Journal of Agricultural and Resource Economics 51(3):1–19
ISSN: 1068-5502 (Print); 2327-8285 (Online)
doi: 10.22004/ag.econ.376284

The Economic Effects of Persistent Plant Diseases: The Case of Fire blight

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This paper analyzes the effects of a reduction of stochastic, yet persistent, plant diseases on prices, quantities, profits, and consumer surplus. We differentiate between short-run, unanticipated changes and long-run, anticipated changes since firms can adapt to anticipated changes. A theoretical model illustrates the short-term impacts of a stochastic shock in the severity of the disease and the associated movement along the demand curve. The model also analyzes an expected, persistent change in the disease and the associated long-run impacts of firms' response to a reduction in the disease. Using pear data, we estimate the short-run and long-run effects of a reduction in fire blight. Given the estimated demand elasticity for pears, we find that, in the short-run, consumers would benefit more than producers from a mitigation of fire blight ($5.23 million vs $745 thousand annually from a 1% increase in yield). Once producers adapt to the absence of fire blight, the imbalance would be even more skewed towards consumers ($5.57 million vs $467 thousand).

Key words: Disease, Profits, Consumer Surplus

Introduction

Understanding the economic impact of plant diseases is essential for designing effective mitigation strategies, especially for endemic diseases that exhibit persistence over time, yet vary in severity across growing seasons. Unlike acute, episodic threats, persistent plant diseases introduce a unique duality in grower response: part of their impact is anticipated and incorporated into long-term production decisions, while year-to-year fluctuations remain stochastic and unanticipated, constraining short-run adaptability. This distinction has critical implications for economic welfare, while expected losses may shift average supply and thus be internalized by producers, unanticipated yield shocks do not shift supply in the same way. Traditional damage assessments often rely on simplified loss estimationsâĂŤmultiplying yield reductions by fixed pricesâĂŤoverlooking dynamic producer responses and the price responsiveness of demand. This study contributes to the literature by explicitly modeling the differential welfare impacts of anticipated versus unanticipated yield shocks, using fire blight in U.S. pear production as an empirical case. By allowing prices to adjust in the short-run and modeling long-run supply adaptation, we offer a framework to evaluate the true economic burden of persistent plant diseases, and the distribution of those burdens across producers and consumers.

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Funding for this research project was provided, in part, by the Idaho Agricultural Experiment Station and the USDA-NIFA.

Review coordinated by Vardges Hovhannisyan.

Many endemic plant diseases may occur annually and are expected by producers, but the exact impact of the disease is unknown.[1] Therefore, while some amount of the disease is anticipated, there is also an unanticipated element with very different effects. For example, a uniquely dry season will impact producers and consumers differently than a gradual change in climate since production can try to adjust to the latter. Similarly, plant disease severity can change quickly or gradually. The speed of producer adaptation and the length of what could be considered short-term, may vary greatly by crop. Nonetheless, understanding how production adapts to persistent changes is vital in understanding long-term changes in prices, output, profits, and consumer welfare. We develop a Cournot model that shows both the short-term economic impacts and the long-term impacts after firms have adjusted. We then use cost and demand estimates for pears to estimate the economic impacts of fire blight.

Similarly to how people might adapt or adjust their behavior in the midst of a pandemic, firms might adapt their behavior in the midst of an expected, long-term plant disease. So, while an average level of disease might be accounted for in production decisions, departures from the mean can be seen as stochastic and firms are unable to adapt their production management or cultivated area. Similar to a monopolistic competition setting, in our model, firms are unable to adapt to the disease severity in the short-run, but can adapt to the disease in the long-run.[2]

There have been a wide variety of methods used to find the economic impacts of plant disease. Models such as input-output (I-O), computable general equilibrium, partial equilibrium, cost-benefit analyses are commonly used to estimate the economic damages due to crop diseases (Alam and Rolfe, 2006). Even though a simple way to calculate damages would be to find the product of lost production and the price of that production, many of these studies use various elasticities in the supply chain to find the effects on producers and consumers. In other words, some economic impact studies use exogenous prices while others allow for changes in prices (McDermott, Finnoff, and Shogren, 2013). Our study suggests that using endogenous prices is a good short-run estimate, but supply will adapt with the severity of the disease in the long-run. Therefore, when facing a persistent disease and estimating its long-run effects on profits and consumer surplus, one should consider an expected response from the producer.

Since persistent diseases will lead to changes in supply, a disease can have an ambiguous effect on profits. A tenet of microeconomics is that firms have an incentive to collude and restrict output, however this can happen in a myriad of ways without collusion, one of which is via plant disease. In a similar example, labor strikes may reduce output and increase profits (Carter et al., 1981). While a labor strike for a single firm will decrease profits for that firm, if the labor strike affects a sizable portion of the industry, this can have a similar effect as collusion in that it may increase profits since production is decreased (Gaudet and Salant, 1991). Similarly, an industry wide plant disease, restricts output and could potentially increase profits depending upon the stage of production that it is restricted as well as the elasticity of demand.

Previous research has also analyzed average industry shocks and firms specific effects (Février and Linnemer, 2004). However, these shocks are different from anticipated and unanticipated effects for the industry. In other words, firms may anticipate an “averageâĂİ or persistent shock which consequently leads to adapting their production decisions. However, shocks are not typically “averageâĂİ and will have unanticipated effects. While previous models have focused on firm-specific shocks, the objective of this study is to analyze the effect of unanticipated and anticipated changes assuming they are the same across firms but vary over time.

The impact of pests and plant diseases can be analyzed using the same conceptual framework as the one used to estimate the impact of weather and climate shocks. A growing literature models climate and weather as random drivers of yields and profits, analyzing how agents optimally adjust inputs, land allocation, and technology before shocks materialize, typically assuming prices are

[1] While the term *endemic* may refer to geographic characteristics, we mean that the plant disease is persistent and expected.

[2] The speed with which firm adapt in a Cournot setting may depend upon the complexity of the changes (Barr and Saraceno, 2005) and there could potentially be heterogeneity among firms (Rassenti et al., 2000).

given. Bareille and Chakir (2024) develop a structural profit-maximizing model that disentangles the agronomic impacts of weather on crop yields from the adaptation impacts operating through within-season fertilizer and pesticide choices, showing that farmers' input adjustments can offset a sizable share of projected yield losses induced by warming. Similarly, Wimmer et al. (2024) estimate a structural model of farm-level responses to weather trends, showing how producers adapt input use and technology as they internalize evolving climatic conditions over time. Ghorbani and Atallah (2024) integrate a mechanistic disease spread model and a farm-level optimization problem involving shade level to decompose the total climate impact into direct and indirect, disease-mediated climate impacts on the expected net present value under different production systems and altitudes. That study models climate and disease as stochastic processes, and farmers choose the shade level that maximizes expected returns while the coffee price is exogenous. Crofils, Gallic, and Vermandel (2025) study the dynamic effects of weather shocks on agricultural production, documenting how shocks propagate through time via production and investment decisions rather than being confined to a single season. Kan et al. (2023) embed climate change in a structural econometric framework, linking climate variables to cropland allocation, crop production, output prices, and social welfare. Their framework connects climate-induced production shifts to welfare, operating within a setting where climate acts as an exogenous state variable that influences supply and land use. Letta, Montalbano, and Pierre (2022) emphasize the role of agent expectations and show how weather shocks affect traders' beliefs and food prices, highlighting that production risk transmits to consumers through expectation-driven price dynamics rather than through strategic quantity setting. Across these studies, the probability of risk occurrence is incorporated into production decisions from an ex-ante risk management perspective, decisions are assumed to be made under a known or estimated distribution of shocks, and output prices are treated as exogenous or competitively determined, with no explicit distinction between anticipated and unanticipated components of shocks.

A parallel body of work focuses more directly on plant disease and broader risk-management strategies but shares the same ex-ante risk management perspective. Rhiney et al. (2021) analyze epidemics and the future of coffee production, integrating agronomic modeling and socio-economic analysis to demonstrate how coffee systems face long-term threats from coffee leaf rust and climate change, and how producers and regions adapt along technological and spatial margins. Chort and Öktem (2024)'s analysis of the coffee leaf rust, similarly emphasizes how disease shocks interact with coping policies and land use decisions, showing that agricultural shocks can trigger deforestation and other environmental externalities as farmers adjust their land use portfolios. In the broader risk management literature, Di Falco and Chavas (2009) use a stochastic production framework to show that crop biodiversity reduces exposure to downside yield risk and enhances food security, effectively treating the distribution of bad yield states as an argument for an ex-ante risk management under price-taking behavior.

These studies treat climate and disease as stochastic drivers of production and welfare, incorporating the probability of risk occurrence into production and adaptation decisions from an ex-ante risk management perspective, generally with prices assumed to be exogenous and without formally separating anticipated from unanticipated shocks. The present paper complements the ex-ante risk management literature by focusing on ex-post short and long-term welfare analysis under imperfect competition. Rather than asking how farmers optimally choose inputs, land, or varieties under a given shock distribution, the paper analyzes how a realized plant disease shock affects prices, quantities, producer profits, and consumer surplus in a Cournot oligopoly. The framework explicitly distinguishes between unanticipated shocks, to which firms cannot adjust their initial quantity choices, and anticipated changes in disease prevalence, which are incorporated into firms' potential output decisions, thereby allowing for a decomposition of the total welfare effects into short-run and long-run effects that are absent from the ex-ante risk management literature. Moreover, by endogenizing price through strategic quantity competition rather than treating it as a fixed, the model can characterize how the burden of disease falls on producers versus consumers as a function of demand and market structure, including the possibility that increased disease prevalence may raise producer profits under specific oligopoly conditions while unambiguously harming consumers. In this way, the paper complements existing climate - and disease-risk studies by providing a market-equilibrium perspective on welfare after the shock has occurred, with explicit roles for anticipated versus unanticipated disease and for market power in shaping welfare distribution.

The paper is organized as follows. The next section provides an overview of fire blight and the effects on pear production. Next, we present a theoretical model of the different effects from anticipated and unanticipated changes in production. Then, we estimate supply and demand for pears to calculate the welfare effects of fire blight and consequently the benefits to consumers and producers of strategies to mitigate the disease.

Fire Blight Background

Fire blight is a devastating disease affecting pome fruit in the United States, with losses exceeding $100 million annually (Norelli, Jones, and Aldwinckle, 2003; Vanneste, 2000). These losses are exacerbated over time due to the increased susceptibility of tree varieties, overbearing trees, antibiotic resistance formation, high density production and absence of disease risk analyses (Doukkali et al., 2022; Nischwitz and Dhiman, 2013; Vanneste, 2000).[3]

Effective management of fire blight requires both preventative and therapeutic treatments due to the nature of the disease and the factors influencing its spread and impact. Preventative strategies to minimize the risk of fire blight include planting resistant cultivars and rootstocks (which reduces the likelihood of disease development by using varieties less susceptible to the disease), reducing planting density (which improves air circulation and lowers humidity, thus decreasing disease spread), maintaining balanced plant nutrition (which strengthens the plants, making them less prone to infection), and using disease forecast models (which predict conditions favorable for disease development enabling preemptive actions to mitigate the risk). Implementing these measures helps reduce the initial risk of infection and creates an environment less conducive to disease development. Additionally, they enhance the plants' natural defenses and mitigate conditions that are favorable for bacterial growth and spread (Biggs, 1994; Elkins et al., 2015; Moltman, 2004; Norelli, Jones, and Aldwinckle, 2003).[4]

However, given the aggressive and unpredictable nature of fire blight, preventative measures alone are often insufficient. Therapeutic treatments, such as removing infected branches and limbs during the dormant season (which reduced the number of disease-causing agents (inoculum) in the orchard) and applying antibiotics or bio-pesticides (which combat the bacteria causing the disease)

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[3] *Erwinia amylovora*, the bacterium responsible for fire blight, is primarily transferred from over-wintered cankers to flowers by rain and insects (physical vectors) in early spring (Thomson et al., 1975; Thomson, 1984; Miller, 1983; Johnson and Stockwell, 1998). Small clusters of bacteria multiply and infect the blossoms. Within a few days, the infected blossoms themselves become infectious (Vanneste, 2000). Physical vectors transfer the bacteria to non-infected trees. Meanwhile, within the tree, the infection spreads to other healthy tissues through the vascular system (systemic movement) (Lewis and Goodman, 1965; Gowda and Goodman, 1970; Momol et al., 1999).

[4] Using fire blight-resistant rootstocks is an effective preventive measure to reduce the risk of tree death caused by rootstock blight. For apple trees, planting rootstocks from the Geneva series is recommended (DuPont et al., 2023). Unfortunately, there are no known resistant rootstocks for pears. Therefore, fire blight management in pears revolve around cultural practices and chemical applications. An important preventive step is to prune out old blight cankers during winter. Applying a late dormant treatment can further enhance orchard sanitation by reducing inoculum levels as spring approaches (Elkins et al., 2015).
To minimize the risk of infection, it is recommended to avoid irrigating during bloom and manage weeds and cover crops to lower relative humidity within the orchard. Additionally, removing blossoms in young orchards and late-blooming flowers can decrease the number of flowers on the tree, thereby reducing the likelihood of infection. Promptly cutting out fire blight-infected material is crucial, as once the infection reaches the xylem, tree death becomes imminent (DuPont et al., 2023). Given that weather conditions significantly influence infection risk, growers should follow temperature risk models, which use established thresholds to predict risk levels.
Chemical control includes the use of antibiotics. If the risk of infection is high according to temperature risk models, it is advised to apply antibiotics while rotating active ingredients to prevent antibiotic resistance. Continue antibiotic applications throughout the bloom season and for 1 to 2 weeks after petal fall (DuPont et al., 2023).

are crucial for managing outbreaks when they occur. These treatments directly reduce the bacterial population and help contain the spread of the disease, thereby mitigating severe economic losses (Bantleon et al., 2021). In addition, copper products can serve both as a preventative measure (to protect against infection) and a therapeutic measure (to reduce bacterial populations after infection) depending on the timing and context (Adaskaveg and Gubler, 2008; Adaskaveg, Förster, and Wade, 2011). Combining both preventative and therapeutic strategies ensures a comprehensive approach, addressing the disease before it takes hold and effectively managing it when it does, thereby reducing the probability of anticipated losses (Steiner, 2000; Wallis and Cox, 2020). However, the unpredictable weather patterns can exacerbate the proliferation of the bacteria, even in the presence of preventative and therapeutical measurements, leading to an increase probability of unanticipated losses.

The studies of economic losses associated with fire blight are limited to ex-post estimations of outbreak damages. In fact, the gross tree or yield losses are the common measures to estimate the economic losses (Van der Zwet, 1968). The control costs, extended yield losses, and tree replacement costs are not included in most studies. The historic estimates of economic losses of fire blight date back to the 1920s and 1930s, when disease outbreaks cost pear growers over 2 million dollars in California (Milbrath, 1930) and wiped out 25-50% of mature apple and pear trees in Missouri (Talbert, 1925). In the 1990s and early 2000s, the estimated cost of disease outbreaks summed \$8,400-\$8,900 per hectare in the United States, including the direct cost of tree maintenance and replacement and indirect losses of lost establishment investment and reduced yields over several years (Momol et al., 1999; Norelli, Jones, and Aldwinckle, 2003).

Theoretical Model

Consider a Cournot model with N symmetrical firms, where producers choose potential output, but also anticipate some yield loss from plant disease.[5] A Cournot model is appropriate since the economic effects of interest hinge on producers choosing potential output based on the anticipated plant disease. The market then determines prices based on the final output. Consequently, each firm plants an amount that could yield a potential output, given by q_i. That is, q_i is the amount of the firm's production if there is no plant disease. However, producers expect a reduction in production due to plant disease, which can be represented as an anticipated output, given by $\bar{q}_i$. Finally, $\hat{q}_i$ represents the firm's actual output. So, the difference between q_i and $\bar{q}_i$ is the anticipated loss from the plant disease and the difference between $\bar{q}_i$ and $\hat{q}_i$ is the unanticipated gain/loss. We assume that producers base their decisions on anticipated output rather than unanticipated shocks.[6] $\bar{\alpha}$ represents the expected percentage of yield lost from plant disease for all producers where $0 < \bar{\alpha} < 1$ and $1 - \bar{\alpha} = \bar{q}_i/q_i$. Similarly, the expected aggregate output for all firms, accounting for the plant disease, is given by $(1 - \bar{\alpha}) \sum q_j = \bar{Q}$. Expected inverse demand is given by $\bar{p} = a\bar{Q}^b$, where a and b are parameters such that $a > 0$ and $b < 0$.

To allow for variation in the cost of diseased and non-diseased production, there are two types of marginal costs: non-harvesting production costs (c_p) and harvesting costs (c_h). Diseased production is not harvested and only has a cost of c_p while non-diseased production has a cost of $c_p + c_h$.

Firm i's expected profit function is then given by,

$$\pi_i = (1 - \bar{\alpha})q_i a\bar{Q}^b - (1 - \bar{\alpha})c_h q_i - c_p q_i \tag{1}$$

[5] For example, a firm might choose acres planted, anticipating some loss from disease.

[6] Given the nature of *unanticipated* effects, it would be impossible for producers to fully account for these shocks in production. However, one could model the distribution of unanticipated shocks and producers could adjust their behavior based on expected values of a non-linear profit function. For simplicity, we assume producers base decisions on anticipated loss from the disease.

The marginal effect of a change in potential quantity on profit is given by,

$$\frac{\partial \pi_i}{\partial q_i} = a(1-\bar{\alpha})^{b+1}\left[q_i b\left(\sum q_j\right)^{b-1} + \left(\sum q_j\right)^{b}\right] - (1-\bar{\alpha})c_h - c_p \tag{2}$$

which gives the usual result that more potential production will increase output, reduce price, and increase costs. If firms set the marginal impact of potential output to zero, and given the symmetry of the firms, the equilibrium potential output for the firm is given by,

$$q = \frac{1}{N}\left[\frac{(1-\bar{\alpha})c_h + c_p}{a(1-\bar{\alpha})^{b+1}\left[\frac{b}{N}+1\right]}\right]^{1/b} \tag{3}$$

Since $\bar{Q} = (1-\bar{\alpha})Nq$, this implies aggregate potential output is given by,

$$\bar{Q} = \left[\frac{(1-\bar{\alpha})c_h + c_p}{a(1-\bar{\alpha})\left[\frac{b}{N}+1\right]}\right]^{1/b} \tag{4}$$

and the associated price is given by,

$$\bar{p} = \frac{(1-\bar{\alpha})c_h + c_p}{(1-\bar{\alpha})\left[\frac{b}{N}+1\right]} \tag{5}$$

Price and quantity can be imputed into equation (1) to find the equilibrium profit for firms. We define consumer surplus as the area under the demand curve between the equilibrium price and an arbitrary higher price, p_1, such that,

$$CS = p_1 Q_1 + \int_{Q_1}^{\bar{Q}} aQ^b\, dQ - \bar{p}\bar{Q} = \frac{b}{b+1}[p_1 Q_1 - \bar{p}\bar{Q}] \tag{6}$$

This functional form allows us to estimate the consumer surplus for various levels of plant disease without using an improper integral.[7]

Unanticipated Gain/Loss From Disease

We now analyze economic effects from unanticipated changes, so that firms cannot adjust their production decisions. Mathematically, q_i is a function of $\bar{\alpha}$, as shown in equation (3), instead of $\hat{\alpha}$. Therefore, an unanticipated amount of disease would cause an unexpected shift in supply and also impact costs. We assume this unexpected shift impacts producers the same, such that all producers still have the same yield as each other. Since $\hat{\alpha}$ represents the actual shock, the disease will actually decrease yield for each firm by $\hat{\alpha}q$. Consequently, the actual yield can be represented as

$$\hat{Q} = (1-\hat{\alpha})Q \tag{7}$$

Therefore, aggregate profit is given by,

$$\Pi = (\hat{p} - c_h)\hat{Q} - c_p Q \tag{8}$$

and the effect of the disease on aggregate profits is given by,

$$\frac{\partial \Pi}{\partial \hat{\alpha}} = Q[c_h - (b+1)\hat{p}] \tag{9}$$

[7] Q_1 can be any value greater than zero and less than $\bar{Q}$. However, the value is undefined if $b = -1$.

First, $-Q(b+1)\hat{p}$ represents the change in revenue and the sign of this is dependent upon demand elasticity, b. Equation (9) shows the common result that an increase in production (a decrease in $\hat{\alpha}$) will increase revenue if demand is elastic, but will decrease revenue if demand is inelastic. So, if demand is inelastic, revenues would increase when the disease is worse. Second, there are cost savings with an unexpected increase in plant disease. These effects are relatively straightforward since it does not impact any production decisions.

The changes in consumer surplus are given by,

$$\frac{\partial CS}{\partial \hat{\alpha}} = bQ\hat{p} < 0 \tag{10}$$

so that an unanticipated increase in the disease decreases consumer surplus.

Anticipated Loss From Disease

In the case of a change in the anticipated disease, producers will adapt. The speed of this adaptation may vary by crop. For example, in the case of pears, the production cycle lasts many years, in which case the long-run equilibrium may not occur for some time. Adaptations may take the form of tree removal or tree planting, but in the theoretical model, we assume that anticipated loss means that producers have been allowed to fully adapt to those anticipted losses.

In this scenario, the effect of an increase in the prevalence of the disease on the firm's initial production is given by,

$$\frac{\partial q}{\partial \bar{\alpha}} = \frac{q}{b} \frac{b(1-\bar{\alpha})c_h + (b+1)c_p}{(1-\bar{\alpha})[(1-\bar{\alpha})c_h + c_p]} \tag{11}$$

This equation shows the effect of a change in the *anticipated* disease on *potential* output. Furthermore, it is not clear if the sign of the derivative is positive or negative. That is, if growers expect a high level of disease, they may either increase or decrease potential production depending upon the costs, the slope of demand, and the number of firms. For example, if demand is extremely inelastic, the a high rate of disease may create more potential production to meet quantity demanded. On the other hand, more disease might increase costs sufficiently that very few consumers are willing to pay for the good.

The effect of an increase of anticipated disease on yield is given by,

$$\frac{\partial \bar{Q}}{\partial \bar{\alpha}} = \frac{\bar{Q}}{b(1-\bar{\alpha})} \frac{c_p}{(1-\bar{\alpha})c_h + c_p} \tag{12}$$

Which is negative, so, while there is an ambiguous effect on q, potential output, the long term effect of the disease is a decrease in actual yield. In other words, as the disease increases, there could be an increase in initial production, but expected yield decreases.

The change in price is given by,

$$\frac{\partial p}{\partial \bar{\alpha}} = \frac{c_p}{(1-\bar{\alpha})^2 \left[\frac{b}{N} + 1\right]} \tag{13}$$

and the effect on profits is given by,

$$\frac{\partial \Pi}{\partial \bar{\alpha}} = \frac{\bar{Q}c_p}{1-\bar{\alpha}} \left[\frac{N-1}{(1-\bar{\alpha})(b+N)} - 1\right] \tag{14}$$

The sign of equation (14) is ambiguous, implying that reducing the incidence of disease may increase or decrease profits. For example, for a monopolist ($N = 1$), an increase in the disease unambiguously decreases profits. In a competitive market ($N = \infty$), the effect goes to zero. This must be the case, since in a competitive market, a persistent plant disease simply results in a shift in aggregate supply, but any profits are still competed away. Consequently, all of the cost of the disease is borne by consumers. However, there are cases in an oligopoly where an increase in the disease increases profits. Consequently, if market power is present there will be an impact on the disease on profits, although the sign of those effects are ambiguous.

The effect on consumer surplus is given by,

$$\frac{\partial CS}{\partial \bar{\alpha}} = -b\bar{p}\frac{\partial \bar{Q}}{\partial \bar{\alpha}} < 0 \tag{15}$$

thereby showing that consumer surplus unambiguously increases as the disease decreases.

If changes in the severity of the disease is unanticipated, the impact of a change on profits is dependent upon demand elasticity and harvest costs. However, the impact from anticipated changes also depends upon production costs and the degree of market power in the market. This makes intuitive sense since any response from firms depends on the number of firms and their market power. So, while a monopolist would want the disease eradicated, they do not necessarily want an unexpected decrease in the disease since they may have over produced the good. Similarly, a very competitive market may not care about anticipated changes since profits are zero regardless, but profits could increase or decrease from unanticipated shocks.

The comparison of unanticipated vs. anticipated changes in the disease might be thought of as short-term effects vs. long-term effects. Similar to an economic model of monopolistic competition, firms are more likely to adjust to the disease in the long-run, although the speed of the adaptation may vary by crop. The time difference between the short and long-run would depend upon the speed at which producers are able to adapt to persistent changes of the severity of the disease.

Empirical Estimation

To empirically estimate the theoretical model, non-harvesting production costs, harvesting costs, and demand estimates are needed. Supply is estimated to alleviate identification concerns regarding the demand estimation, however, it is not necessary to identify which shifts in supply are due to anticipated or unanticipated shifts. Rather, demand and cost estimates are sufficient to use the theoretical model and estimate changes in output, prices, profit, and consumer welfare in both the short-run and long-run.

The analysis draws on weekly data from the Washington State Tree Fruit Association (WSTFA), from the 2014-15 season to the 2021-22 season, to estimate supply and demand relationships for fresh pears. The dataset includes variety-specific observations for three primary pear cultivarsâĂŤBartlett, Bosc, and D'Anjou. For each cultivar and week, the data report the total volume of shipments, measured in 44-pound box equivalents, along with the corresponding average price per 44-pound box. The panel is unbalanced due to seasonal gaps in shipments, depending on the production volume, availability of each variety differs across the year. In terms of fire blight, the years in the sample include a variety in the severity of fire blight in Washington State.[8] Our empirical estimates rely on Washington pear markets because Washington provides the most consistent long-run data on disease incidence, prices and quantities. Nevertheless, production structures, disease pressure, and market responses may differ across other pear-producing regions.

[8] Washington orchard records indicate that minor fire blight outbreaks have occurred annually since 1991, while serious damageâĂŤaffecting roughly 5âĂŞ10% of orchardsâĂŤwas documented in 1993, 1997, 1998, 2005, 2009, 2012, 2015, 2016, 2017, and 2018. Within the 2014âĂŞ2022 window, the years 2015 through 2018 stand out as clearly identified statewide epidemic years for both apples and pears, each associated with severe, region-wide infections consistent with the âĽĚ5âĂŞ10% orchard-damage benchmark reported by extension specialists (DuPont et al., 2024). Also, WSU field trials document extremely high infection pressure in 2022 under warm bloom conditions, with some treatments underperforming relative to streptomycin under these âĂIJextremely highâĂİ pressure scenarios (DuPont, 2025).

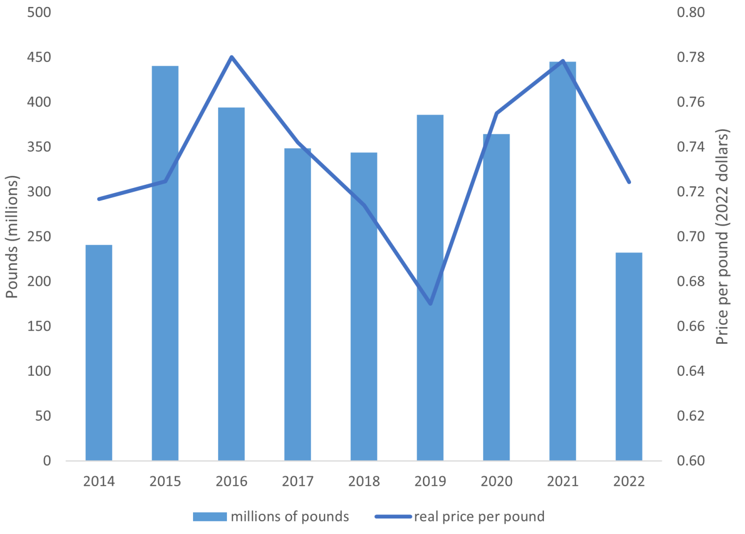

Figure 1. Pounds and prices per pound from the Washington State Tree Fruit Association by year

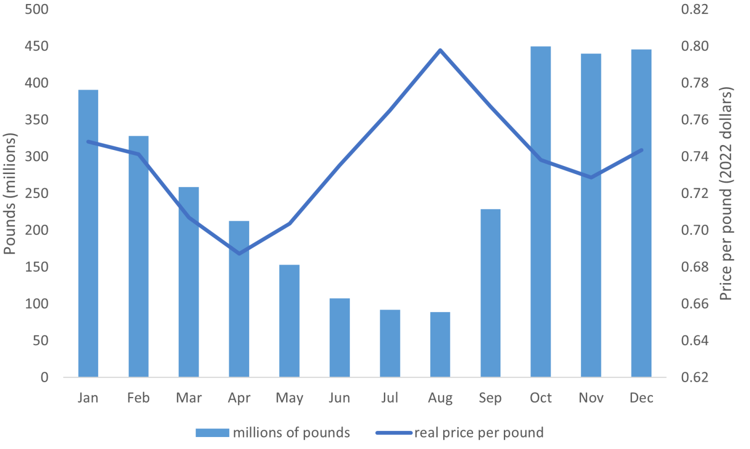

Figure 2. Pounds and prices per pound from the Washington State Tree Fruit Association by month

As a result, extrapolating welfare changes to the national level should be interpreted as illustrative rather than definitive. The results are dependent upon the assumption that the elasticity of demand for Washington pears is similar to the elasticity of demand in the national pear market.

We use these data to estimate demand for pears and then use those estimates to calculate the economic effects of unanticipated and anticipated changes in fire blight. Figure 1 shows the quantities shipped in pounds and price per pound of pears over the sample period. The amount of production ranges from 232 million pounds (5.3 million 44-pound boxes) in 2022 to 445 million pounds (10.1 million 44-pound boxes) in 2021. However, 2022 shows lower production because it only shows data from the 2021-2022 season and not the 2022-23 season. Figure 2 shows monthly pounds shipped and prices per pound, indicating clear seasonality in the pear market.

This data represents 27% of pear production in the United States.[9] The data used to estimate demand elasticity for pears, which is then applied to the national market. For national production,

[9] This is calculated by comparing these data with NASS production data for the corresponding years.

we use a value of 1.25 billion ($1.25 * 10^9$) pounds of produced pears, which is the value the National Agricultural Statistics Service (NASS) gives for 2025.[10]

Regression Model

To apply the theoretical model, an estimate of demand and costs are required. We estimate supply and demand for pears and then use the estimates for demand elasticity to estimate the effects of anticipated and unanticipated changes in fire blight. The WSTFA data give weekly shipment quantities along with prices negotiated by the packinghouse on behalf of the grower for the Bartlett, Bosc, and D'Anjou varieties.[11] For each of these varieties, the data provide total 44 lb equivalent boxes and the average price of a 44 lb box. The data are then converted into pounds and pricr per pound. The supply and demand models include other supplemental variables.

The supply estimation is given by,

$$\begin{aligned} ln(p_{it}) = \beta_0 + \beta_1 ln(q_{it}) + \sum_{m=2}^{12} \beta_m MONTH_t + \beta_{13} FFR_t + \beta_{14} ln(PPI_{t-12}) \\ + \beta_{15} ln(LV_{t-12}) + \sum_{y=16}^{23} \beta_y YEAR_t + \sum_{b=24}^{25} \beta_b TYPE_i + \epsilon_{it} \end{aligned} \tag{16}$$

where p_{it} represents the real price per pound of pears for type i in time t, and q_{it} is the number of pounds shipped during that week. q_{it} is included in the model to capture the relationship between price and quantities supplied. $MONTH_t$ is the month of the shipment which included every month but October, which was omitted to avoid perfect multicollinearity among the monthly indicators. Monthly fixed effects capture the seasonal pattern in pears due to harvest time, storage, and marketing cycles. Pears are harvested once annually and shipped over a marketing season; therefore, supply fluctuates across months. FFR_t is the federal funds rate for the month and acts as a proxy for macroeconomic conditions, borrowing costs, and the cost of storage. If the cost of storage changes, this can impact the amount of pears on the market. PPI_{t-12} is the pear producer price index lagged by 12 months, and reflects past market returns to growers.[12] Pear producer price index serves as a proxy for price expectations. This variable is indexed to a starting point (1982=100) and is logged for the estimation. LV_{t-12} is the previous year's Land Value since the price of land can be seen as an opportunity cost for growers.[13] High land values indicate supply-side pressure or broader market conditions affecting agricultural production incentives. This variable is in dollars per acre and is also logged for the estimation. Yearly fixed effects are also used as well as dummy variables for the type of pear. $TYPE$ includes variables for Bartlett and Bosc while D'Anjou is omitted due to dependency. All continuous variables that are not a percentages are logged.

Two of the variables are lagged since pears have a long production process. Given the condition of perennial crops, current production decisions (e.g., input use, labor hiring, marketing volume) are often based on price expectations formed from past prices, especially prices observed in the previous harvest season. A 12-month lag aligns with the annual production cycle: decisions for the current season (e.g., pruning, thinning, harvesting intensity) are likely influenced by last year's prices. Land value reflects long-term capital costs and opportunity cost of land use. These values typically influence long-term investment decisions, such as whether to maintain, remove, or replant

[10] From 2015 to 2024, annual production averaged 1.397 billion pounds, but was falling over that time period, https://www.nass.usda.gov/Charts_and_Maps/Noncitrus_Fruits/histuppr.php. In 2025, NASS gives a value of 625,000 tons of production for pears, https://quickstats.nass.usda.gov/results/01C6E1C3-FEC7-3507-A9E3-CAF868061E59.

[11] The data used is for non-organic pears. While organic pears were reported in the data, it was not used due to the small quantities produced of organic pears.

[12] This data can be found at, https://fred.stlouisfed.org/series/WPU01110221.

[13] This data is yearly and can be found at, https://www.nass.usda.gov/Publications/Todays_Reports/reports/land0821.pdf.

an orchard block. The use of a 12-month lag acknowledges that changes in land value do not affect short-term production directly, but may influence annual planning decisions, such as allocating land to pears versus other crops or leaving land fallow.

The empirical specification of the demand function was as follows:

$$\begin{aligned} ln(q_{it}) = \gamma_0 + \gamma_1 ln(p_{it}) + \gamma_2 ln(FAO_t) + \gamma_3 ln(FV_t) + \gamma_4 ln(GROCERIES_t) \\ + \gamma_5 ln(WAGES_t) + \gamma_6 ln(IMPORTS_t) + \gamma_7 ln(EXPORTS_t) \\ + \sum_{y=8}^{15} \gamma_y YEAR_t + \sum_{b=16}^{17} \gamma_b TYPE_i + \epsilon_{it} \end{aligned} \tag{17}$$

Economic theory predicts a negative relationship between quantity demanded and own price. The coefficient estimate for this variable represents the price elasticity of demand. FAO_t represents the FAO food price index and reflects the overall level of global food prices and is often used as a proxy for the price of substitutes and complements.[14] This index could have a substitution and income effect. Substitution: if pear prices are lower compared to other global fruit prices, then demand for pears increases. Income: If higher food prices reduce real income, this can potentially reduce the demand for pears. This variable is indexed so that 2014-16 = 100. FV_t is also a food index and is similar to the FAO food price index, but it is indexed so that 1982-84 = 100 and it is specifically for fruits and vegetables. Therefore this variable may have an additional effects to the FAO index.[15] $GROCERIES_t$ is the amount spent on groceries in the U.S. per capita. This variable controls for the types of food purchased, especially during the Covid era.[16] $WAGES_t$ is aggregate U.S. wages divided by population and serves as a proxy for income, capturing income effects on demand.[17] $IMPORTS_t$ and $EXPORTS_t$ represent imports and exports of pears in and out of the United States. The data are from the Global Agricultural Trade System (GATS) and converted into pounds. Imported pears represent a close substitute for U.S. pear producers. Pear exports represent the size of the foreign market for U.S. pear producers. Both may impact demand for pears.[18] Year fixed effects capture unobserved temporal effects such as changes in consumer preferences, technology, advertising, etc. Product type captures unobserved heterogeneity across different varieties of pears, that differ in taste, appearance, availability, and consumer appeal. As with supply, all continuous variables that are not a rate are logged. Because equations (16)-(17) represent a system of over-identified simultaneous equations, a three-stage least squares estimation procedure was used to obtain estimates of the parameters of the model.

Estimation Results

Table 1 gives the summary statistics of the data. The mean price of a pound of pears, in 2022 dollars, was 0.728 dollars. On average, each observation shows just over 2.5 million pounds of pears shipped for the week for that variety within the WSTFA. While imports and exports are also in pounds, it is important to note that those averages are for the month for all varieties of pears. Table 1 also shows that 27.9% of observations are Bartlett pears and 32% are Bosc pears (the remaining 40.1% are D'Anjou pears).

Table 2 shows the regression results. For the supply estimation, the estimate for quantity was -0.007 and was insignificant from zero, implying an elastic supply curve. Fixed effects for July, August, and September were significant at the 5% level. The coefficients for the Federal Funds

[14] This variable can be found at https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

[15] This variable can be found at https://fred.stlouisfed.org/series/CUSR0000SAF113.

[16] This variable can be found at https://fred.stlouisfed.org/series/RSGCSN. This data was then divided by population, https://fred.stlouisfed.org/series/POPTHM.

[17] This variable can be found at https://fred.stlouisfed.org/data/A576RC1.txt.

[18] This variable can be found at https://apps.fas.usda.gov/gats/ExpressQuery1.aspx.

Table 1. Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Price	0.728	0.120	0.285	1.317
ln(Price)	-0.331	0.167	-1.254	0.275
Quantity	2,560,284	2,037,222	176	8,364,677
ln(Quantity)	13.923	1.995	5.170	15.940
Constant	1.000	0.000	1	1
January	0.097	0.297	0	1
February	0.089	0.285	0	1
March	0.088	0.284	0	1
April	0.071	0.257	0	1
May	0.067	0.250	0	1
June	0.052	0.223	0	1
July	0.051	0.221	0	1
August	0.082	0.275	0	1
September	0.101	0.301	0	1
November	0.092	0.289	0	1
December	0.111	0.314	0	1
Fed Funds Rate	0.792	0.804	0.050	2.420
Lagged PPI	144	17	110	204
ln(Lagged PPI)	4.961	0.115	4.696	5.316
Lagged Land Value	3592	96	3364	3758
ln(Lagged Land Value)	8.186	0.027	8.121	8.232
2015	0.125	0.331	0	1
2016	0.128	0.334	0	1
2017	0.129	0.335	0	1
2018	0.122	0.327	0	1
2019	0.122	0.327	0	1
2020	0.123	0.328	0	1
2021	0.126	0.332	0	1
2022	0.070	0.256	0	1
Bartlett	0.279	0.449	0	1
Bosc	0.320	0.467	0	1
FAO food price index	121	13	105	165
ln(FAO food price index)	4.792	0.104	4.658	5.105
Fvcpi	356	10	341	381
ln(FVcpi)	5.874	0.028	5.832	5.944
Groceries	206	12	183	253
ln(Groceries)	5.327	0.056	5.211	5.532
Wages	32,067	1,362	29,285	34,677
ln(Wages)	10.37	0.04	10.28	10.45
Imports	13,573,354	12,012,538	618,837	52,741,345
ln(Imports)	16.026	0.931	13.336	17.781
Exports	26,364,832	11,123,521	6,132,000	61,845,000
ln(Exports)	16.989	0.466	15.629	17.940

Rate and Lagged PPI were also statistically significant. Many of the year effects were significant and the coefficient for Bartlett pears was statistically significantly significant, indicating supply is statistically different from D'Anjou pears.

On the demand side, many of the variables were statistically significant. The FAO food price index, the fruits and vegetables consumer price index, per capita grocery sales, pear imports, and pear exports were all significant at the 5% level. Since all of these variables are logged, the coefficients represent percentage changes. None of the year indicator variables were statistically significant. Demand for Bartlett and Bosc pears were significantly less than D'Anjou pears.

The estimate of price on quantity demanded is -1.827. This allows us to use the theoretical model and construct a national demand for pears. However, since the data only represents a subset of the national market, the estimated elasticity is used with the national quantity numbers, which is approximately 1.25 billion pounds of pears produced. Using the estimated elasticity, we get an estimate of $b = \frac{1}{-1.827} = -0.547$. Since the average price per pound was 0.728 dollars and there were 1.25 billion pounds in the market, we further estimate that $a = \frac{.728}{1.25^{-0.547}} = 0.823$. Therefore, our demand estimate is given by $p = 0.823\bar{Q}^{-0.547}$ where p is price per pound and $\bar{Q}$ is in billions of pounds.[19]

Effects of Fire Blight

Non-harvest production costs and harvest costs were estimated using 2022 enterprise budgets (Gallardo, Galinato, and Nottingham, 2022).[20] If a 10 percent discount rate is used, non-harvest production costs are estimated to be 0.363 dollars per pound and harvest costs are estimated to be 0.272 per pound of pears. These cost estimates are used for an average sized firm, although these costs may vary depending on the size of the firm due to economies of scale. In particular, non-harvest costs may vary due to the size of the firm due to economies of scale. However, harvest costs are largely proportional to the size of the firm.

Using these numbers and equation (5), we can find the market structure for various levels of $\bar{\alpha}$ (the expected loss from disease). In other words, if firms are maximizing profit, we can extrapolate the number of firms in the market given prices, output, costs, and disease rates.[21] Thus, even if the exact rate of disease is unknown, we can estimate the effects of the disease at various initial disease rates. Given the average prices and costs, $\bar{\alpha}$ should be between 0 and 0.2039. In other words, if the expected loss from fire blight is more than 20.39%, then we would expect firms to have negative profits since $(1 - 0.2039) * 0.728 - 0.363 - (1 - 0.2039) * 0.272 = 0$. This disease rate, given these prices and costs, would be consistent with a perfectly competitive market with no profits and in infinite number of firms. Conversely, an $\bar{\alpha}$ of 0 would indicate $N = 4.282$. That is to say that the profit margin, under the assumption that fire blight has no impact, would be consistent with the profit margin found in an industry with 4.282 symmetrical firms.

We now analyze three different scenarios related to changes in production due to anticipated and unanticipated effects of plant disease. The first scenario uses the assumption that there is no change in price. While this is unrealistic, it is simple and sometimes used as an estimate of economic impact. The second scenario uses the demand curve to find the change in price, but assumes no response from firms in their production other than direct effects from a change in disease. In this scenario, the disease directly reduces output, but the growers do not respond to the disease. Therefore, non-harvest costs will not change, but harvest costs are dependent upon the severity of the disease. The

[19] We use the price per pound and use billions of pounds for mathematical simplicity, but any changes in price are not dependent upon units, but rather the percentage change in quantity. For example, if the price per pound is 0.728, than an change in output of $x\%$ would yield a new price of $0.728(1 + x)^{-0.547}$. Therefore, results do not depend on consistency of units between p and $\bar{Q}$.

[20] The budget can be found at https://wpcdn.web.wsu.edu/cahnrs/uploads/sites/5/FS034E.pdf

[21] While equation (5) allows us to infer the number of firms, it may be more accurate to say that the level of market power is inferred. The model assumes symmetrical firms and does not model a supply chain. Regardless, N is used as a proxy for market power, which allows us to simulate the output effects from a change in the rate of the disease.

Table 2. Supply and Demand Estimation

	Parameter Estimate	Standard Error	t-Statistic
Supply			
Constant	−3.741	5.405	−0.692
ln(Quantity)	−0.007	0.017	−0.428
January	0.003	0.025	0.127
February	0.025	0.023	1.056
March	−0.055*	0.031	−1.776
April	−0.046	0.030	−1.556
May	−0.036	0.037	−0.967
June	−0.011	0.048	−0.219
July	0.177***	0.058	3.029
August	0.130**	0.059	2.207
September	0.085***	0.032	2.674
November	−0.010	0.019	−0.530
December	−0.004	0.018	−0.214
Fed Funds Rate	−0.077***	0.014	−5.656
ln(Lagged PPI)	−0.347***	0.075	−4.633
ln(Lagged Land Value)	0.634	0.656	0.966
2015	−0.006	0.052	−0.122
2016	0.119**	0.057	2.066
2017	0.096*	0.049	1.957
2018	0.127***	0.046	2.752
2019	0.053	0.050	1.055
2020	0.048	0.040	1.204
2021	0.103***	0.022	4.638
2022	0.045	0.028	1.626
Bartlett	0.065**	0.028	2.335
Bosc	−0.001	0.035	−0.027
Demand			
Constant	−150.411***	50.378	−2.99
ln(Price)	−1.827**	0.929	−1.966
ln(FAO food price index)	2.760**	1.394	1.979
ln(FVcpi)	9.184**	4.454	2.062
ln(Groceries)	−3.152***	1.141	−2.763
ln(wages)	7.460*	4.418	1.689
ln(Imports)	0.134**	0.067	2.009
ln(Exports)	2.011***	0.145	13.874
2015	0.322	0.395	0.815
2016	0.824	0.480	1.716
2017	0.555	0.520	1.067
2018	0.715	0.658	1.085
2019	0.559	0.761	0.735
2020	1.196	0.770	1.553
2021	0.960	0.778	1.233
2022	−0.024	0.754	−0.032
Bartlett	−1.357***	0.140	−9.721
Bosc	−1.904***	0.114	−16.649
R^2 - Supply	0.341		
R^2 - Demand	0.378		
Observations	1109		

Notes: *, **, *** denote statistical significance at the 10%, 5%, and 1% level respectively

Table 3. Fire blight Simulation

	Constant Price			Changing Price				Changing Production & Price			
percentage loss	$\bar{Q}$	p	Π	$\bar{Q}$	p	Π	CS	$\bar{Q}$	p	Π	CS
0	1316	0.728	122.4	1316	0.708	95.8	279.9	1320	0.707	94.7	281.4
0.01	1303	0.728	116.4	1303	0.712	95.2	274.8	1306	0.711	94.2	276.0
0.02	1289	0.728	110.4	1289	0.716	94.5	269.7	1292	0.715	93.8	270.6
0.03	1276	0.728	104.4	1276	0.720	93.8	264.5	1278	0.719	93.3	265.2
0.04	1263	0.728	98.4	1263	0.724	93.1	259.3	1264	0.724	92.8	259.6
0.05	**1250**	**0.728**	**92.4**	**1250**	**0.728**	**92.4**	**254.1**	**1250**	**0.728**	**92.4**	**254.1**
0.06	1237	0.728	86.4	1237	0.732	91.6	248.8	1236	0.733	91.9	248.5
0.07	1224	0.728	80.4	1224	0.737	90.8	243.5	1222	0.737	91.4	242.8
0.08	1211	0.728	74.4	1211	0.741	90.0	238.2	1208	0.742	90.9	237.0
0.09	1197	0.728	68.4	1197	0.745	89.1	232.9	1193	0.747	90.5	231.2
0.1	1184	0.728	62.4	1184	0.750	88.3	227.5	1179	0.752	90.0	225.4

third scenario analyzes what might be considered longer term effects and uses the theoretical model to estimate effects if firms respond by changing their production capacity. In this situation, both harvest and non-harvest costs can change.

We assume that the current loss from fire blight is 5%. In other words, base case is that 5% of production is typically lost to fire blight so initially, $\bar{\alpha} = .05$. Using equation (4), this gives us a level of market power consistent with 5.392 firms in the market.[22] The number of firms is then used to calculate the expected long-term quantity adjustment. As the percentage loss from fire blight changes, the number of firms used in the calculations remains constant. That is to say, the level of market power is calculated using the assumed current state of 5% loss, but the level of market power does not change as the loss from fire blight changes.

Table 3 shows the effects of a fire blight reduction on output, prices, profits, and consumer surplus and Figures 3 and 4 show the marginal effects. Therefore, in the first scenario with no change in price, the increase in revenue from completely eliminating fire blight would be equal to $30 million annually (from profits of $92 million to $122 million). This is because 66 million additional pounds would be produced at a price of $0.728 per pound and a harvesting cost of $0.272 per pound. However, this result is sensitive to the assumption that 5% of production is lost from fire blight. If we look at a 1% increase in yield due to a reduction in fire blight, the effects would be a $6 million increase in profits due to 13 million more pounds of pears.[23] Because of the constant price assumption, we do not include in the analysis the estimation of consumer surplus.

In the second scenario, quantity still increases at the same rate as the first scenario, but price decreases. In this situation, changes from disease are unanticipated and the percentage loss from fire blight is $\hat{\alpha}$. With these unanticipated or short term changes, the changes to profits are dependent upon the elasticity of demand, which was estimated to be -1.827. If fire blight were eliminated, we estimate the price of pears would be $0.708 per pound. Given the price elasticity, revenue increases as production increases. Consumer surplus is calculated between the price given in the table and a price of one dollar per pound. Since $Q = (\frac{p}{a})^{1/b}$, by setting $p_1 = 1$, it reduces equation (6) to $CS = \frac{1}{a^{1/b}} \frac{b}{b+1}[1 - p^{\frac{b+1}{b}}]$, which is what is used for the consumer surplus estimations. While a difference reference price will give a different value for consumer surplus, this allows us to calculate changes in consumer surplus. In this scenario, reducing fire blight so that yield increases 1% would increase profits by $745,000 and consumer surplus would increase by $5.23 million.

[22] While 5.392 firms might seem low given the number of pear growers, output may be influenced by downstream firms. In other words, while there are clearly more than 5.392 pear producers, it could be that there exists the level of market power associated with 5.392 symmetrical firms because of the asymmetry of size and/or market concentration in downstream packers. For example, Winfree et al. (2004) found seasonal market power in the pear market.

[23] This would be a 1% increase in relation to the potential output. For example, actual output would go from 95% to 96% of potential output, meaning that output would increase 1.0526% from the baseline output.

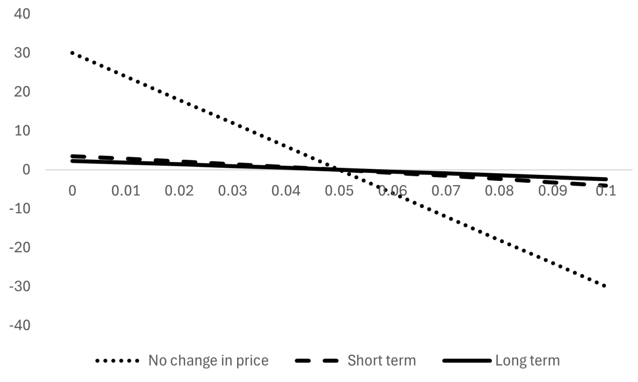

Figure 3. Yearly changes in profit under various assumptions (in millions)

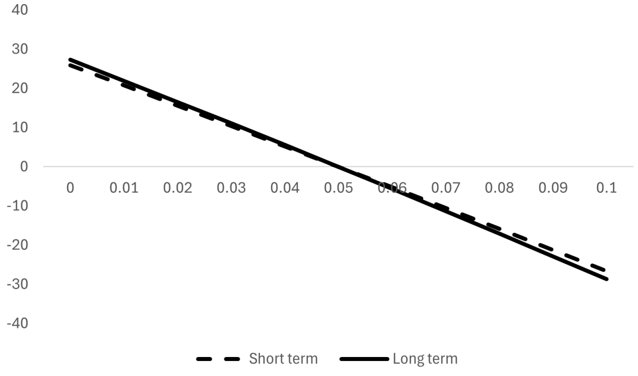

Figure 4. Yearly changes consumer surplus under various assumptions (in millions)

The third scenario incorporates changes from production decisions by the firms. This would be the equivalent in a change in $\bar{\alpha}$, the expected loss from fire blight. As fire blight decreases so that yields increase by 1%, output increases by 14 million pounds. This is slightly more than a 1% increase in output because firms adjust and firms will plant more pear tress as fire blight decreases. Thus, there are more pears sold because more trees are being planted and fewer of the trees are diseased. This result is not obvious and depends on the elasticity of demand. Since more pears are being brought to the market, price decreases slightly more in scenario 3 than scenario 2. In this scenario, reducing fire blight so that yield increases 1% would increase profits by $467,000 and consumer surplus would increase by $5.57 million.

In the second and third scenarios, the changes in profits and consumer surplus are not dramatically different. In both scenarios, consumers gain much more than firms. Yet, the long-term adjustment from firms shifts the benefits even more to consumers. The magnitude of the numbers are dependent upon how much the reduction of fire blight is able to increase yields.

Conclusions

This paper shows that the economic effects of disease may differ between unanticipated or anticipated disease-related losses. With unanticipated losses where the firms cannot adjust their production capacity, the effects on profits depend upon the elasticity of demand and harvest costs. However, if a change in a disease is permanent and the firm changes their production behavior based on new disease levels, the effects depend on market power and the scale of the effects can be different.

In the case of fire blight, we estimate that a reduction in the severity of fire blight would not only increase the number of marketed pears, but also result in an increase in the number of trees/acres planted. We show that the elasticity of demand and harvesting costs are such that a decrease in fire blight would increase profits both in the short- and long-run, although long-run profits are smaller than in the short-run. Finally, we show that consumer surplus increases more in the long-run than the short-run. While the estimated changes in profits and consumer surplus for pears were not dramatically different between short-run and long-run, differences could be large for production changes in other commodities depending on the estimates.

The implications of the study rely on the inclusion of anticipated and unanticipated disease-related losses and how these level of anticipation relates with the short- and long-term disease impact. This dynamic aspect is often not included when estimating disease impacts. The study findings also show how firms could adapt production strategies in view of persistent changes in disease prevalence. Understanding these adaptations provides insights into long-term industry behavior and profitability. This model and estimation can help with the estimation of the economic impact of various agricultural diseases. Also, the model could be easily adapted to other factors that impact production such as weather/climate or agronomic technology.

Our findings indicate that consumers capture the majority of the welfare gains from a reduction in fire blight, both in the short-run and after producers adapt in the long-run. This distribution of benefits has important policy relevance. When the social gains from disease mitigation exceed the private gains to producers, there is a rationale for public support. Apart from the fact that fire blight generates externalities, affects market stability, and can impose costs that individual growers cannot efficiently internalize, it is also true that consumers benefit from the elimination of fire blight. Thus, policies such as cost-share programs, support for extension and research, or incentives that lower the private cost of adopting effective control measures could improve overall welfare. The magnitude and distribution of estimated welfare gains provide an economic justification for considering targeted public investment in disease mitigation, although any policy recommendations might account for regional heterogeneity, budget constraints, and producer-level incentives.

Future work could incorporate the heterogeneity of firms and/or include costs related to mitigation strategies. For example, some firms may gain a first mover advantage with disease mitigation strategies and have the ability to increase production before competitors. Also, in the case of fire blight, there are a variety of mitigation effects with various costs associated with them. These costs should be compared to the economic effects estimated in this paper. If the mitigation costs are higher than the benefits to the firm, but less than the benefits of consumers, policy intervention may be warranted.

This analytical framework applies more broadly to other stochastic but persistent plant diseases that generate yield shocks and affect market outcomes through supply responses. Many perennial crop diseases share structural features with fire blight, including multi-year biological persistence. In these settings, short-run welfare effects would similarly reflect movements along the demand curve following an unanticipated production shock, while long-run effects would depend on producers' adaptive responses to expected reductions in disease pressure.

[First submitted July 2025; accepted for publication March 2026.]

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