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

Steven W. Wilcox, David R. Just, C.-Y. Cynthia Lin Lawell, Miguel I. Gómez, Heather Lee Grab*

February 10, 2026

Abstract

We empirically study managed pollination demand using nationally representative farm-level data from US apple farmers, and establish new stylized facts. Using a shift-share instrumental variables strategy, as well as demand shocks to inform and bound demand elasticities, we undertake the first known estimate of an own-price managed pollination demand elasticity using farm-level data. We find that honey bee demand may be more elastic than prior work suggests. We reconcile these perspectives by showing that the extensive margin binary choice to rent bees is relatively price inelastic and is instead driven by other factors such as crop insurance. Results also show that honey bee demand is concave in the scale of production, and that farmers seem to adjust their demand for managed pollination according to variation in local wild pollinator habitat.

Keywords: agriculture, pollination, demand, specialty crops
***JEL* Classification:** Q12, Q11, Q29, Q57

---

*Corresponding author: Steven W. Wilcox (steven.wilcox@usu.edu). Wilcox is affiliated with the Department of Applied Economics at Utah State University. Just: Cornell University; drj3@cornell.edu. Lin Lawell: Cornell University; clinlawell@cornell.edu. Gómez: Cornell University; mig7@cornell.edu. Grab: Penn State University; hlc30@psu.edu. We gratefully acknowledge financial support from three awards from the Cornell Atkinson Center for Sustainability: a Sustainable Biodiversity Award, an Atkinson Venture Fund (AVF) Grant, and an AVF-Engaged Cornell grant for undergraduate involvement. We are indebted to Craig Khalke and the Lake Ontario Fruit Program for assistance and very helpful details on apple production in the Northeast. We also appreciate comments from a number of apple growers and consultants in the Northeast, including Debbie Biltonen, Mike Biltonen, and Ian Merwin. Carrie Jones at USDA-ERS and Donnie Fike at USDA-NASS kindly assisted us with many aspects of USDA-ARMS data. Anna Espinoza, Adeline Sutton, Jacob Llodra, and Katie Warner provided excellent research assistance. We thank Todd Gerarden, Ivan Rudik, Bryan Danforth, Maria Van Dyke, Mia Park, Chris Barrett, Kathy Baylis, Jo Albers, Christian Langpap, Adeline Yeh, Brian Adam, and Dominic Parker for helpful comments; and we thank seminar and conference participants at Cornell University, the Food Studies International Conference, the Association of Environmental and Resource Economists (AERE) Summer Conference, and the Agricultural and Applied Economics Association (AAEA) Annual Meeting. Just, Lin Lawell, and Gómez are Faculty Fellows at the Cornell Atkinson Center for Sustainability. Wilcox is a faculty affiliate of the USU Ecology Center. All errors are our own.

1 Introduction

Farmers of pollination-dependent crops, which include high-value fruits, nuts, and vegetables, face important decisions in how to pollinate their crops. In settings where pollination markets are well-developed, many farmers rent domesticated honey bee colonies during the bloom period.[1] However, at the farm level, pollination decisions are not well understood (Baylis, Lichtenberg, and Lichtenberg, 2021). This is problematic because farmer pollination choices 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).

In this paper, we undertake the first known empirical study of managed pollination demand using farm-level production data. For our analysis, we use farm-level data from US apple farmers and a novel instrumental variables (IV) strategy that exploits well-documented supply shifts caused by high early-season demand for managed pollination from California's almond sector. We estimate that the managed pollination demand elasticity is -2.04, which implies that demand for managed pollination services is somewhat elastic. Several robustness checks provide support for this result. Our econometric estimate is also consistent with bounds on the demand elasticity we obtain from applying new methods from Petterson, Seim, and Shapiro (2023) using demand shocks.

Our empirical analysis suggests that, while not perfectly elastic, managed pollination demand may be more elastic than prior work has assumed and perhaps conventional wisdom sometimes suggests. We reconcile these perspectives and deepen understanding of farmer decision-making around pollination in the process.

In particular, to further understand the elasticity of demand for managed pollination, we apply our IV strategy to empirically examine the extensive margin binary choice to use managed

[1] Additional market-based options for managed pollination services include single season purchase of colonies of bumble bees (Park et al., 2020), as well as bloom season rental of mason bees or blue orchard bees (Ward, Whyte, and James, 2010).

pollination. We find that while honey bee demand is somewhat elastic, the extensive margin binary choice to rent bees does not have a statistically significant response to price, and is therefore relatively price inelastic.

Our results provide empirical evidence that what may be inelastic is the choice to rent bees itself, not the quantity of honey bees to rent. In addition, we find that having federal crop insurance makes farmers more likely to rent bees, but has no statistically significant effect on the quantity of honey bees rented. We also find that pollination demand has a small concave relationship with measures of scale (e.g., block size), and that pollination demand is positively associated with output price and correlated with land cover measures. These findings suggest that a variety of factors determine pollination choices and that apple farmers may make the binary choice to rent bees *ex ante* in conjunction with, say, choices about crop insurance, among other factors, and that their quantity choice may be based on how much budget they have left during the bloom period of each production year.

To our knowledge, our paper is the first empirical study of managed pollination demand using farm-level production data. We build on the work of Willett and French (1991), who estimate the demand for pollination services at the aggregate level using time series data on the price and quantity of pollination services in California. 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 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.[2] Moreover, to the best of our knowledge, 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), there are no directly comparable empirical contributions to ours in the economics, entomology, or ecology literatures.

The remainder of our paper proceeds as follows. Section 2 describes our data. Section 3 presents our econometric analysis of managed pollination demand. Section 4 applies new methods from Petterson, Seim, and Shapiro (2023) to inform and bound demand elasticities. We discuss and conclude in Section 5.

2 Data

To study managed pollination demand we use data on apple production in the US. Apples are a useful crop to study farmer pollination behavior. Apples are a widely produced and consumed commodity around the world, and their production sectors underpin economically important value chains (Schmit et al., 2018). 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). From a pollination perspective, apples are also unique because wild pollinators have been shown to be much more effective at inducing fruit set[3] than honey bees (Blitzer et al., 2016; Russo et al., 2017) with important implications for fruit quality and price received. For additional background information on apple production, see Wilcox et al. (2026b).

[2]Economic analyses of pollination include advances in understanding the decision-making by pollination-dependent farmers (Ferrier et al., 2018; Simpson, 2019; Wu and Atallah, 2019; Wilcox et al., 2026a), 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 colony collapse disorder on beekeepers and pollination markets (Champetier, Sumner, and Wilen, 2015; Rucker, Thurman, and Burgett, 2019), and the use of beekeeping for poverty alleviation (Albers and Robinson, 2011).

[3]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, fruit is considered to be more appealing (e.g., consistent shape and fruit quantity/quality), which generally means a higher price received for farmers.

For our empirical analysis, we use farm-level 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 on the use of 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).

The 2007 USDA-ARMS provides 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 A.1 in the Appendix, 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.

We merge the 2007 USDA-ARMS data with several sources of publicly available data. For our instrument we employ a shift-share strategy that leverages well-documented supply shifts in honey bee colonies from California's almond sector (see Sections 3.1 and 3.2 for further details). For our exogenous "share" we calculate distances from zip code centroids to the centroid for Fresno County, California.[4] For our exogenous "shift" variable we use California's total annual almond

[4] Specifically, we compute Euclidean distances using R. Although the 2007 USDA-ARMS gathered farm-level GPS coordinates, the USDA-ERS reports high error with that data and we were not permitted to use it.

acreage from USDA-NASS. We also gather data on state-level apple prices from USDA-NASS,[5] and derive land cover measures from the USDA Cropland Data Layer (CDL) (Boryan et al., 2011).

To capture relevant variation from the CDL we use the closest[6] and most reliable coverage year 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 use the CDL to construct variables that characterize land cover heterogeneity and 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.[7]

Although the 2007 USDA-ARMS collected data on the binary choice to rent honey bees over 2006-2007, the costs to rent honey bees per colony over 2006-2007, and the quantity of honey bees rented in 2007, data on the quantity of honey bees rented 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 adjust all prices to real terms using an implicit price deflator from the US Federal Reserve (base

[5]The output price response rate from the 2007 USDA-ARMS was very low. So we use the state-level total utilized production price from USDA-NASS, which is a weighted average of fresh market and processed prices.

[6]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 time-point 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.

[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.

year 2017) (U.S. Federal Reserve Bank of St. Louis, 2025) and we use four different subsamples for our analyses of managed pollination demand.

In the first subsample, we use data from 2007 only. Since the 2007 USDA-ARMS collected data on the quantity of honey bees demanded in 2007, this subsample does not require any quantity imputation.

The second subsample employs an unbalanced panel over 2006-2007 that includes all observations from 2007, as well as the 430 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). Thus, this subsample does not require any quantity imputation for missing 2006 quantity.

The third subsample is a balanced panel that includes all growers in the data for both 2006 and 2007. We impute missing 2006 quantity as follows. For the 578 growers who rented bees in both years, we impute the number of colonies rented in 2006 to be the number of colonies rented in 2007. For the 49 growers who rented bees in 2006 but not in 2007, we impute the quantity rented in 2006 using regression-based imputation.

The fourth subsample is a balanced panel that includes all growers in the data for both 2006 and 2007. We impute missing 2006 quantity using regression-based imputation for all 627 growers who rented bees in 2006 and therefore do not have data on 2006 quantity.

For the regression-based quantity imputation, we use data from 2007 to regress the number of honey bee colonies rented on a dummy for renting bees that year, a dummy for the block being focused on fresh market production, block bearing apple acres, block number of apple trees, block average age of trees, and state dummies. To impute the 2006 quantity using the 2007 quantity imputation regression, we evaluate the quantity imputation regression using the 2006 values for the dummy for renting bees that year.

For growers who rented honey bees in a given year, we use the grower's rental fee for the price. For growers who did not rent in a given year and therefore did not report a bee rental fee for that year, we impute the missing price for that grower-year using regression-based imputation.

For the regression-based price imputation, we regress the honey bee rental fee on a dummy for the block being deliberately scouted for insects, weeds, disease; a dummy for the operator attending pest management training; a dummy for the block orchard floor system being a grass alley way; a dummy for the apple trees on the block being predominantly semi-dwarf; a block fresh market dummy; a dummy for the year 2007; and state dummies.

The West Coast states in our data set (which we refer to as the 'Western' states) 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).

Table A.1 in the Appendix presents summary statistics of our data. Figure A.2 in the Appendix shows weighted boxplots by state for the number of honey bee colonies rented and the honey bee rental fee ($/colony).

3 Demand for Managed Pollination

3.1 Econometric Models

We use our farm-level data from US apple farmers to estimate the demand for managed pollination. To accomplish this, we use 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 (Goldberger, 1991; Manski, 1995; Angrist, Graddy, and Imbens, 2000; Lin, 2011). Our first-stage equation is given by:

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

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, which interacts almond acreage in California with distance to California; $\mathbf{X}'_{\mathbf{isct}}$ is a vector of covariates, including measures of farm production scale (to proxy for total factor productivity), remotely sensed measures of natural open cover and natural forest cover (to proxy for wild pollinator stocks and landscape heterogeneity), and output price; γ_t are year fixed effects (which, for our two-period panel, is a dummy for 2007); $\mathscr{D}_l$ are state dummies; and ν_{isct} is the first-stage error term.

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

$$M_{isct} = \beta_M \widehat{p}_{m,isct} + \mathbf{X'}_{\mathbf{isct}} \theta_{\mathbf{M}} + \gamma_t + \mathscr{D}_l + \varepsilon_{isct}, \tag{2}$$

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.

The own-price elasticity of demand for managed pollination, η_{M,p_m}, is given by:

$$\begin{aligned} \eta_{M,p_m} &= \frac{dM}{dp_m}\frac{p_m}{M} \\ &= \widehat{\beta}_M \frac{p_m}{M}, \end{aligned} \tag{3}$$

where $\widehat{\beta}_M$ is the estimated coefficient on managed pollination price from our second-stage managed pollination demand equation (2) and both p_m and M can be evaluated at their respective means.

To further understand managed pollination demand, we also use our IV strategy to empirically examine the extensive margin binary choice to use managed pollination. For the extensive margin binary choice to use pollination service markets (in our case, renting honey bees), we estimate the following IV probit regression:

$$\Pr(R_{isct} = 1) = \beta_R \widehat{p}_{m,isct} + \mathbf{X'}_{\mathbf{isct}} \theta_{\mathbf{R}} + \gamma_t + \mathscr{D}_l + \varepsilon_{isct}, \tag{4}$$

where R_{isct} is a dummy variable for farmer i in state s and county c renting honey bees in year t.

The own-price elasticity for the extensive margin binary choice to use managed pollination, η_{R,p_m}, is given by:

$$\begin{aligned} \eta_{R,p_m} &= \frac{d\Pr(R=1)}{dp_m}\frac{p_m}{\Pr(R=1)} \\ &= \widehat{\beta}_R \frac{p_m}{\Pr(R=1)}, \end{aligned} \tag{5}$$

where $\widehat{\beta}_R$ is the estimated coefficient on managed pollination price from our IV probit regression in equation (4) and p_m and $\Pr(R=1)$ can be evaluate at mean rental price the mean proportion of farmers that rent bees respectively.

3.2 Identification Strategy

To identify β_M, the coefficient on managed pollination price in the second-stage managed pollination demand equation (2), and β_R, the coefficient on managed pollination price in the extensive margin binary choice IV probit regression (4), we use a shift-share instrument Z_{sct} for price.[8] 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).

The main insight we leverage for our identification strategy is that California almonds exert tremendous influence on pollination service markets in the US. This is because California is essentially the only place in the US where almond production takes place with any real scale,[9] and almonds require imported pollination services to produce marketable almonds: during the almond bloom period, almonds use an estimated 80% of US colonies, some coming from places as distant as Florida (Rucker, Thurman, and Burgett, 2012; Goodrich, 2017; Goodrich, Williams, and Goodhue, 2019). After the almond pollination season is done in early spring (e.g., March), many beekeepers migrate to different parts of the country chasing bloom periods for various crops (Rucker, Thurman, and Burgett, 2012; Goodrich, 2017; Goodrich, Williams, and Goodhue, 2019).

For the exogenous, time-varying "shift" s_t in our shift-share instrument Z_{sct}, we use total almond acres in California in period t. Figure A.3 in the Appendix shows the time-series of total al-

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

[9] According to USDA-NASS Quick Stats, California is the only state where production is reported for almonds. This can be easily verified by a query of the USDA-NASS Quick Stats portal by searching for 'AREA BEARING & NON-BEARING' for almonds: `https://quickstats.nass.usda.gov`.

mond acreage in California since 1995, broken out with total bearing and non-bearing acreage. An increase in acreage and supply of almonds in California has a well-documented effect of increasing demand for pollination services nationally (e.g., see Ward, Whyte, and James 2010; Rucker, Thurman, and Burgett 2012; Goodrich, Williams, and Goodhue 2019), which in turn affects the equilibrium price to rent bees. On the other hand, since the apple farmers in our sample were not almond growers,[10] for our sample of apple farmers, the option to grow almonds, and the acreage and supply of almonds in California, should have no bearing on the number of honey bee colonies they rent for a random block of apples. As a consequence, almond acreage in California is correlated with the price of managed pollination, but does not affect the demand for managed pollination from apple growers except through its price.

Since pollination services require transportation (generally by semi-trucks), distances and other transportation costs become important determinants of prices and exposure to "shifts" from places like California. An important factor driving the pollination fees charged by beekeepers is the distance commercial bee colonies must travel to service a pollination contract (Bond et al., 2021). Thus, for the exogeneous, time-invariant "share" d_{sc} in our shift-share instrument Z_{sct}, we use Euclidean distances from zip code centroids to the centroid for Fresno County, California (a credible center for California almond production).[11]

Our instrument therefore interacts total almond acres in California in period t with the distance from zip code centroids to the centroid for Fresno County, California. As explained in more detail in Section 3.3, since we control for the 2007 year dummy and individual dummies for each of the Western states (California, Oregon, and Washington), the variation we use for our shift-share instrument within any given year for each Western state is the within-state variation for that Western

[10]Only one of the 1057 farmers in the 2007 USDA-ARMS who have sufficient responses for our research reported growing both almonds and apples; this sole grower is in California. There were four others growers in the 2007 USDA-ARMS who also reported growing both almonds and apples, all in California, but none of these other four growers filled out the Phase II survey, which suggests that their apples may be non-bearing (see Section 2 for more information on the USDA-ARMS Phase II survey).

[11]We also studied road distances, which show similar results. We favor Euclidean distances because they have advantageous properties as fixed, time-invariant exogenous shares as part of a shift-share IV identification strategy (Borusyak, Hull, and Jaravel, 2022). Road distances, for example, can vary over time and are more vulnerable to being endogenous.

state; for Eastern states (all of which are further away from California), we are using variation in distance to Fresno, CA between zip codes in the Eastern states and variation in distance to California in Eastern versus Western states in explaining price.

Although there is important well-documented sub-annual variation in the seasonality of pollination service market migration routes and markets, our annual price data may be limited in how responsive it may be to sub-annual variation of these routes. Similarly, there are well-documented Eastern migration pollination market routes as well (Jabr, 2013; Bond, Plattner, and Hunt, 2014; Hitaj, Smith, and Hunt, 2018; Bond et al., 2021). Nevertheless, while it may not fully capture all the factors that affect prices, almond market demand nevertheless presents important exogenous variation in annual pollination service market prices.[12]

3.3 Regression Specifications

We use a linear demand specification (e.g., rather than a log-log specification) for several reasons. First, to allow the elasticity to depend on managed pollination price and managed pollination, 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.[13] 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.

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 the four aforementioned subsamples of

[12] Indeed, we studied shift-share IVs that used North Dakota distances, Florida distances, among others, but in our data these relationships were weak.

[13] 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.

data to estimate managed pollination demand (see Section 2). Specification (1) uses data from 2007 only. Specification (2) employs 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). Specification (3) is a balanced panel that includes all growers in the data for both 2006 and 2007: if the grower rented bees in both years, we impute the number of colonies rented in 2006 to be the number of colonies rented in 2007; if the grower rented bees in 2006 but not in 2007, we impute the quantity rented in 2006 using regression-based imputation. Specification (4) is a balanced panel that includes all growers in the data for both 2006 and 2007: we impute missing quantity using regression-based imputation. Our preferred specification is specification (4). We describe these four subsamples of data in more detail in Section 2.

For specification (1), which uses data from 2007 only, the instrument Z_{sct} is the 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 these specifications comes from variation in the distance from the centroids of zip codes where farms are located to the centroid of almond production in Fresno, County California. For specifications (2), (3), and (4), which use observations from both 2006 and 2007, the instrument Z_{sct} 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.

For the state dummies, we use individual dummies for each of the Western states (California, Oregon, and Washington) since instrument correlation remains relatively high and statistically significant with this subset of state dummies, since there are notable differences between Western and Eastern states in apple farmer production strategies and outcomes (Wilcox et al., 2026b), and since honey bee rental costs for apple farmers are higher in Eastern states than in Western states (Wilcox et al., forthcoming). The variation we use for our shift-share instrument within any given year for each Western state is therefore within-state variation for that Western state; for Eastern states (all of which are further away from California), we are using variation in distance to Fresno, CA between zip codes in the Eastern states and variation in distance to California in Eastern versus Western states in explaining price. It may make sense that, conditional on transporting the bees from California to some state in the East, the additional variation within that state in distance to California might not matter as much for rental bee price.[14]

There are several challenges to estimating demand elasticities in our 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). We employ a subset of state-specific dummies rather than the full set of state fixed effects because state fixed effects 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. Similar challenges have been encountered by Bruno and Jessoe (2021) and Wilcox, Just, and Ortiz-Bobea (2025), who find that excessive application of fixed effects remove essential variation in prices when studying of groundwater demand and deforestation, respectively. In Section 4, we use new methods developed by Petterson, Seim, and Shapiro (2023) to assess the bounds and robustness of our results.

3.4 Elasticity of Demand for Managed Pollination

Table 1 presents the honey bee demand IV estimation results from estimating the second-stage regression in equation (2). As required by USDA-ERS, all estimations are weighted using provided replicate weights. Table A.2 in the Appendix presents the respective first-stage results. The own-price demand elasticity for managed pollination use, as calculated using equation (3), is evaluated at the weighted mean price and quantity in the data for the respective sample of data.

We find that demand for managed pollination declines in its own price, and is somewhat elastic. The estimated elasticity of demand for managed pollination in our preferred specification

[14]For example, some beekeepers traveling from California may rent out their bees to pollinate crops elsewhere in California before moving East while others may rent out their bees at locations in the middle of the country before arriving in the East; and there is a separate East Coast migratory beekeeping circuit that overwinters in and around Florida, then moves north, culminating in Maine (Jabr, 2013; Bond, Plattner, and Hunt, 2014; Hitaj, Smith, and Hunt, 2018; Bond et al., 2021).

(4) is -2.04. In contrast, the analogous OLS estimates, reported in Table A.3 in the Appendix, are inelastic and statistically insignificant. Kleibergen and Papp first-stage F-statistics, F_{kp}, are well-above conventional levels indicating sufficient instrument strength (F_{kp} is equal to the robust first-stage F-statistics suggested by Montiel Olea and Pflueger (2013) when the model is just-identified (Andrews, Stock, and Sun, 2019)). Regression-based Durban-Wu-Hausman (DWH) statistics (Wooldridge, 2010) reject exogeneity of the endogenous variable. Model diagnostic statistics also offer support for our identification strategy.

To further understand the elasticity of demand for managed pollination, we also empirically examine the extensive margin binary choice to use managed pollination by estimating the IV probit regression in equation (4). No quantity imputation is required for any specification of the IV probit regression of the binary choice to rent bees since quantity information is not needed. Specification (5) uses data from 2007 only. Specification (6) uses a balanced panel that includes all growers in the data for both 2006 and 2007. The own-price elasticity for the extensive margin binary choice to use managed pollination, as calculated using equation (5), is evaluated at the mean price and rented bees dummy in the data for the respective sample of data.

Results for the IV probit regression of the extensive margin binary choice to rent bees in equation (4) are shown in Table 2. The estimated elasticity for the extensive margin binary choice to rent bees is statistically insignificant in both specifications. The extensive margin binary choice to rent bees does not have a statistically significant response to price, and is therefore relatively inelastic.

Thus, results of our empirical analyses of the elasticity of demand show that honey bee demand is somewhat elastic, while the extensive margin binary choice to rent bees is relatively inelastic.

3.5 Other Determinants of Managed Pollination Use

There are several other main findings from our honey bee demand IV estimation results in Table 1 and our extensive margin binary choice to rent bees IV probit regression results in Table 2.

First, honey bee demand is increasing and concave in measures of farm scale, including block-level apple bearing acres, the total number of operation-level bearing apple blocks, and the number of trees per acre. Similarly, the likelihood of renting bees has a significant positive association with these measures of scale and a statistically significant concave relationship with block-level apple bearing acres and the total number of operation-level bearing apple blocks. Nevertheless, the effect of farm scale on the likelihood of renting honey bees is small in magnitude: an increase in bearing acreage at the block level increases the likelihood of renting honey bees by around 1% to 1.5% and an increase in the number of bearing apple blocks increases the likelihood of renting by 3.5% to 4.5%.

Second, the choice to rent bees has a significant positive and concave relationship with natural open cover across all specifications, and honey bee demand has a positive and concave relationship with natural open cover across all specifications that is statistically significant in our preferred specification (4). 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, and therefore may require managed pollination. For natural forest cover, results are insignificant but suggest a possible negative and convex relationship. There is some empirical work that indicates that natural forest cover near apple orchards can be source areas for wild pollination stocks that can enhance production (Park et al., 2015; Kammerer et al., 2016).

Third, both honey bee demand and the likelihood of renting bees have a significant positive association with our measure of apple output price, the total utilized production price (a weighted average of the fresh market and processed prices).

In addition to differences in elasticity (with honey bee demand being somewhat elastic, while the extensive margin binary choice to rent bees is relatively inelastic), results show two other main differences between honey bee demand and the extensive margin binary choice to rent bees. First, having federal crop insurance makes farmers more likely to rent bees, but has no statistically significant effect on the quantity of honey bees rented. Second, farmers were slightly less likely to rent bees in 2007, but the year 2007 dummy has no statistically significant effect on the quantity of honey bees rented in our preferred specification (4) of honey bee demand.

3.6 Robustness

We estimate several alternative specifications of the demand for managed pollination for robustness. First, as an alternative to our 2SLS regressions of honey bee demand, we estimate an IV-tobit censored regression model, where managed pollination use is left-censored at zero. For our IV-tobit censored regressions, the own-price demand elasticity for managed pollination use, as calculated using equation (3), is evaluated at the mean price and quantity among grower-years with positive quantity (which we refer to as the conditional mean) in the respective sample of data. As shown in Table 3, the elasticity at the conditional mean in our preferred specification (4) is -1.98.

Second, we also estimate alternative specifications of 2SLS and IV-tobit honey bee demand using the number of honey bee colonies rented per acre instead of the number of honey bee colonies as the dependent variable. As seen in Tables A.4 and A.5 in the Appendix, respectively, the results using the number of honey bee colonies rented per acre are similar to the respective 2SLS and IV-tobit honey bee demand results using the number of honey bee colonies in Tables 1 and 3, albeit with elasticities for the number of honey bee colonies rented per acre that are slightly larger in magnitude.

Third, for the extensive margin, as an alternative to our IV probit regressions of the binary choice to rent bees, we also estimate probit and IV-probit regressions of the binary choice to *never* rent honey bees during 2006-2007.[15] As seen in Table A.6 in the Appendix, consistent with our results for the IV probit regressions of the binary choice to rent bees shown in Table 2, results for the probit and IV-probit regressions of the binary choice to *never* rent honey bees during 2006-2007 in Table B.6 have the opposite sign and are of similar or greater statistical significance.

4 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)

[15] For these regressions, the dummy for 2007 is omitted as there is no temporal variation in our dependent variable.

show that economic intuitions about the plausible size of demand shocks can be informative about and help bound the elasticity of demand, and they develop methods for determining elasticities that are consistent with a given bound B on the plausible size of shocks. Examples of shocks to managed pollination demand in our setting include demand shocks associated with colony collapse disorder (National Research Council, 2007).

4.1 Methodology for Bounding Demand Elasticity

Following the approach of Petterson, Seim, and Shapiro (2023), we determine the range of demand elasticities consistent with a range of demand shocks. In particular, following 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 (similar to their Figure 3). 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 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 this approach for different demand shock bounds B, obtain the range of demand elasticities consistent with each demand shock bound B, and then, following Petterson, Seim, and Shapiro (2023), we plot the range of demand elasticities consistent with the range of demand shocks (similar to their Figure 4).

For the demand shocks for our demand shock bound B, 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. In other words, we use the size of demand shocks for observations without price changes to inform intuitions about the plausible size of demand shocks for observations with price changes. We use the same balanced panel of 1,028 farmers that we use in our preferred specification (4) for managed pollination demand in Table 1, which has observations in both 2006 and 2007.[16]

Large magnitude changes in quantity among those who rent bees in one year but not the other in our data present challenges for cleanly applying results from Petterson, Seim, and Shapiro (2023). To address this 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.[17]

4.2 Results for Bounds on Demand Elasticity

Following Petterson, Seim, and Shapiro (2023), the shaded region in Figure 1 depicts the set of all demand functions consistent with a demand shock bound *B* of twice the maximum absolute value

[16]We are unable to use the subsample used in specification (1) of Table 1, which consists of data from 2007 only, as the new methods developed by Petterson, Seim, and Shapiro (2023) involve taking first differences in price and quantity, and therefore cannot be applied to observations from one year only. We are unable to use the subsample of 430 farmers from the sample used in specification (2) in Table 1 who reported not renting bees in 2006, and therefore for whom we have data in both 2006 and 2007 since we know the number of colonies rented in 2006 is zero (thereby eliminating the need for quantity imputation), as this subsample 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 demand shock. We do not use the subsample in specification (3) since owing to the quantity imputation used for this subsample, which imputes the number of colonies rented in 2006 to be the number of colonies rented in 2007 for the 578 growers who rented bees in both years, as there is a lack of changes in quantity for these growers.

[17]To address large magnitude first differences and comply with USDA NASS conditions and restrictions on data confidentiality, we smooth the first differenced quantity when calculating our 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.

of the differenced quantity for observations for which the differenced price is equal to zero. A demand function consistent with a demand shock bound B is a downward sloping line that passes through the origin as well as through all of the dotted intervals. A demand shock bound B of twice the maximum absolute value of the differenced quantity for observations for which the differenced price is equal to zero implies a bound on the demand elasticity (when evaluated at mean price and quantity) of -2.43.

Then, following Petterson, Seim, and Shapiro (2023), Figure 2 plots the range of honey bee demand elasticities that are consistent with bounds on the plausible size of shocks to demand ranging from the mean absolute value of the differenced quantity for observations for which the differenced price is equal to zero, to twice the maximum absolute value of the differenced quantity for observations for which the differenced price is equal to zero.[18] The implied elasticities (when evaluated at mean price and quantity) range from -1.71 to -2.43. These results are consistent with our econometric estimate of the demand elasticity from our preferred specification (4) in Table 1 of -2.04, which lies within this range.

5 Discussion and Conclusion

The pollination choices of pollination-dependent farmers have important implications for production outcomes, food supplies, and pollination resources within and beyond the farm gate. In this paper, we undertake the first known empirical study of pollination use in conjunction with farm-level production data, and establish new stylized facts. To our knowledge, many of these empirical measurements are the first of their kind, which by itself emphasizes how little is known about these production sectors and associated pollination demand around the world.

Our empirical results show that demand for managed pollination is somewhat elastic among US apple growers. Employing a novel IV strategy that exploits well-documented supply shifts from high early-season demand for managed pollination from California's almond sector, we estimate

[18]Figures A.4 and A.5 in the Appendix plot analogous results using the number of colonies rented per acre (rather than the number of colonies rented) as our measure of quantity.

that the managed pollination demand elasticity is -2.04. These results are consistent with bounds on the elasticity we calculate using new methods from Petterson, Seim, and Shapiro (2023).

Using the same IV strategy, we also empirically examine the extensive margin binary choice to use managed pollination, and find that the extensive margin binary choice to rent bees is price inelastic. In particular, the choice to rent bees does not have a statistically significant response to price, but is instead driven by other factors such as crop insurance.

Prior work and perhaps conventional wisdom has tended to assume or suggest that managed pollination demand is inelastic for many specialty crops. For example, Rucker, Thurman, and Burgett (2012) and Ferrier et al. (2018) examine farmer pollination demand through the lens of stocking densities, and use theory and aggregate cost data to argue that honey bee stocking densities are likely to be held more or less fixed by farmers, suggesting that demand is either perfectly inelastic or at least strongly inelastic.[19] There are reports that some apple growers in the Northeast consider honey bee rental an inconsequential cost analogous to "cheap insurance" (Biltonen, 2020; Kahlke, 2019), suggesting that demand may be highly inelastic. When estimating the demand for pollination services using aggregate data from California, Willett and French (1991) find that demand for pollination services is very inelastic, which they explain to be the result of little substitution between pollination and other inputs and the low cost of pollination relative to the total value of crop production. In contrast, our empirical analyses of the elasticity of demand suggest that, while not perfectly elastic, managed pollination demand may be more elastic than prior work has assumed and perhaps conventional wisdom sometimes suggests. Instead, what may be inelastic is the choice to rent bees itself, not the quantity of honey bees to rent.

A possible explanation is as follows. For apple farmers, honey bee rental costs may be a small part of their budget. For example, according to self-reported cost shares from the 2022 Northeast Apple Grower Survey, a survey we designed and implemented among apple farmers in the Northeastern US, which focuses on the 2019-2021 production years, pollination costs accounted for only 1.66% of total apple production costs on average, with a range from under 1% to as high

[19] Rucker, Thurman, and Burgett (2012) assume fixed bee stocking densities to sign comparative statics.

as 5% of total apple production costs (Wilcox et al., forthcoming).[20] Since honey bee rental may be an inconsequential cost analogous to "cheap insurance" (Biltonen, 2020; Kahlke, 2019), apple farmers may not respond much to price when making the binary choice of whether or not to rent bees. It is possible that some apple farmers may instead make the binary choice of whether to rent bees *ex ante* in conjunction with choices about crop insurance; furthermore, it is also possible that some forms of crop insurance may require renting bees. Indeed, our empirical results show that having federal crop insurance makes farmers more likely to rent bees, but has no statistically significant effect on the quantity of honey bees rented. Then, in any given year, farmers who have pre-committed to renting bees that year may then base their quantity choice on how much budget they have left over that year, and adjust the quantity to rent over the course of the growing season accordingly. The price sensitivity of the quantity of honey bees to rent may be further amplified by substitution with wild pollinators.

To our knowledge, our work is the first to use an instrumental variables strategy to estimate managed pollination demand, as well as the first to use the new methods from Petterson, Seim, and Shapiro (2023) to bound the managed pollination demand elasticity. While our OLS estimates of honey bee demand are consistent with conventional wisdom that managed pollination demand is inelastic, we find that once we instrument for honey bee rental price to address its endogeneity, honey bee demand is somewhat elastic.

Several additional findings arise from our empirical analysis that are informative of farmer pollination decision-making. For example, we find that both honey bee demand and the likelihood of renting honey bees are increasing and concave in the scale of production (e.g., size of block, number of bearing blocks) as well as in natural open cover. Our results suggest that production scale may have a limited influence on the choice to rent bees, and that pollinator habitat and availability of local wild pollination stocks may have substitution effects on pollination choice.

One caveat regarding our empirical analysis is that we use data from 2006-2007, and it is

[20] Honey bee rental cost shares calculated using the USDA-ARMS data by dividing the total in bee rental fees per acre by the total production costs per acre for each selected block (Table A.1 in the Appendix), which may tend to overestimate cost shares because the total costs in the denominator do not account for costs in non-bearing years before the orchard matures, are small as well.

possible that our parameter estimates and elasticity point estimates may not necessarily apply years later. A second caveat is that the time period of our analysis, was potentially a time of disruption in pollination markets due to fuel price shocks and early recognition of colony collapse disorder (National Research Council, 2007). It is possible that these disruptions may have magnified apple growers' price sensitivity and demand elasticity. If so, one possible implication is that in the face of any ongoing or future such disruptions – perhaps owing to continued concern over the state of wild and domesticated pollination resource stocks, and climate change concerns – our result that honey bee demand is somewhat elastic might still be relevant and meaningful years later.

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. Future refinements to our contributions might be made for advising farmers on optimal pollination strategies; uncovering the complexities of where wild pollination stocks do or do not subsidize production effectively and why; and analyzing the spatial externalities that arise from wild pollination resources. A better understanding of pollination resources and pollination decision-making is critical for placing policy-making on better footing, and helping pollination-dependent farmers find innovative ways to resolve pollination resource needs within bioeconomy value chains (Zilberman, Lu, and Reardon, 2019).

References

Albers, H., and E. Robinson. 2011. "The trees and the bees: Using enforcement and income projects to protect forests and rural livelihoods through spatial joint production." *Agricultural and Resource Economics Review* 40:424–438.

Andrews, I., J.H. Stock, and L. Sun. 2019. "Weak instruments in instrumental variables regression: Theory and practice." *Annual Review of Economics* 11:727–753.

Angrist, J.D., K. Graddy, and G.W. Imbens. 2000. "The interpretation of instrumental variables estimators in simultaneous equations models with an application to the demand for fish." *Review of Economic Studies* 67:499–527.

Baylis, K., E.M. Lichtenberg, and E. Lichtenberg. 2021. "Economics of pollination." *Annual Review of Resource Economics* 13:335–354.

Biltonen, M. 2020. personal communication.

Blitzer, E.J., J. Gibbs, M.G. Park, and B.N. Danforth. 2016. "Pollination services for apple are dependent on diverse wild bee communities." *Agriculture, Ecosystems and Environment* 221:1–7.

Bond, J., K. Plattner, and K. Hunt. 2014. "Fruit and tree nuts outlook: Economic insight: U.S. pollination-services market." FTS-0357SA, United States Department of Agriculture Economic Research Service.

Bond, J.K., C. Hitaj, D. Smith, K. Hunt, A. Perez, and G. Ferreir. 2021. "Honey bees on the move: From pollination to honey production and back." Economic Research Report Number 290, United States Department of Agriculture Economic Research Service.

Borusyak, K., P. Hull, and X. Jaravel. 2022. "Quasi-experimental shift-share research designs." *Review of Economic Studies* 89:181–213.

Boryan, C., Z. Yang, R. Mueller, and M. Craig. 2011. "Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program." *Geocarto International* 26:341–358.

Bruno, E.M., and K. Jessoe. 2021. "Missing markets: Evidence on agricultural groundwater demand from volumetric pricing." *Journal of Public Economics* 196:104374.

Champetier, A., D.A. Sumner, and J.E. Wilen. 2015. "The bioeconomics of honey bees and pollination." *Environmental and Resource Economics* 60:143–164.

Cheung, S.N.S. 1973. "The fable of the bees: An economic investigation." *Journal of Law and Economics* 16:11–33.

Danforth, B.N., R.L. Minckley, and J.L. Neff. 2019. "Solitary bees and agricultural pollination." In *The Solitary Bees: Biology, Evolution, Conservation*. Princeton University Press, chap. 13.

Fei, C.J., K.M. Williamson, R.T. Woodward, B.A. McCarl, and J. Rangel. 2021. "Honey bees, almonds, and colony mortality: An economic simulation of the US pollination market." *Land Economics* 97:688–703.

Ferrier, P.M., R.R. Rucker, W.N. Thurman, and M. Burgett. 2018. "Economic effects and responses to changes in honey bee health." Economic Research Report Number 246, United States Department of Agriculture Economic Research Service.

Garibaldi, L.A., I. Steffan-Dewenter, R. Winfree, M.A. Aizen, R. Bommarco, S.A. Cunningham, C. Kremen, L.G. Carvalheiro, L.D. Harder, O. Afik, et al. 2013. "Wild pollinators enhance fruit set of crops regardless of honey bee abundance." *Science* 339:1608–1611.

Goldberger, A. 1991. *A Course in Econometrics*. Cambridge, MA: Harvard University Press.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift. 2020. "Bartik instruments: What, when, why, and how." *American Economic Review* 110:2586–2624.

Goodrich, B.K. 2017. "The California Almond Pollination Market: Contracts and Honey Bee Colony Health." PhD dissertation, University of California, Davis.

Goodrich, B.K., J.C. Williams, and R.E. Goodhue. 2019. "The great bee migration: Supply analysis of honey bee colony shipments into California for almond pollination services." *American Journal of Agricultural Economics* 101:1353–1372.

Grab, H., K. Poveda, B. Danforth, and G. Loeb. 2018. "Landscape context shifts the balance of costs and benefits from wildflower borders on multiple ecosystem services." *Proceedings of the Royal Society B: Biological Sciences* 285:20181102.

Hitaj, C., D.J. Smith, and K.A. Hunt. 2018. "Pollination services: Honeybee movements across the US and the impact of travel on honeybee health." Working paper, U.S. Department of Agriculture Economic Research Service.

Jabr, F. 2013. "Where the wild bees are: Documenting a loss of native bee species between the 1800s and 2010s." *Scientific American* 309:88.

Kahlke, C. 2019. personal communication.

Kammerer, M.A., D.J. Biddinger, N.K. Joshi, E.G. Rajotte, and D.A. Mortensen. 2016. "Modeling local spatial patterns of wild bee diversity in Pennsylvania apple orchards." *Landscape Ecology* 31:2459–2469.

Kennedy, C.M., E. Lonsdorf, M.C. Neel, N.M. Williams, T.H. Ricketts, R. Winfree, R. Bommarco, C. Brittain, A.L. Burley, D. Cariveau, et al. 2013. "A global quantitative synthesis of local and landscape effects on wild bee pollinators in agroecosystems." *Ecology Letters* 16:584–599.

Lin, C.Y.C. 2011. "Estimating supply and demand in the world oil market." *Journal of Energy and Development* 34:1–32.

Lippert, C., A. Feuerbacher, and M. Narjes. 2021. "Revisiting the economic valuation of agricultural losses due to large-scale changes in pollinator populations." *Ecological Economics* 180:106860.

Manski, C.F. 1995. *Identification Problems in the Social Sciences*. Cambridge, MA: Harvard University Press.

Martins, K.T., A. Gonzalez, and M.J. Lechowicz. 2015. "Pollination services are mediated by bee functional diversity and landscape context." *Agriculture, Ecosystems and Environment* 200:12–20.

Meade, J.E. 1952. "External economies and diseconomies in a competitive situation." *Economic Journal* 62:54–67.

Mid Valley Agricultural Services. 2006. "Fruit Set Factors." *Mid Valley Agricultural Services Newsletter* October 2006.

Montiel Olea, J.L., and C. Pflueger. 2013. "A robust test for weak instruments." *Journal of Business and Economic Statistics* 31:358–369.

National Research Council. 2007. "Status of Pollinators in North America." Washington, DC: The National Academies Press. URL: `https://doi.org/10.17226/11761`.

Park, M.G., E. Blitzer, J. Gibbs, J.E. Losey, and B.N. Danforth. 2015. "Negative effects of pesticides on wild bee communities can be buffered by landscape context." *Proceedings of the Royal Society B: Biological Sciences* 282:20150299.

Park, M.G., N.K. Joshi, E.G. Rajotte, D.J. Biddinger, J.E. Losey, and B.N. Danforth. 2020. "Apple grower pollination practices and perceptions of alternative pollinators in New York and Pennsylvania." *Renewable Agriculture and Food Systems* 35:1–14.

Park, M.G., R.A. Raguso, J.E. Losey, and B.N. Danforth. 2016. "Per-visit pollinator performance and regional importance of wild Bombus and Andrena (Melandrena) compared to the managed honey bee in New York apple orchards." *Apidologie* 47:145–160.

Penn, J., W. Hu, and H.J. Penn. 2019. "Support for solitary bee conservation among the public versus beekeepers." *American Journal of Agricultural Economics* 101:1386–1400.

Petterson, M.S., D.G. Seim, and J.M. Shapiro. 2023. "Bounds on a slope from size restrictions on economic shocks." *American Economic Journal: Microeconomics* 15:552–572.

Reilly, J., D. Artz, D. Biddinger, K. Bobiwash, N. Boyle, C. Brittain, J. Brokaw, J. Campbell, J. Daniels, E. Elle, et al. 2020. "Crop production in the USA is frequently limited by a lack of pollinators." *Proceedings of the Royal Society B* 287:20200922.

Roubik, D.W. 2002. "Tropical agriculture: the value of bees to the coffee harvest." *Nature* 417:708.

Rucker, R.R., W.N. Thurman, and M. Burgett. 2019. "Colony collapse and the consequences of bee disease: Market adaptation to environmental change." *Journal of the Association of Environmental and Resource Economists* 6:927–960.

—. 2012. "Honey bee pollination markets and the internalization of reciprocal benefits." *American Journal of Agricultural Economics* 94:956–977.

Russo, L., M. Park, E. Blitzer, and B. Danforth. 2017. "Flower handling behavior and abundance determine the relative contribution of pollinators to seed set in apple orchards." *Agriculture, Ecosystems and Environment* 246:102–108.

Schmit, T.M., R.M. Severson, J. Strzok, and J. Barros. 2018. "Economic contributions of the apple industry supply chain in New York State." Extension Bulletin EB 2018-03, Charles H. Dyson School of Applied Economics and Management, Cornell University.

Simpson, R.D. 2019. "Conservation incentives from an ecosystem service: How much farmland might be devoted to mative pollinators?" *Environmental and Resource Economics* 73:661–678.

U.S. Federal Reserve Bank of St. Louis. 2025. "Implicit Price Deflator (base year 2017)." `https://fred.stlouisfed.org/series/GDPDEF`, Accessed March 21, 2025.

USDA Economic Research Service (ERS). 2022. "ARMS Farm Financial and Crop Production Practices: Contact Us." URL: `https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/contact-us/`.

Ward, R., A. Whyte, and R. James. 2010. "A tale of two bees: Looking at pollination fees for almonds and sweet cherries." *American Entomologist* 56:170–177.

Wilcox, S.W., D.R. Just, H. Grab, C.Y.C. Lin Lawell, and D.A. Yeh. forthcoming. "Apple pollination costs and strategies: Trends and outlook." *Choices*, pp. forthcoming.

Wilcox, S.W., D.R. Just, C.Y.C. Lin Lawell, M.I. Gómez, and H. Grab. 2026a. "A dynamic model of farmer pollination resource decision-making." Working paper, Utah State University, Cornell University, and Penn State University.

Wilcox, S.W., D.R. Just, C.Y.C. Lin Lawell, M.I. Gómez, H. Grab, and D.A. Yeh. 2026b. "Pollination, production, and profits." Working paper, Utah State University, Cornell University, and Penn State University.

Wilcox, S.W., D.R. Just, and A. Ortiz-Bobea. 2025. "The role of staple food prices in deforestation: Evidence from Cambodia." *Land Economics* 101:89–118.

Willett, L.S., and B.C. French. 1991. "An econometric model of the US beekeeping industry." *American Journal of Agricultural Economics* 73:40–54.

Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wu, L., and S.S. Atallah. 2019. "Farm and landscape-level trade-offs between pest control and pollination service provision: The case of neonicotinoid insecticides." Working paper, University of Illinois at Urbana-Champaign.

Zilberman, D., L. Lu, and T. Reardon. 2019. "Innovation-induced food supply chain design." *Food Policy* 83:289–297.

Table 1: Honey bee demand own-price elasticity estimation, 2SLS results (weighted).

Dependent variable is the number of honey bee colonies rented	(1)	(2)	(3)	(4)
honey bee rental fee ($/colony)	-0.809**	-0.687**	-0.757***	-0.571***
	(0.359)	(0.292)	(0.261)	(0.199)
apple bearing acres	1.098***	0.981***	1.106***	0.882***
	(0.060)	(0.047)	(0.041)	(0.031)
apple bearing acres, squared	-0.00074***	-0.00048***	-0.00076***	-0.00008
	(0.00016)	(0.00013)	(0.00011)	(0.00008)
total bearing apple blocks	0.110	0.106	0.128**	0.129***
	(0.095)	(0.074)	(0.065)	(0.049)
total bearing apple blocks, squared	-0.00146	-0.00151**	-0.00143**	-0.00134***
	(0.00095)	(0.00076)	(0.00066)	(0.00050)
trees per acre	0.029***	0.026***	0.029***	0.023***
	(0.010)	(0.007)	(0.007)	(0.005)
trees per acre, squared	-0.00002***	-0.00002***	-0.00002***	-0.00001***
	(0.00001)	(0.00001)	(0.00001)	(0.000004)
average age of trees	-0.016	-0.003	-0.030	-0.033
	(0.142)	(0.099)	(0.097)	(0.074)
average age of trees, squared	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)
natural forest cover	-10.97	-7.14	-7.13	-8.44
	(10.71)	(8.06)	(7.60)	(5.79)
natural forest cover, squared	24.22	14.24	20.06*	18.27**
	(15.40)	(10.66)	(11.34)	(8.63)
natural open cover	32.05	15.18	31.64*	35.53***
	(25.15)	(16.97)	(18.04)	(13.73)
natural open cover, squared	-25.04	-12.33	-24.27	-32.24**
	(27.71)	(18.73)	(19.65)	(14.95)
total utilized production price ($/pound)	113.54***	73.50***	55.35***	41.65***
	(35.53)	(23.39)	(17.02)	(12.95)
has federal crop insurance in 2007 (dummy)	-0.193	-1.116	-0.154	0.912
	(1.538)	(1.176)	(1.066)	(0.811)
CA (dummy)	-32.95***	-24.52***	-25.44***	-19.30***
	(11.48)	(8.45)	(7.31)	(5.56)
OR (dummy)	-29.38***	-17.79***	-19.11***	-14.40***
	(10.27)	(6.50)	(5.98)	(4.55)
WA (dummy)	-32.23***	-19.11***	-17.67***	-13.70***
	(11.33)	(7.10)	(5.77)	(4.39)
year 2007 (dummy)		7.093***	-0.772	-0.655
		(1.470)	(1.170)	(0.891)
constant	12.49	10.44	20.41**	15.59**
	(12.91)	(11.04)	(10.26)	(7.81)
Elasticity at mean	-2.97**	-3.11**	-2.72***	-2.04***
Data included in sample:				
All observations from 2007	Y	Y	Y	Y
Growers who did not rent in 2006	N	Y	Y	Y
Growers who rented bees in 2006	N	N	Y	Y
First-stage F-statistic, F_{kp}	9.83	13.17	14.9	14.9
DWH t-statistic	1.62	1.63	2.13	2.20
Adjusted R^2	0.439	0.464	0.449	0.600
# Observations	1,020	1,438	2,056	2,056

Notes: Table presents IV results for honey bee demand (weighted). Specification (1) uses data from 2007 only. Specification (2) employs 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). Specification (3) is a balanced panel that includes all growers in the data for both 2006 and 2007: if the grower rented bees in both years, we impute the number of colonies rented in 2006 to be the number of colonies rented in 2007; if the grower rented bees in 2006 but not in 2007, we impute the quantity rented in 2006 using regression-based imputation. Specification (4) is a balanced panel that includes all growers in the data for both 2006 and 2007: we impute missing quantity using regression-based imputation. For specification (1), the instrument for price (honey bee rental fee) is the distance from the centroids of zip code units of farm locations to the centroid of Fresno Countys, California. For specifications (2), (3), and (4), the instrument for price (honey bee rental fee) 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. Elasticity is evaluated at the mean price and quantity in the data for the respective sample of data. Huber-White robust standard errors are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 2: Binary choice to rent bees, IV-probit results (weighted).

Dependent variable is probability of renting honey bees	(5)	(6)
honey bee rental fee ($/colony)	-0.0227	-0.0203
	(0.0297)	(0.0223)
apple bearing acres	0.0156*	0.0125**
	(0.0085)	(0.00565)
apple bearing acres, squared	-0.000034*	-0.000024*
	(0.000019)	(0.000013)
total bearing apple blocks	0.0611***	0.0612***
	(0.0146)	(0.0101)
total bearing apple blocks, squared	-0.000537***	-0.000529***
	(0.000163)	(0.000113)
trees per acre	0.00012	0.00023
	(0.00123)	(0.00090)
trees per acre, squared	0.0000014	0.0000015
	(0.0000014)	(0.0000010)
average age of trees	0.0052	0.0161
	(0.0172)	(0.0121)
average age of trees, squared	-0.00023	-0.000349*
	(0.00023)	(0.000182)
natural forest cover	-1.680	-0.0125
	(1.313)	(0.948)
natural forest cover, squared	2.558	0.691
	(1.595)	(1.186)
natural open cover	6.623***	5.970***
	(2.379)	(1.680)
natural open cover, squared	-5.960**	-5.145***
	(2.376)	(1.689)
total utilized production price ($/pound)	10.85***	7.169***
	(2.431)	(1.492)
has federal crop insurance in 2007 (dummy)	0.526***	0.570***
	(0.150)	(0.106)
CA (dummy)	-2.296***	-1.756***
	(0.806)	(0.567)
OR (dummy)	-2.099***	-1.186***
	(0.711)	(0.456)
WA (dummy)	-2.163**	-1.083**
	(0.880)	(0.516)
year 2007 (dummy)		-0.219*
		(0.12)
constant	-2.264	-1.930*
	(1.423)	(1.051)
Elasticity at mean	-1.47	-1.27
Data included in sample:		
All observations from 2007	Y	Y
All observations from 2006	Y	Y
# Observations	1,020	2,056

Notes: Table presents results (weighted) from IV-probit regressions of the binary choice to rent honey bees. No quantity imputation is required for any specification since quantity information is not needed for the IV probit regression. Specification (5) uses data from 2007 only. Specification (6) uses a balanced panel that includes all growers in the data for both 2006 and 2007. For specification (5), the instrument for price (honey bee rental fee) is the distance from the centroids of zip code units of farm locations to the centroid of Fresno County, California. For specification (6), the instrument for price (honey bee rental fee) 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. Elasticity is evaluated at mean price and rented bees dummy in the data for the respective sample of data. Huber-White robust standard errors are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3: Honey bee demand own-price elasticity estimation, IV-tobit results (weighted).

Dependent variable is the number of honey bee colonies rented	(1)	(2)	(3)	(4)
honey bee rental fee ($/colony)	-1.269	-1.978**	-1.002*	-0.730*
	(0.784)	(0.981)	(0.538)	(0.394)
apple bearing acres	1.175***	1.124***	1.179***	0.937***
	(0.153)	(0.159)	(0.105)	(0.090)
apple bearing acres, squared	-0.00091***	-0.00078**	-0.00093***	-0.00020
	(0.00033)	(0.00034)	(0.00022)	(0.00026)
total bearing apple blocks	0.330*	0.402*	0.386***	0.322***
	(0.189)	(0.228)	(0.130)	(0.104)
total bearing apple blocks, squared	-0.00345**	-0.00446*	-0.00363***	-0.00298***
	(0.00198)	(0.00240)	(0.00134)	(0.00111)
trees per acre	0.042*	0.050**	0.0396***	0.0302***
	(0.020)	(0.023)	(0.0132)	(0.0100)
trees per acre, squared	-0.000030**	-0.000032*	-0.000029***	-0.000018**
	(0.000015)	(0.000017)	(0.000010)	(0.000007)
average age of trees	0.117	0.238	0.105	0.0625
	(0.263)	(0.277)	(0.165)	(0.130)
average age of trees, squared	-0.00531	-0.00733*	-0.00481*	-0.00348*
	(0.00411)	(0.00431)	(0.00268)	(0.00205)
natural forest cover	-16.92	-15.40	-7.179	-8.564
	(17.72)	(19.18)	(12.15)	(9.411)
natural forest cover, squared	39.20	33.57	25.41	21.96
	(29.46)	(28.44)	(20.41)	(15.44)
natural open cover	74.69	95.53**	63.76**	61.71***
	(45.85)	(45.06)	(30.36)	(23.50)
natural open cover, squared	-67.39	-97.59**	-56.76*	-59.93**
	(45.07)	(43.63)	(29.95)	(23.30)
total utilized production price ($/pound)	236.7***	393.1***	110.8***	81.75***
	(71.70)	(83.30)	(29.71)	(20.49)
has federal crop insurance in 2007 (dummy)	4.205*	6.127**	4.059**	4.101***
	(2.409)	(2.697)	(1.722)	(1.412)
CA (dummy)	-61.94**	-92.95***	-42.43***	-31.28***
	(25.32)	(29.82)	(15.15)	(10.98)
OR (dummy)	-53.90**	-73.16***	-29.37***	-21.59***
	(21.13)	(21.50)	(11.10)	(7.975)
WA (dummy)	-60.17**	-89.54***	-27.39***	-20.72***
	(23.40)	(23.90)	(10.77)	(7.559)
year 2007 (dummy)			-3.396	-2.608
			(2.163)	(1.627)
constant	-8.813	-16.22	4.068	2.454
	(26.75)	(32.80)	(20.35)	(15.14)
Elasticity at conditional mean	-3.52	-5.49**	-2.72*	-1.98*
Data included in sample:				
All observations from 2007	Y	Y	Y	Y
Growers who did not rent in 2006	N	Y	Y	Y
Growers who rented bees in 2006	N	N	Y	Y
# Observations	1,020	1,438	2,056	2,056

Notes: Table presents IV-tobit results for honey bee demand (weighted). Specification (1) uses data from 2007 only. Specification (2) employs 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). Specification (3) is a balanced panel that includes all growers in the data for both 2006 and 2007: if the grower rented bees in both years, we impute the number of colonies rented in 2006 to be the number of colonies rented in 2007; if the grower rented bees in 2006 but not in 2007, we impute the quantity rented in 2006 using regression-based imputation. Specification (4) is a balanced panel that includes all growers in the data for both 2006 and 2007: we impute missing quantity using regression-based imputation. For specification (1), the instrument for price (honey bee rental fee) is the distance from the centroids of zip code units of farm locations to the centroid of Fresno County, California. For specifications (2), (3), and (4), the instrument for price (honey bee rental fee) 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. Elasticity at conditional mean is evaluated at the mean price and quantity among grower-years with positive quantity in the respective sample of data. Huber-White robust standard errors are in parentheses. Significance codes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

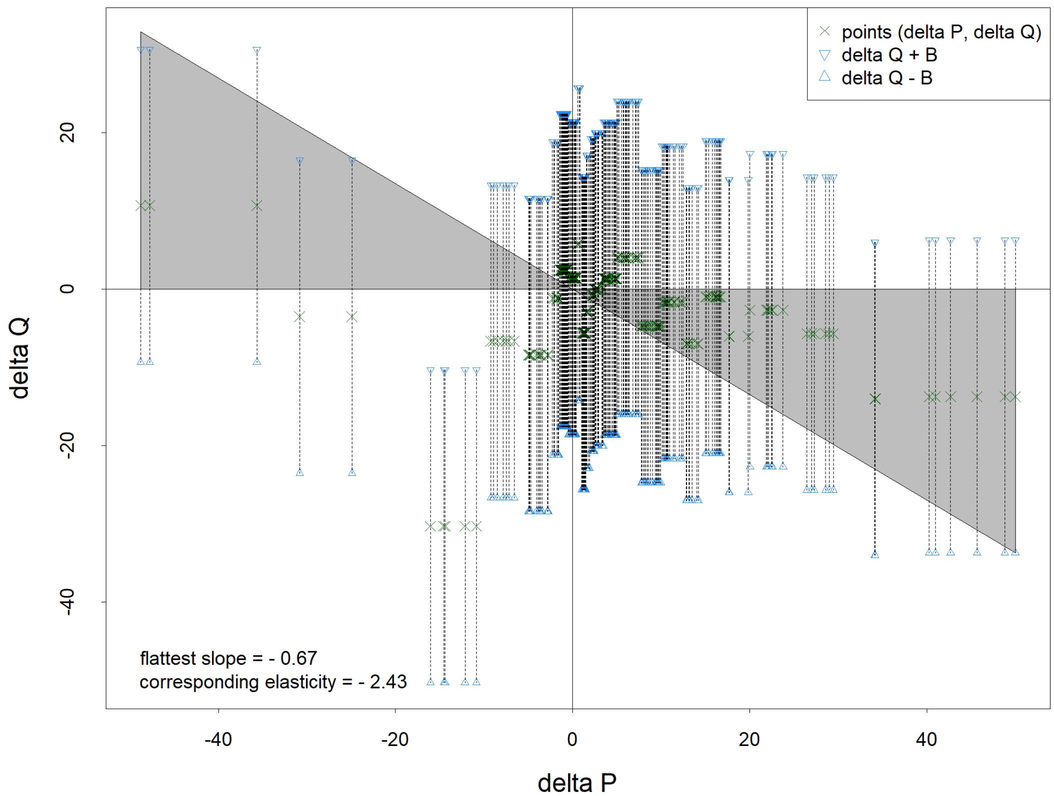

Figure 1: Figure illustrates the construction of bounds on the honey bee demand elasticity from using the absolute value of the differenced quantity for observations for which the differenced price is equal to zero as our demand shock and a demand shock bound B of 20, which is twice the maximum absolute value of the differenced quantity for observations for which the differenced price is equal to zero. The subsample is the same balanced panel of 1,028 farmers that we use in specification (4) in Table 1. 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 has radius of $B = 20$. The shaded region depicts all demand functions consistent with an upper bound of $B = 20$ 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 -0.67 and the corresponding bound on demand elasticity (when evaluated at mean price and quantity) is -2.43.

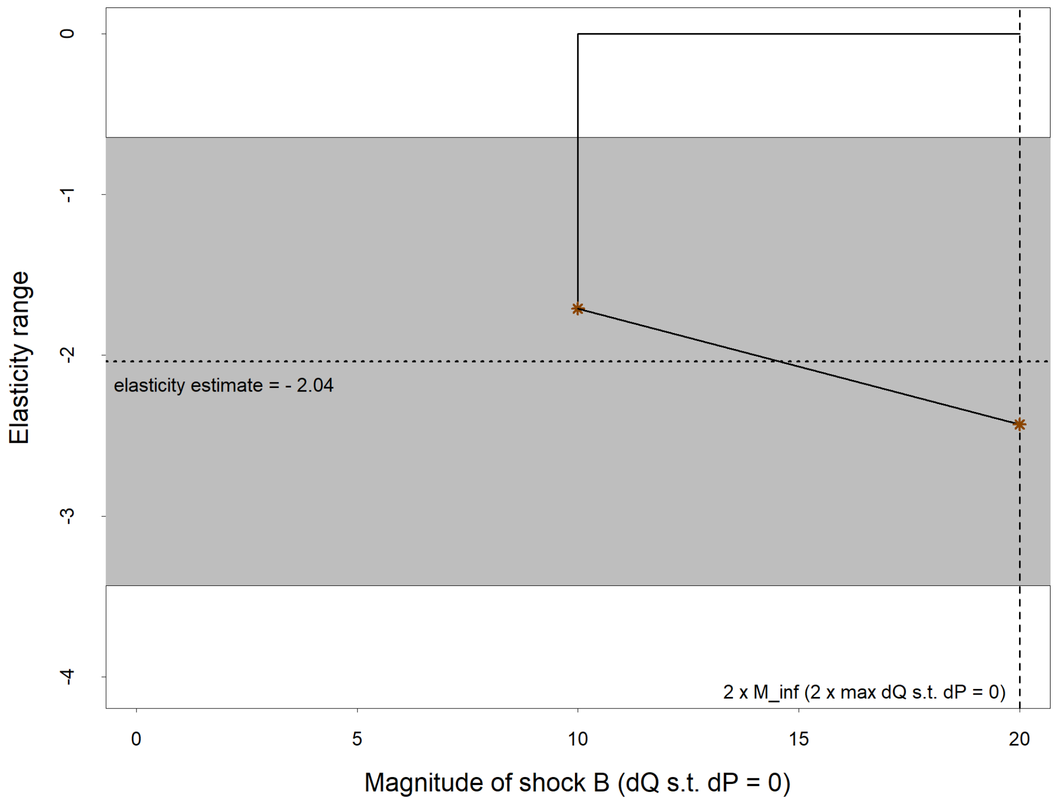

Figure 2: Figure plots the range of honey bee elasticities (when evaluated at mean price and quantity) that are consistent with bounds on the plausible size of shocks to demand ranging from the mean absolute value of the differenced quantity for observations for which the differenced price is equal to zero, to twice the maximum absolute value of the differenced quantity for observations for which the differenced price is equal to zero. The subsample is the same balanced panel of 1,028 farmers that we use in specification (4) in Table 1. The dashed vertical line is at twice the maximum absolute value of the differenced quantity for observations for which the differenced price is equal to zero. The horizontal dotted lines and shaded region depict the point estimates and associated 95% confidence interval, respectively, for the demand elasticity from specification (4) in Table 1.