts to estimate these relationships, the returns to pollination input use are difficult to estimate and the potential to apply basic theory to inform these decisions remains unrealized.

We focus in particular on apple production. Apples are a widely produced and consumed commodity around the world. Pollination is an important input for apple production (Ramírez and Davenport, 2013; Wilcox et al., 2025a). Apples are not considered a honey-producing crop (Rucker, Thurman, and Burgett, 2012), as apple blossoms yield little or no honey (Cheung, 1973), 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).

For our study of the relationship between production outcomes and use of managed pollination, we employ semi-parametric optimal binscatter developed by Cattaneo et al. (2024) applied to farm-level data on apple farmers in the US to estimate response functions relating yield and profits to honey bee colonies per acre. We interpret our results as semi-parametric marginal product and marginal value product curves, respectively. We also apply semi-parametric methods developed by Cattaneo et al. (2024) to estimate the respective first and second derivatives, which enables us to identify global and local maxima of yield and profits where the first derivative is zero and the second derivative is negative; and to test for the parametric form of the response function and for shape restrictions (i.e., monotonicity, concavity, and convexity). For robustness, we also estimate fixed effects regression models and employ second-order polynomials in honey bee colonies per acre and other covariates.

Our empirical results provide strong evidence for at least local concavity in these relationships. We use estimated first derivatives to locate local optima for honey bee colony density, which we find is around 2 and 4 colonies rented per acre for Eastern and Western states, respectively. We further find that apple farmers in Western states get a larger return to the marginal honey bee colony rented than apple farmers in Eastern states, and that yield in Eastern states may be concave in natural forest cover. Results of formal hypothesis tests regarding the parametric form of the response function and shape restrictions are consistent with the visual observation of concavity and diminishing returns to managed pollination use.

Our empirical application to apple farmers in the US builds on the majority of directly related economics literature, which has focused heavily on beekeepers, almond growers, and the West Coast of the US (Baylis, Lichtenberg, and Lichtenberg, 2021). Indeed, since the seminal work by Meade (1952), who uses the example of an apple farmer and a beekeeper to model and analyze externalities, and the subsequent examination of this fable of the bees through the lens of pricing and contractual arrangements in the beekeeping industry by Cheung (1973), little direct focus appears to have been placed on the setting of apple production and pollination.[3] Moreover, to the best of our knowledge, there are no directly comparable empirical contributions to ours in the

[3]Economic analyses of pollination resources and pollination-dependent sectors include advances in understanding the value provided by pollination resources to society (Penn, Hu, and Penn, 2019; Lippert, Feuerbacher, and Narjes, 2021), the state and nature of pollination service markets (Willett and French, 1991; Rucker, Thurman, and Burgett, 2012; Goodrich, Williams, and Goodhue, 2019; Fei et al., 2021), the impacts of CCD on beekeepers and pollination markets (Champetier, Sumner, and Wilen, 2015; Rucker, Thurman, and Burgett, 2019), the use of beekeeping for poverty alleviation (Albers and Robinson, 2011) and decision-making by pollination-dependent farmers (Ferrier et al., 2018; Simpson, 2019; Wu and Atallah, 2019; Wilcox et al., 2025b). The majority of directly related economics literature has focused heavily on beekeepers, almond growers, and the West Coast of the US; and there is a paucity of theoretical and empirical work focused on farmers (Baylis, Lichtenberg, and Lichtenberg, 2021).

economics literature or related entomology or ecology literatures.[4]

The remainder of our paper proceeds as follows. Section 2 describes our empirical setting. Section 3 describes our semi-parametric optimal binscatter methods. Section 4 presents the results of our empirical analysis of the relationship between yield, profit, and managed pollination use. We discuss and conclude in Section 5.

2 Empirical Setting

2.1 Background on Apple Production and Crop Pollination Metrics

Apples are a widely produced and consumed commodity around the world with high economic and cultural value.[5] Pollination is an important input for apple production (Wilcox et al., 2025a), and pollination rental fees tend to be higher for apple farmers since beekeepers do not gain forage resources to produce palatable honey from pollinating apples (Rucker, Thurman, and Burgett, 2012). Apples are also unique from a pollination perspective as wild pollinators have been shown to be much more effective at inducing fruit set than honey bees are, with potentially important implications for fruit quality and price received (Blitzer et al., 2016; Russo et al., 2017).[6] 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 in-

[4]For example, although many studies from ecologists have studied various measures of pollinator presence and measures of production in great detail (e.g. Roubik 2002; Park et al. 2016; Blitzer et al. 2016; Reilly et al. 2020), no work to our knowledge has measured these variables outside of small-scale experiments, nor have they combined such observations with the realized production behavior of the farmers from whose land they are collecting data. An example in the setting of apple and pear production in Argentina comes from Geslin et al. (2017).

[5]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.

[6]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.

crease investment in remaining fruit. Some prior work has also suggested that apple production may be pollination limited in some parts of the US (Reilly et al., 2020).

Apple production is entirely dependent on insects for pollination services as the majority of commercial cultivars are self-sterile and require a compatible pollinizer variety (Ramírez and Davenport, 2013). Efforts to define optimal pollinator densities have used a range of empirical approaches from the scale of pollen transfer to individual flower in a single visit (Park et al., 2016) up to the scale of whole orchards (Rollin and Garibaldi, 2019). Studies assessing pollinator efficiency among apples' diverse set of wild and managed visitors have utilized measures of average pollen deposition rates per taxa, which is then weighted by the average abundance of that taxa, to define estimates of pollinator importance (Park et al., 2016). However, these estimates have rarely been scaled up to estimate the number of bees required to set a high-quality crop. Studies focused on managed honey bees more frequently utilize experiments comparing production outcomes across varying stocking densities to estimate optimal stocking densities. Yet these experiments often yield inconsistent or difficult-to-generalize recommendations – particularly when changes in hive density do not directly correspond to changes in visitation rates, or when different studies focus on different production metrics such as fruit set, weight, shape, or seed number (Rollin and Garibaldi, 2019).

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 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).

2.2 Data

For our empirical analysis, we leverage rich, farm-level data 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 accessed the USDA-ARMS data via the NORC Data Enclave.

The 2007 USDA-ARMS provides rich farm-level data from apple farmers across 207 counties and in seven US states, including: California (CA), Michigan (MI), New York (NY), North Carolina (NC), Oregon (OR), Pennsylvania (PA), and Washington (WA). The USDA-ARMS is designed to be nationally representative as well as representative at the level of a state. 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 includes all the main aspects of production, including input use, costs, yield, and honey bee rental data for the 2007 production year (roughly March-November). There are 1057 farmers who have sufficient responses for our research, which comprises the vast majority of the farmers sampled; Figure A.1 in the Appendix shows their distribution by state. The West Coast states in our data set are California, Oregon, and Washington. The Midwest and East Coast states in our data set (which we refer to collectively as the 'Eastern' states) are Michigan, New York, North Carolina, and Pennsylvania.

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 merge the 2007 USDA-ARMS data with publicly available data on weather from PRISM (Daly et al., 2008) and remotely sensed measures of land cover from the USDA Cropland Data Layer (CDL) (Boryan et al., 2011). We use the closest[7] and most reliable coverage year from the CDL 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 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 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).

Although the 2007 USDA-ARMS requested information on apple output prices, response rates for respective questions were very low. 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.

[7]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 the 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.

2.3 Patterns and Relationships in Raw Data

At an aggregate level, our data reveal significant features and structural differences in the apple production sector that are well known to industry veterans. One prominent stylized fact in the data is that there are notable differences between production strategies and outcomes between apple farmers in West Coast states (California, Oregon, and Washington), and apple farmers in Midwest and East Coast states (Michigan, New York, North Carolina, and Pennsylvania – which we refer to collectively as the 'Eastern' states) – differences that reportedly have much to do with the higher volume of production that comes from Washington State, and the higher prevalence of plant diseases that farmers in Eastern states face, which are associated with higher moisture (Kahlke, 2019; Biltonen, 2020). In Tables A.1-A.5 in the Appendix, we present summary statistics of our data to highlight average values for a number of dimensions across all states, West Coast states, and Eastern states; and test for differences in means between Western and Eastern states. The tables show that, on average, Western operations are larger, more recently established, are more likely to rent honey bees, are more intensively farmed (more trees per acre), use more labor inputs, have more natural open cover, achieve higher yields, and are also more profitable ($7,220 per acre versus $3,880 per acre for Eastern states on average); while Eastern operations face higher honey bee rental costs,[8] have slightly more natural forest cover, and use honey bee colonies more intensively (more colonies per acre).

Another prominent feature in the data is that while the majority of farmers rented honey bees (64% of Eastern farmers, 81% of Western farmers in 2007), not all farmers rented honey bees. Not renting honey bees (or not using managed pollination) is a notable strategy as it suggests that farmers may be relying on local wild pollination stocks.[9] Our data suggests that apple farmers in Eastern states, who have slightly more natural forest cover on average, may be more likely to rely on local wild pollination stocks.

[8] Wilcox et al. (2025a) show that these patterns in honey bee rental costs have remained consistent to the present day and even become accentuated in that honey bee rental costs have increased markedly in real terms for growers in Eastern states compared to growers in Western states.

[9] Although other strategies are possible, such as locating next to an apiary, the more likely scenario is that wild pollinators are the primary source of pollination for apple farmers who do not rent honey bees.

To delve deeper into these aggregate differences, in the Appendix we construct a range of nested boxplots that showcase variation by state in honey bee rental quantity and costs (Figure A.2), and farm and orchard characteristics (Figure A.3). Most growers rent between 1 to 4 colonies per acre, though the median seems to be closer to 1-2 colonies per acre.

In Figures A.4 and A.5 in the Appendix, we see very interesting variation in production outcomes, costs, revenues, and profits, not only by state, but also within states by whether or not a farmer rents honey bees. Growers who rent honey bees have higher median production, and a higher interquartile-range of production. This is particularly the case for total output in bushels per acre and fresh market production, but less so for processed yield.[10] The same observation can be made for revenues and profits per acre. Although this simple observation is provocative, it is only an association as it may well be the case the farmers who rent bees are farming more intensely than farmers who do not rent bees, or some other unobserved factor may account for this structural difference. We examine the extent to which there is genuinely a marginal gain from renting honey bees or not in our study of yields, profits and honey bee use.

3 Methods

To study how yield and profits vary with managed pollination use, we rely on optimal binscatter estimators from Cattaneo et al. (2024) to estimate the following semi-parametric function:

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

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

[10]The distinction between fresh market yield and processed yield is fruit quality and point of sale. Fresh market production is sold for sale in outlets like grocery stores (e.g., a box or bag of whole apples), and generally receives a higher per unit price because the fruit is more evenly shaped and appealing to consumers. In contrast, processed yields are sold to firms that process apples for products like apple juice, apple sauce, etc. and farmers receive lower prices for this output because fruit is of lower quality.

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

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, which include measures of production scale (trees per acre, trees per acre squared, average age of trees, and average age of trees squared), remotely sensed land cover measures to proxy for wild bee habitat and landscape heterogeneity (natural forest cover, natural forest cover squared, natural open cover, natural open cover squared),[11] labor inputs (pruning/thinning hours, harvesting hours, land prep and machine hours, pest scouting hours, and full time hours), and monthly average temperature and precipitation over January-September (the months leading into the main harvest period); and where in some specifications we expand the model to also include state dummies for state 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 rely on semi-parametric methods developed by Cattaneo et al. (2024) in order to estimate response functions $\mu(x_{isct})$, plot them with confidence bands, and estimate the respective first and second derivatives. With estimation of the first derivative we can identify global and local maxima of yield and profits where the first derivative is zero and the second derivative is negative. Finally, we apply formal t-tests developed by Cattaneo et al. (2024) for the parametric form of the

[11] As described in more detail in Section 2.2, our natural open cover variable is the proportion of land area in natural open cover, and our natural forest cover variable is the proportion of land area in natural forest 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 types: clover, wildflowers, shrubland, herbaceous wetlands, developed open space, and wetlands.

response function and for shape restrictions on the first and second derivatives (i.e., monotonicity, concavity, and convexity). For robustness, we also estimate fixed effects regression models and employ second-order polynomials in honey bee colonies per acre and other covariates.

Cattaneo et al. (2024) 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,[12] including: formalization within the framework 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.[13]

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. (2024) 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. In our setting, 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. Thus, while farmers may base their honey bee rental decisions

[12]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.

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

on expected yield and profits, their choice of honey bee colonies rented per acre is uncorrelated with realized yield and profits and unobserved shocks to yield and profits, and therefore uncorrelated with the error term. 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 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, they are unable to precisely control insect pollination. There are therefore good reasons to view insect pollination as an exogenous process on some level, and therefore that honey bee colonies rented per acre is uncorrelated with realized yield and profits and unobserved shocks to yield and profits, and therefore uncorrelated with the error term. Hence, omitted variable bias may be the larger issue and we employ a highly relevant set of controls in $\mathbf{w_{isct}}$ (including monthly weather variation, farm labor, landscape cover measures, and farm scale measures) and state fixed effects to mitigate this concern and control for as many factors as possible that may affect honey bee colonies rented per acre as well as yield and profit.

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. (2024) and the novel data we collect. To assess the stability of the relationships between colonies per acre and production outcomes, we also assess these relationships using standard fixed effects regressions models that employ second-order polynomials in honey bee colonies per acre and other covariates.[14]

4 Results

Figures 1 and 2 show estimated response curves for block-level yield (bushels/acre) and profits ($/acre), respectively, as semi-parametric functions of honey bee colonies per acre, from applying optimal binscatter with quantile-spaced bins. Each figure presents results for the pooled sample of all states, and for the Eastern and Western states subsamples, and range from including no covariate adjustment, to covariate adjustment, to covariate-adjustment with state dummies. Therefore, column 3 in each figure reflects the greatest degree of controls and fixed effects. Each figure also includes a trimmed scatter between y_{isct} (yield or profits) and x_{isct}, honey bees colonies rented per acre, which excludes the 99th centile as it can make a tremendous difference in the legibility of the figure. Results for parametric tests and shape restriction tests are provided in Tables A.6 and A.7 in the Appendix. Table 1 presents results for fixed effects regressions of yield. Supplementary results are provided in the Appendix for fixed effects regressions of profits (Table A.8), and alternative versions of Figures 1 and 2 that use equally spaced bins (Figures A.6 and A.7).

The main takeaway from these empirical results are as follows. First, as is apparent in results using either quantile-spaced bins (Figures 1 and 2), equally spaced bins (Figures A.6 and A.7), or fixed effects regression models (Tables 1 and A.8), yield and profits are concave in honey bee colonies per acre. For both yield and profits, the optimal number of honey bee colonies per acre is approximately 3 to 4 for the pooled sample of all states, around 2 honey bee colonies per acre for Eastern states, and around 4 honey bee colonies per acre for Western states. We also see that the marginal returns for Western states for 1 additional colony per acre tends to be larger than for Eastern states.

Second, formal parametric tests shown in Table A.6 for the pooled sample reject hypotheses

[14] We have explored a two-stage least squares set-up, using prior year pollination prices and/or the shift-share instrument employed in Wilcox et al. (2025b), 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.

that the response function for yield is constant or linear in honey bee colonies per acre, but generally do not reject that the function is non-linear (quadratic or cubic). Third, in Table A.7 we see that for the pooled sample, a monotonically decreasing (non-positive) function for yield is rejected, and convexity is sometimes rejected, but a monotonically increasing function (non-negative) is not rejected, and concavity is not rejected.[15] Respective tests focused on the subsamples of Western and Eastern states yield qualitatively similar results, particularly in the Western states.

A variety of additional noteworthy findings are apparent from respective fixed effects regressions of yield (Table 1) and profits (Table A.8). First, results from fixed effects regressions show that yield and profits are concave in honey bee colonies, and these relationships are highly statistically significant and economically meaningful in the pooled sample as well as in the Western states subsample and the Eastern states subsample.

Second, in terms of relationships between yields and profits and measures of production scale, we find that yields and profits are increasing in trees per acre in the Eastern states and concave in trees per acre in the full sample, but trees per acre do not have a statistically significant effect on yields or profits in the Western states. For both yields and profits, the relationship with age of trees exhibits concavity and significance, more so than that with trees per acre.

To further explore the relationship between yield and trees per acre, Figure 3 shows the estimated response curve for block-level yield (bushels/acre) as a semi-parametric function of the number of trees per acre, from applying optimal binscatter with quantile-spaced bins. Over the range and distribution of trees per acre in our data, most values of which are less than 600 trees per acre, yield is weakly increasing and concave in trees per acre.

Third, for labor input variables, labor prep and machine hours increase both yields and profits. Yields also increase with harvesting hours. While pest scouting hours increase yield in both the East and West, and increase profits in the East, they decrease profits in the West. Pruning/thinning hours decrease yields and tend to decrease profits as well.

Fourth, we find that both yields and profits decrease with natural open cover in the Eastern

[15] Results are similar when profits are the outcome of interest.

states. It is possible that areas with more natural open cover (and hence less vegetative structure) may have lower wild pollinator stocks suitable for apple pollination. Alternatively, areas with more open natural cover may support apple pests.

Fifth, although the coefficients on the natural forest cover terms are not statistically significant, our results suggest a possible concave relationship between yield and natural forest cover in Eastern states. This is noteworthy given existing evidence for natural forests in some contexts being sources of wild pollinator stocks which may enhance apple yield and fruit quality (Park et al., 2015; Kammerer et al., 2016; Urban-Mead et al., 2023). To explore the durability of this finding, we run additional fixed effects regression models for the Eastern states with alternative measures of natural forest cover that reflect buffers of 1000 and 3000 meters around apple production areas within counties observed in the 2007 USDA-ARMS, and find that the concave relationship holds, albeit generally without statistical significance (Table A.9 in the Appendix). We also estimate optimal binscatter curves focused on yield and natural forest cover (Figure 4), which provide further suggestive evidence that yield may be concave in natural forest cover for Eastern states.

Finally, weather covariates exhibit a variety of logical relationships with profits and yield that are worthy of deeper analysis in subsequent research. For example, a wet May is negative and significant for yield, which may reflect conditions that result in poor fruit set (i.e., adequate pollination inducing fruit set is difficult in rainy conditions) as is a warm January (which can prematurely bring trees out of dormancy). Nevertheless, since we only have a cross-section to work with for yield and profits, we expect our weather-related findings are not capturing the full range of relationships with weather shocks.

5 Discussion and Conclusion

Pollination-dependent agriculture is critical to food security and welfare around the world, as well as the value chains that these production sectors underpin (Schmit et al., 2018). Knowledge of the shape of the relationship between yields and profits and managed pollination use is therefore of interest to theory and practice.

Using semi-parametric optimal binscatter developed by Cattaneo et al. (2024) applied to farm-level data on apple farmers in the US to estimate response functions relating yield and profits to honey bee colonies per acre, we find that yield and profits are concave in managed pollination use. Our estimated response curves also suggest that farmers in Western states experience a greater return to the marginal honey bee colony than farmers in Eastern states.

The methods that we employ from Cattaneo et al. (2024) permit us to estimate first and second derivatives of underlying response functions, which in turn allow us to estimate optimal honey bee stocking densities for yield and profits. For both yield and profits, the optimal number of honey bee colonies per acre is approximately 3 to 4 for the pooled sample of all states, around 2 honey bee colonies per acre for Eastern states, and around 4 honey bee colonies per acre for Western states.

In contrast, according to Wilcox et al. (2025a), who calculate actual stocking densities among those who rented honey bees in 2007-2008 as the total colonies deployed divided by the number of bearing apple acres at the block level, the actual stocking densities for apple growers is 1.87 honey bee colonies per acre on average at the national level, and 1.65 colonies per acre on average in Western states, both of which are lower than the respective optimal stocking densities for the pooled sample of all states and for Western states, respectively, suggested by our empirical analysis. For Eastern states, Wilcox et al. (2025a) calculate actual stocking densities to be 2.22 colonies per acre on average in 2007-2008; and 1.48 colonies per acre on average among those who rented bees in the 2022 Northeast Apple Grower Survey, a non-representative survey designed and implemented among apple farmers in the Northeastern US, which includes responses from 21 apple growers in New York and 1 apple grower in Connecticut, and which focuses on the 2019-2021 production years – both of which are more in line with the optimal stocking densities for Eastern states.[16]

[16]The block-specific data used by Wilcox et al. (2025a) to calculate actual stocking densities show much higher stocking densities than aggregate statistics from the USDA Cost of Pollination survey suggest. For example, the implied stocking density (ratio of colonies used to paid pollinated acres) in 2017 for Region 1 (Northeast) and Region 5 (Northwest) are 0.51 and 0.93 colonies per acres, respectively. Similarly, the implied stocking density (ratio of colonies used to paid pollinated acres) for apple growers in 2015 is 0.70 colonies per acre (Ferrier et al., 2018). Reasons for the discrepancy between estimated stocking densities at the regional versus block level are not precisely known, but may reflect that regional estimates do not account for block-specific variation (Wilcox et al., 2025a).

Thus, our results suggest that Eastern farmers may be closer to being at optimal levels of managed pollination use than farmers in Western states, and that apple farmers in Western states may have lower stocking densities on average than may be optimal.

Adjusting production practices into modern trellis systems to increase the number of trees per acre (many more trees per row) seems key to the advice that farmers get from pomologists. For example, in their simulation analysis of the effect of tree density on profits (calculated as the net present value over 20 years) using data from orchard systems trials in New York, Robinson et al. (2013) estimate that optimal profit-maximizing number of trees per acre would be around 1,000 trees per acre. Using a replicated field trial compared 8 tree densities ranging from 598-5382 trees per hectare (approximately 242-2178 trees per acre), Robinson (2007) finds that tree density had a highly significant negative effect on cumulative yield per tree, but had a highly significant positive effect on yield per hectare. Using a 2-hectare replicated field trial in New York, Lordan et al. (2019) find that a decrease in apple yield is especially critical for profitability at densities greater than approximately 809 trees per acre; and that the best option for 'Empire', 'McIntosh', and 'Gala' apple cultivars was a conic tree shape and approximately 809, 1012, and 1214 trees per acre, respectively, while the best option for 'Fuji' was a V tree shape at approximately 405 trees per acre.

Over the range and distribution of trees per acre in our data, most values of which are less than 600 trees per acre, we find in our empirical analysis using farm-level data that yield is weakly increasing and concave in the number of trees per acre. Yields and profits are increasing in trees per acre in the Eastern states and concave in trees per acre in the full sample, but trees per acre do not have a statistically significant effect on yields or profits in the Western states. In terms of measures of production scale, we find that for both yields and profits, the relationship with age of trees exhibits concavity and significance, more so than that with trees per acre.

Our finding of significant regional differences in optimal managed pollination use levels, and differing marginal returns per marginal colony, raise questions about the underlying factors in these agro-ecological systems that produce these divergent scenarios. Indeed, it is plausible that sources of wild pollination stocks from forested regions, particularly in the Eastern states, may be providing a significant pollination subsidy to apple farmers in these states, and this may in part explain why apple farmers in Eastern states do not see larger marginal returns for the marginal honey bee colony. This notion is in fact consistent with our finding that yield may be concave in natural forest cover for Eastern states. Indeed, if this hypothesis could be more rigorously tested the implications may be significant. For example, whether and how this correlates with Conservation Reserve Program (CRP) Pollinator Habitat Initiative (CP-42) land (USDA Farm Service Agency, 2013) may help inform program design and sustainable pollination management. Credible ways to measure the state of wild pollination stocks at the farm level, perhaps through combinations of remote sensing and traditional field methods from entomology, could greatly enhance such research endeavors and provide a much clearer picture as to whether pollination dependent sectors are over- or under-supplied from a pollination perspective.

Moving forward, we suggest that fruitful research endeavors abound to replicate the kinds of empirical work we have accomplished in this paper with more recent data and in other pollination-dependent sectors around the world. This type of work seems to us, critical for bridging theory and empirical work, and placing policy-making on better footing. Gaining a better understanding of the shape of the relationship between yields and profits and managed pollination use would better allow pollination-dependent farmers to manage pollination resources sustainably and to find innovative ways to resolve pollination resource needs within bioeconomy value chains (Zilberman, Lu, and Reardon, 2019).

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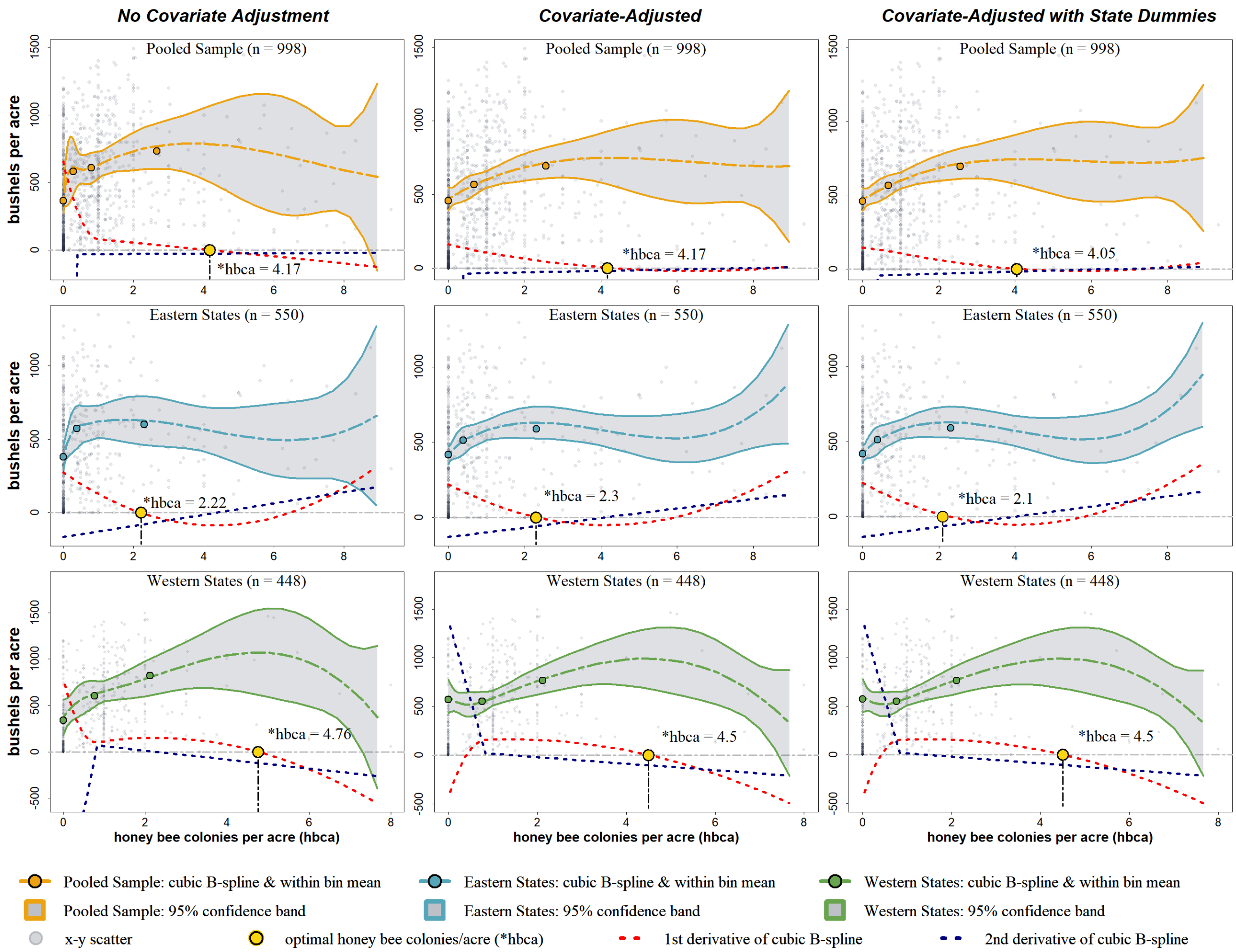

Figure 1: Optimal binscatter of yield on honey bee colonies per acre.
Notes: Optimal binscatter (following Cattaneo et al. 2024) of *yield* in bushels per acre on the semi-parametric function $\mu(x)$, where x is *honey bee colonies per acre*, which is defined as the number of honey bee colonies rented 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 fixed effects regression models in Table 1, 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 based on Huber-White robust standard errors. 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.

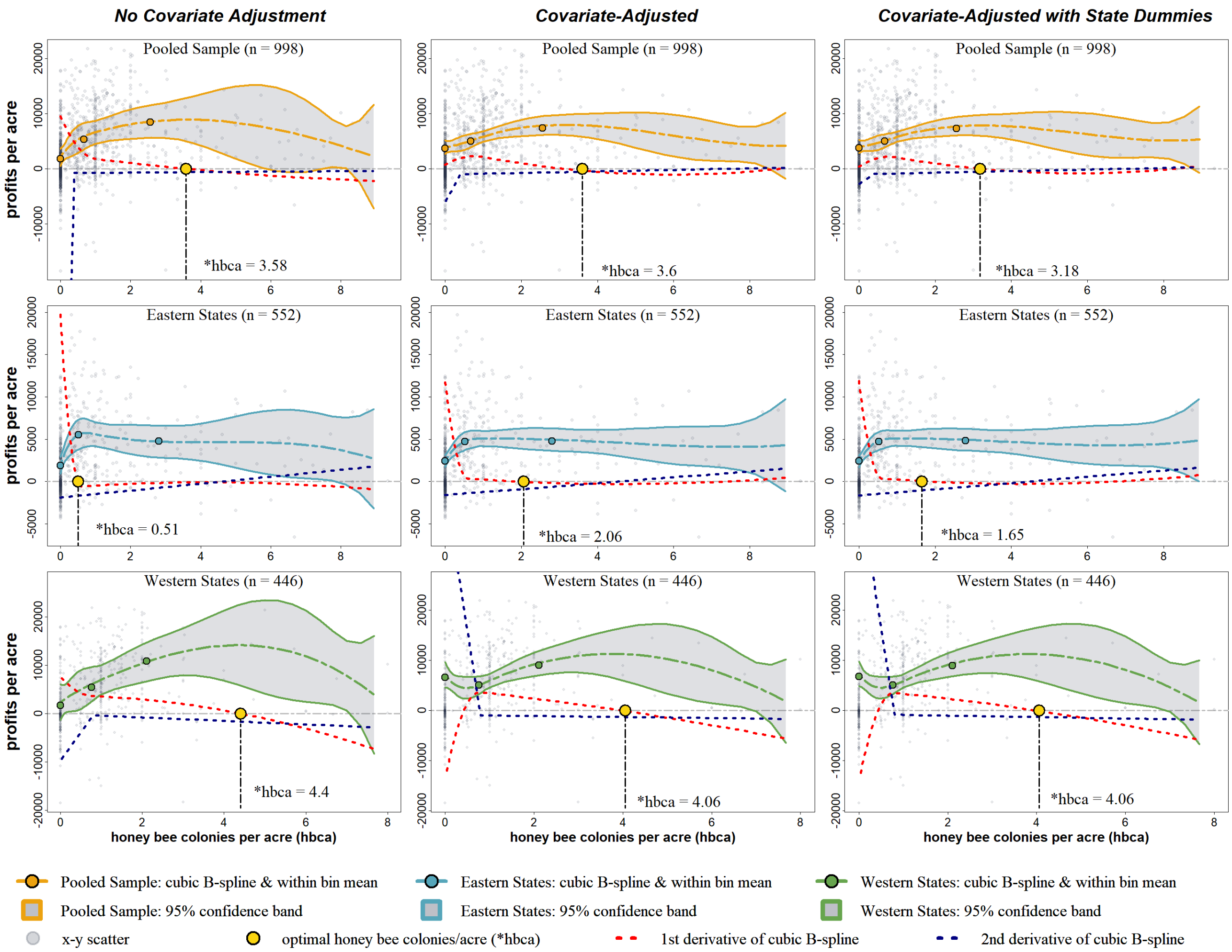

Figure 2: Optimal binscatter of profits on honey bee colonies per acre.
Notes: Optimal binscatter (following Cattaneo et al. 2024) of *profits* in dollars per acre on the semi-parametric function $\mu(x)$, where x is *honey bee colonies per acre*, which is defined as the number of honey bee colonies 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 fixed effects regression models in Table 1 and Table A.8 in the Appendix, 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 based on Huber-White robust standard errors. 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 1: Weighted fixed effects regressions of yield.

Dependent variable is block-level apple yield (bushels/acre)			
	(1)	(2)	(3)
Honey bee colonies per acre			
honey bee colonies per acre	113.827***	151.587***	72.599***
	(19.814)	(40.690)	(21.606)
honey bee colonies per acre, squared	-11.412***	-14.022**	-6.266*
	(3.166)	(7.071)	(3.231)
Measures of production scale			
trees per acre	0.135	-0.189	0.681**
	(0.142)	(0.216)	(0.316)
trees per acre, squared	-0.0002*	-0.00001	-0.001
	(0.0001)	(0.0002)	(0.0005)
average age of trees	10.354***	8.085**	16.431***
	(2.270)	(3.384)	(3.164)
average age of trees, squared	-0.115***	-0.079	-0.156***
	(0.033)	(0.048)	(0.047)
Labor input variables			
pruning/thinning hours	-0.058***	-0.037*	-0.113*
	(0.018)	(0.022)	(0.060)
harvesting hours	0.068***	0.037*	0.109*
	(0.014)	(0.020)	(0.056)
land prep and machine hours	0.237**	0.250*	0.566**
	(0.104)	(0.130)	(0.256)
pest scouting hours	0.140***	0.139***	0.627**
	(0.040)	(0.049)	(0.285)
part-time and seasonal hours	0.002	-0.0005	-0.002
	(0.011)	(0.014)	(0.052)
full-time hours	0.076***	0.063**	0.048
	(0.023)	(0.028)	(0.073)
Land cover variables			
natural forest cover	-206.976	-302.344	753.911
	(185.996)	(410.748)	(725.909)
natural forest cover, squared	136.535	338.777	-1,023.746
	(248.506)	(737.830)	(638.490)
natural open cover	-155.258	-1,198.461	-3,358.664**
	(523.749)	(1,313.433)	(1,689.764)
natural open cover, squared	-617.708	337.864	6,979.986
	(592.730)	(1,455.729)	(5,287.149)
Weather variables			
Jan. average precipitation (mm)	-39.953	7.821	-38.140
	(29.698)	(115.938)	(45.761)
Jan. average temperature (C)	-110.144***	-44.144	-205.052***
	(33.321)	(104.820)	(75.385)
Feb. average precipitation (mm)	5.566	-70.791	190.787***
	(14.415)	(49.702)	(44.533)
Feb. average temperature (C)	63.302	-123.693	141.195*

	(49.111)	(173.119)	(79.342)
Mar. average precipitation (mm)	16.192	47.274	-183.174***
	(28.688)	(115.939)	(56.775)
Mar. average temperature (C)	21.030	68.415	145.733*
	(50.696)	(265.108)	(75.717)
Apr. average precipitation (mm)	25.779	175.775	39.080
	(29.619)	(226.342)	(32.462)
Apr. average temperature (C)	43.625	-170.414	-91.581
	(62.759)	(299.294)	(85.800)
May average precipitation (mm)	-102.598**	-342.737	-51.362
	(45.988)	(270.795)	(47.461)
May average temperature (C)	-18.891	8.818	121.719
	(59.173)	(167.749)	(103.157)
Jun. average precipitation (mm)	-58.869*	292.158*	-5.309
	(34.875)	(158.164)	(35.290)
Jun. average temperature (C)	-20.554	107.831	-29.398
	(55.336)	(201.115)	(122.010)
Jul. average precipitation (mm)	-90.059**	-212.676	-77.793**
	(35.390)	(296.091)	(37.383)
Jul. average temperature (C)	84.927	-219.324	92.001
	(55.238)	(241.996)	(97.469)
Aug. average precipitation (mm)	19.343	-777.911	-12.973
	(19.609)	(538.103)	(25.668)
Aug. average temperature (C)	-76.167	19.837	-179.321*
	(58.301)	(146.328)	(96.254)
Sep. average precipitation (mm)	130.882***	-59.591	98.825**
	(44.423)	(190.032)	(43.530)
Sep. average temperature (C)	19.746	294.640*	37.583
	(63.689)	(1723.387)	(107.264)
State fixed effects	Y	Y	Y
Sample	All	West	East
Adjusted R^2	0.311	0.326	0.352
# Observations	998	448	550

Notes: Table presents results from weighted 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. Specifications use observations from all states ('All'), the Western states subsample ('West'), and the Eastern states subsample ('East'), respectively. Huber-White robust standard errors are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

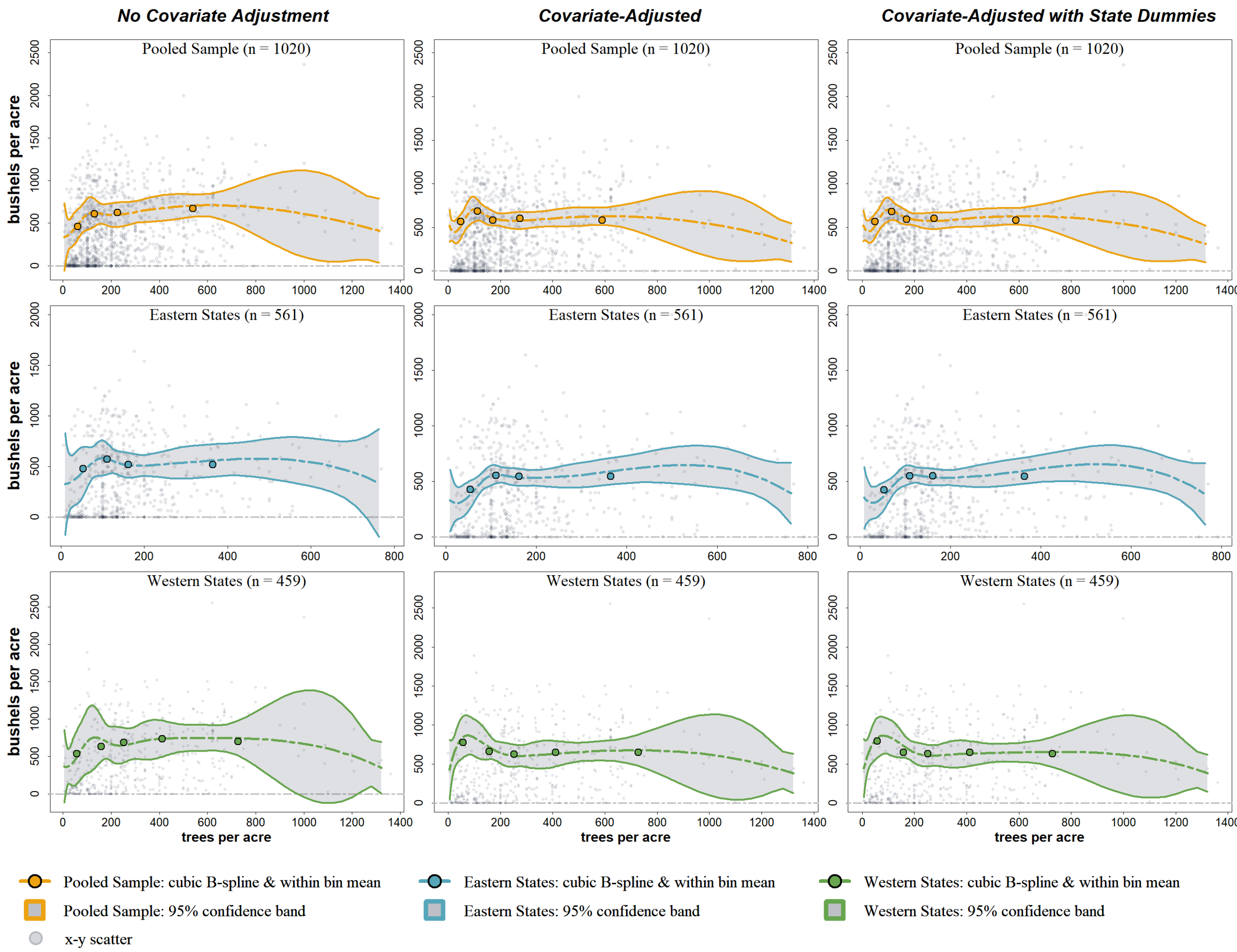

Figure 3: Optimal binscatter of yield on trees per acre.
Notes: Optimal binscatter (following Cattaneo et al. 2024) of *yield* in bushels per acre on the semi-parametric function $\mu(x)$, where x is *number of trees per acre*. Each panel trims the 99% centile of the outcome variable and honey bee colonies 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 number of trees per acre. Column 2 includes covariate-adjustment using the same covariates employed in the fixed effects regression models in Table 1, 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 based on Huber-White robust standard errors.

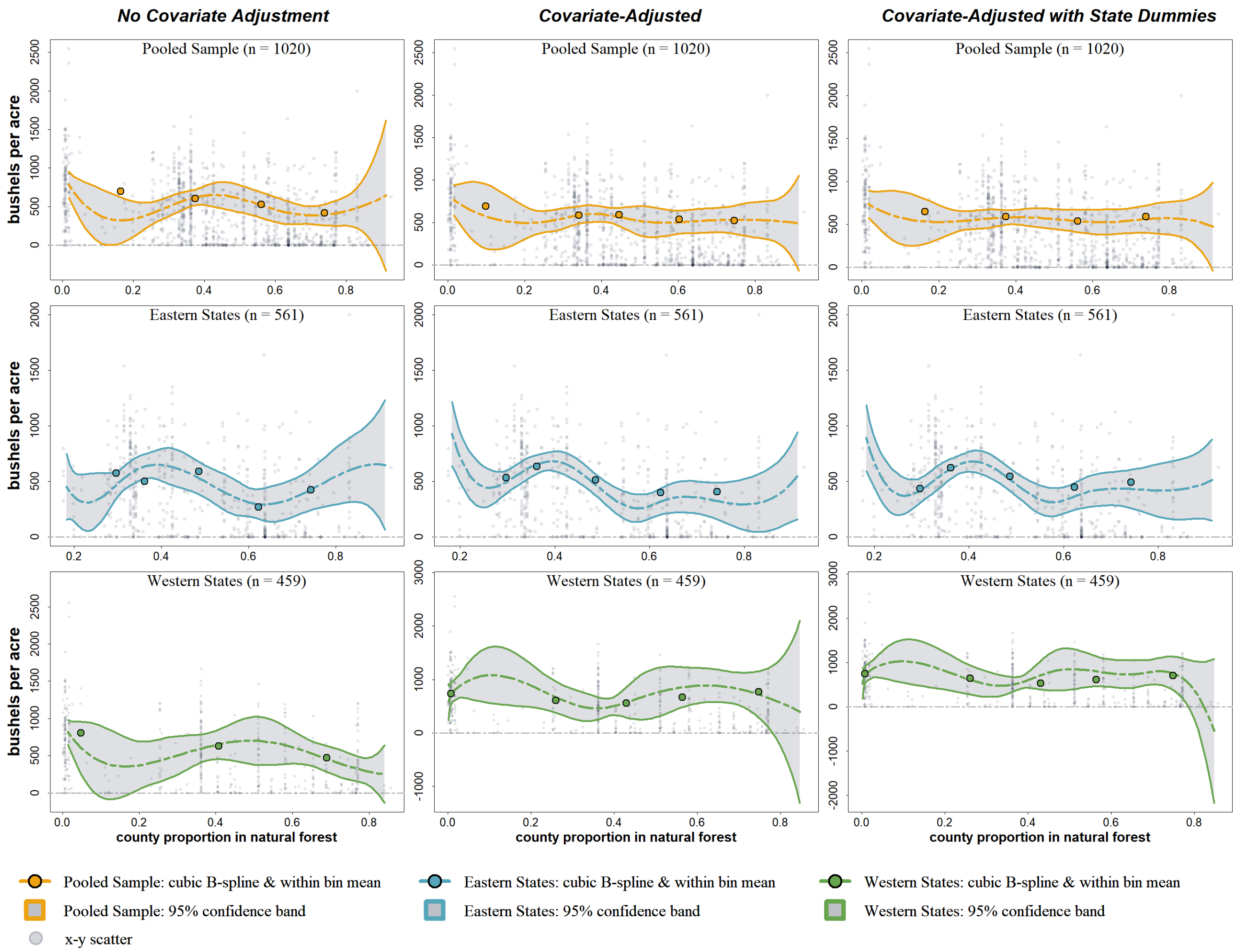

Figure 4: Optimal binscatter of yield on natural forest cover.
Notes: Optimal binscatter (following Cattaneo et al. 2024) of *yield* in bushels per acre on the semi-parametric function $\mu(x)$, where x is the *county-level proportion in natural forest cover*. Each panel trims the 99% centile of the 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 fixed effects regression models in Table 1, 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 based on Huber-White robust standard errors.