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Research

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Technology Adoption and Risk Preferences: The Case of Machine Harvesting by Southeastern Blueberry Producers

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Abstract

This research investigates the effect of producers' risk preferences on the adoption of a new technology—machine harvesting—among blueberry producers in the Southeastern United States. Technology adoption literature assumes that risk aversion decreases the likelihood of adopting a new technology, but findings reveal that growers with higher levels of risk aversion are more likely to adopt machine harvesting. One explanation for this discrepancy is that we assume there are risks in both forms of harvest technology. The current patchwork or immigration policy and enforcement has made the availability of manual labor—the status quo technology—increasingly volatile.

Keywords: machine harvesting, perennial crops, risk preferences, technology adoption, uncertainty

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Introduction

This research investigates the effect of risk and producer risk preferences on technology adoption and intensity of use of machine harvesting (measured by percentage of machine-harvested acres) among Southeastern commercial blueberry operations. Given current conditions in both the labor regulatory environment and historical harvesting methods, commercial blueberry growers located in the four largest blueberry-producing states in the Southeastern United States were identified as the target population for this study to explore producer risk preferences on the adoption of a new technology. Using theoretical work by Feder (1980), Feder and O'Mara (1981), and Just and Zilberman (1983),[1] we model the decision to adopt machine harvesting and the extent of land allocated to machine harvesting as a function of risk attitudes, the stochastic relationship between the returns of the new and existing technology, and other factors including wealth, farm size, and sources of income. We find that producers that exhibit higher levels of risk aversion are more likely to adopt and use machine harvesting. We also find that increased labor uncertainty has a positive effect on the likelihood of adopting machine harvesting and on the intensity of its use.

Calvin and Martin (2011) analyzed five labor-intensive specialty crops (raisins, oranges, lettuce, strawberries, and asparagus) in the United States. They established differences in machine harvesting-labor substitution across these crops and determined the impact that new legislation would have on that substitution effect. They concluded that uncertainty in labor force availability due to immigration enforcement and new legislation would stimulate farmers to try harvest mechanization; however, responses in adoption, production, and price would vary by commodity. In recent years, the largest blueberry-producing Southeastern states of North Carolina, Georgia, Florida, and Mississippi have proposed statewide legislation affecting immigrant status and enforcement, leading to documented labor shortages and wage volatility among seasonal agricultural laborers (Passel and Cohn, 2012, McCissick and Kane, 2011; Rosson, 2012).

From 2002 to 2011, 69 jurisdictions—including Southeastern counties in North Carolina, Florida, Georgia, and Alabama—adopted Section 287(g) (Kostandini, Mykerezi, and Escalante, 2014).[2] Kostandini, Mykerezi, and Escalante (2014) concluded that counties with Section 287(g) agreements experience declines in farm worker availability. The effect of the resulting increase in labor uncertainty can lead blueberry producers to view the existing, labor-intensive harvesting technology as the riskier option and the new machine-harvesting technology as a risk-reducing option. This represents an important distinction from previous research. Research on adoption of new technology commonly assumes that the new technology (in this case machine harvesting) is the riskier option and the existing technology (labor harvesting) the safer option.

[1] Additional empirical work includes O'Mara (1980); Binswanger et al. (1980); Binswanger (1980); Byerlee and Hesse de Polanco (1986); Marra and Carlson (1987); Kebede (1992); Shapiro, Brorsen, and Doster (1992); Smale and Heisey (1993); Smale, Just, and Leathers (1994); and Abadi Ghadim (2000).

[2] Section 287 (g) of the Illegal Immigration Reform and Immigrant Responsibility Act of 1996 (IIRIRA) allowed federal Immigration and Customs Enforcement (ICE) officials to enter into agreements with local law enforcement officials, such as sheriff's departments, to perform immigration enforcement functions previously exclusively performed by ICE (U.S. Department of Homeland Security, 2014). However, no U.S. counties adopted this section until 2002.

While machinery manufacturers have offered various types of berry-harvesting equipment to the industry since the 1960s, yhese early machine harvesters were designed to shake the berries free of the bush and were most commonly used on the shorter Northern Lowbush (*Vaccinium angustifolium*) variety grown in the northern regions of the United States and Canada to harvest blueberries destined for the processed market. Early machine-harvested blueberries, which were often bruised and smashed, did not require the same quality as fresh market blueberries. As the market for fresh blueberries expanded, research and development into mechanical harvesters sensitive enough for fresh market blueberry species such as Northern Highbush (*Vaccinium corymbosum L.*), Southern Highbush (*Vaccinium corymbosum X darowii*), and Rabbiteye (*Vaccinium ashei*) has increased (Peterson et al., 1997).

While Southeastern cultivated blueberry production started in the late 1960s, commercial-scale operations—which relied on relatively accessible, mostly immigrant workforce for hand harvesting (Martin, 1998)—were establishedin the last two decades. Between 2002 and 2012, total U.S. cultivated blueberry acreage nearly doubled, from 40,820 to 77,700 acres (USDA, 2013a), in response to increased consumer demand, placing added pressure on labor availability. In the four study states (NC, GA, FL, and MS), cultivated blueberry acreage rose from 9,600 to 24,700 acres between 2000 and 2012 (USDA, 2013b), a 157% increase in a region that harvests berries destined primarily for the higher-valued fresh consumer markets.

While nationwide grower fresh prices rose from $1.29/lb to $2.19/lb between 2000 and 2012, it is notable that unharvested blueberries rose from 450,000 pounds in 2007 to nearly 17.5 million pounds in 2013, and another 2.4 million pounds of harvested fruit went unsold. Although experiments with new harvester models have demonstrated a marginally equivalent quality, the technology has not been widely adopted by fresh market blueberry growers in the Southeast. However, recent Southeastern state and county legislation concerning worker verification has led farm workers to migrate out of certain Southeastern states, threatening labor shortages for specialty crop producers (Passel and Cohn, 2012; McCissick and Kane, 2011; Rosson, 2012).

Previous studies have shown that shortages of agricultural workers lead to increases in agricultural worker wages and an increased interest in labor-saving machine technologies (Borjas, 2003; Zahniser et al., 2012). These concerns about labor shortages combined with the newer commercial operations established in this region motivated the need to further understand the potential of mechanical harvesters to reduce risk exposures resulting in higher production input prices and reduced farm profitability.

Feder (1980) developed a theoretical model that incorporates risk preference as an important factor in the technology adoption decision-making process. Other studies (Feder, Just, and Zilberman, 1985; Feder and Umali, 1993; Knight, Weir, and Woldehanna, 2003) have shown the importance of producers' risk preferences on the adoption of new technologies. Marra, Pannell, and Abadi Ghadim (2003) provided an excellent summary of literature on agricultural technology adoption and specifically on the role of uncertainty and risk in the decision-making process, but empirical studies evaluating the effect of producer risk preferences on the adoption of new technologies are limited. Liu (2013) found that more risk-averse Chinese cotton producers would be late adaptors of Bt cotton. Ward and Singh (2014) found that more risk-averse Indian producers are more willing to adopt new risk-reducing, drought-tolerant seeds.

Finally Sanou, Liverpool-Tasie, and Shupp (2015) found that more risk-averse Nigerien producers have a lower likelihood of using fertilizer.

Conceptual Model

A risk-averse farmer may choose to use both new (machine-harvested) and traditional (hand-picked) technologies. A number of key models in the adoption literature present land allocation among technologies as a portfolio selection problem (Feder, 1980; Feder and O'Mara, 1981; Just and Zilberman, 1983). The extent of land allocated to the new technology is determined by risk attitudes, the stochastic relationship between the returns of the two technologies, and the effects of scale factors such as wealth and fixed costs.

Like Just and Zilberman (1983), we assume that producers are risk averse with utility function $U(\cdot)$ defined on wealth and $U' > 0$, $U'' \leq 0$. Further, wealth at the end of the period is assumed to equal the sum of the land value, $p_L\bar{L}$, and the economic profits from production. The producer can allocate all land, $\bar{L}$, to the hand-picked technology or allocate the land between the hand-picked and the machine-harvest technology. In the latter case, the producer will face a new fixed cost, c, for the machine-harvest technology. The producer thus faces a discrete choice ($I \in \{0,1\}$) regarding the investment decision, where I is the adoption indicator (I=1 for adoption of machine-harvest technology and I=0 for nonadoption). Where I=1, the producer faces a continuous choice $\{L_0, L_1\}$ regarding the land-allocation decision, where L_0 and L_1 are the amounts of land allocated to the hand-picked and machine-harvest technology, respectively. The two decisions can be represented by

$$\max_{\substack{I=0,1 \\ L_0, L_1, f}} EU[p_L\bar{L} + \pi_0 L_0 + I(\pi_1 L_1 - c)] \tag{1}$$

$$\text{subject to} \quad \begin{array}{c} L_0 + IL_1 \leq \bar{L} \\ L_0, L_1, f \geq 0 \end{array}$$

where π_0 and $\pi_1 L_1 - c$ are the economic profits per unit of land from the hand-picked and the machine-harvest technology, respectively, and f is the input associated with the machine-harvest technology (machine harvester in this case).

Just and Zilberman (1983) showed that the amount of land allocated to the traditional and new technology is a function of the economic profits for each technology, the variance of the economic profits, and the covariance between the economic profits. This serves as a basis for the specification of the empiric equation to model the producer's continuous decision of land allocation between the two technologies. Additionally, the specification of the empirical model includes other explanatory variables to control for categories defined in Daberkow and McBride's (2003), such as human capital and tenure, risk, credit constraints, production, and agronomic constraints. According to Koundouri, Nauges, and Tzouvelekas (2006), both level of educational attainment and years of experience act as proxies for management abilities and learning and are often correlated, leading to model misspecification. Thus, we use experience variables in our model. Experience variables also measure "learning by doing," which is practical education specific to the farm task that reduces costs and increases the profit differential (Sunding and Zilberman, 2001).

Other variables in the human capital and tenure category include size of household (Fernandez-Cornejo, Hendricks, and Mishra, 2005), plans to transfer ownership to a family member, and a ratio of rented land over total land. Marra, Pannell, and Abadi Ghadim (2003) discussed different approaches used by previous work to measure producer risk preferences. Binswanger et al. (1980) elicited the risk preferences of a sample of Indian farmers using several elicitation techniques, one of which included gambling questions with real monetary pay-offs. In Shapiro, Brorsen, and Doster (1992) producer risk preference was measured by a Pratt–Arrow measure of risk attitude elicited using the method reported in King and Robison (1981). Abadi Ghadim (2000) elicited Arrow–Pratt coefficients of risk aversion based on a set of questions related to hedging. In this research, producer risk preferences were elicited using observed blueberry crop insurance purchases as well as producers' assessment of their willingness to accept risk relative to other blueberry producers. The amount of financed property (Feder, 1980) and income from off-farm activities (Fernandez-Cornejo, Hendricks, and Mishra, 2005) are included to control for the producer's financial position. Production variables include acreage and yield data. Agronomic variables include cultivar and location.

Data and Empirical Model

Data

This study uses cross-sectional data collected from a survey of blueberry producers in the Southeastern United States. A mailed survey instrument was chosen, as answers in mail surveys tend to be the least biased (Salant and Dillman, 1994). We followed the survey method proposed by Salant and Dillman (1994), sending announcement letters, followed by the questionnaire with a cover letter and a return envelope, followed by a reminder postcard, followed by a secondary questionnaire mailing to non-responders.

Prior to the mail survey, researchers personally interviewed eleven blueberry producers representing small, medium, and large-scale commercial operations in each of the study states. Using this feedback, the questionnaire was developed and pre-tested prior to the mailing effort. With assistance from state extension specialists and blueberry associations, 692 commercial blueberry producers were identified in the study area. Of the 692 surveys mailed during July 2011, 234 responded, for a usable response rate of 33.8%. The 2012 Census of Agriculture reported 2,509 blueberry farms in the Florida, Georgia, North Carolina, and Mississippi, thus the 234 survey respondents represented 9.3% of blueberry farms in these states. The 2012 Census of Agriculture also estimated 24,749 acres of tame blueberries in the four selected states. The 234 survey responses represented blueberry acreage of 12,386 acres, which represents 50.0% of total commercial blueberry acreage in the four surveyed states. Our survey data is therefore more oriented toward larger commercial farms than small farms or hobby farms (USDA, 2014).

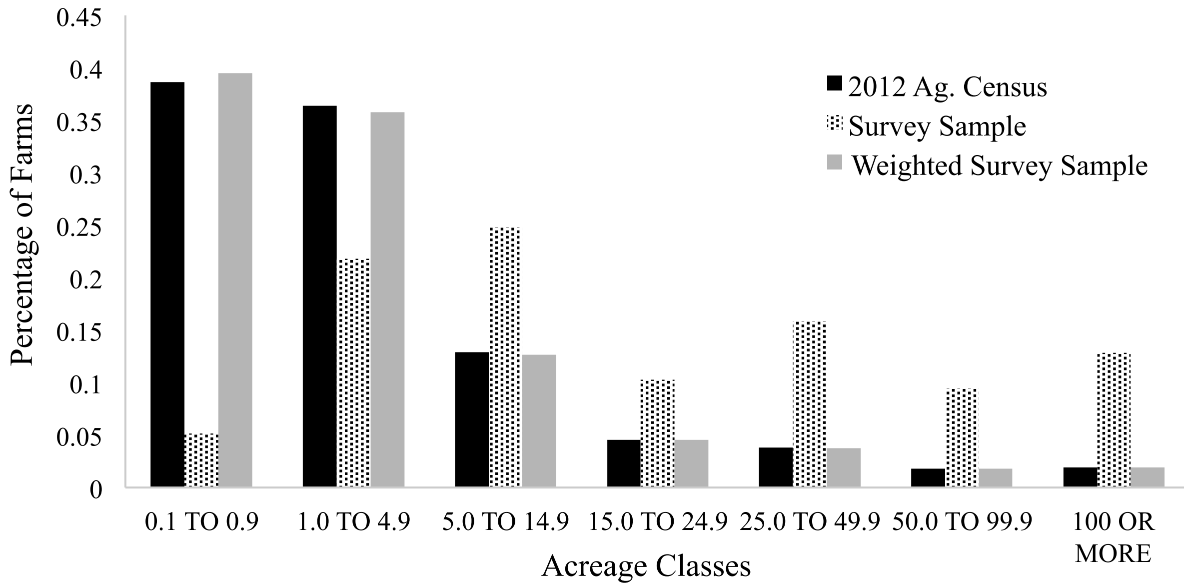

Figure 1. Blueberry Acreage Distribution for the Survey Sample Data Compared with the 2012 Census of Agriculture and the Survey Weighted Sample

Given this response pattern, post-stratified weights (ω) were estimated using the procedure developed by Binder and Théberge (1988). Figure 1 presents the non-weighted and weighted distributions of blueberry acreage for the survey sample. The weighted distribution of the survey responses closely approximates the distribution of blueberry producers for these four states based on the 2012 Census of Agriculture data.

The survey contained 32 questions pertaining to economic conditions, farmer characteristics, production, preferences and perceptions, and social characteristics of their enterprise. Of the 234 responses, 202 were suitable for use in our empirical mode. Summary statistics based on these observations are provided in Table 1.

Survey data were augmented with wage data acquired from The Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW) observed quarterly from 2001 to 2009 (U.S. BLS, 2013). The wage data represents county level annualized weekly wages based on the North American Industry Classification System (NAICS). The wage data were used to derive a historical measure of the average wage and the standard deviation of wage for each county in the study area.

The Economic Research Service (ERS) of the USDA collected data on the average yield per acre for all blueberry farms of the four states in our survey (USDA, 2015). ERS data on average yields for the four states is compared to average yields from our survey data (Table 1). The average yield per acre data reported by our survey respondents is within one standard deviation of the average yield per acre from ERS for the four states, and our four-state average yield data is within a half-ton per acre of the ERS data (Table 2).

Table 1. Summary Statistics of Variables

Variable Name	Variable Description	Mean	Std. Dev.	Min.	Max.
L_1 (percent)	Percent of machine harvested acres	27	39	0	100
I	Adoption of machine harvesting (Yes/No)	0.40	0.49	0	1
PRATIO	Ratio of fresh to frozen grower price received	3.03	1.74	0.52	7.70
SIZE (1,000 lbs./acre)	Farm size in volume of blueberries produced	0.352	0.78	0.0008	4.82
AVGWAGE($)	Annualized weekly farm labor wages (BLS)	493.90	113.94	250.56	843.64
WAGESTD ($)	Standard deviation of annualized weekly farm labor wages	89.47	39.01	32.32	281.96
INS (indicator variable)	Producer has purchased four or more times blueberry insurance in the past ten years	0.28	0.45	0	1
CONCERN_AVG_PRICE	Level of concern about average price received	0.82	0.38	0	1
CONCERN_STAB_PRICE	Level of concern about stability of prices received	0.57	0.50	0	1
EXP (years)	Number of years' experience with blueberry production	11.6	11.6	1	75
OFF_FARM_INCOME (percent)	Percent of total income earned off-farm	59	40	0	100
FINANCED_LAND (percent)	Percent of blueberry land and establishment costs that were financed	21	35	0	100
TRANSFER_OWN (indicator variable)	1 if producer plans to transfer ownership	0.68	0.47	0	1
FAMILY	Number of family members employed in the blueberry operation	3.36	3.99	1	21
GA (indicator variable)	Respondent from Georgia	0.34	0.47	0	1
NC (indicator variable)	Respondent from North Carolina	0.11	0.31	0	1

Table 2. Comparison of Average Commercial Blueberry Yield per Acre Reported by USDA and Survey Respondents for 2010 Harvest

State	2010 ERS Data (Avg. lbs./acre)	2010 Survey Response Data (Avg. lbs./acre)
North Carolina	7,100	6,309 (4,194)
Florida	4,690	6,135 (3,624)
Georgia	4,460	5,124 (3,239)
Mississippi	2,960	5,353 (2,943)
Four state average	4,802	5,730

Source: USDA, 2015.
Notes: Standard deviations reported in parentheses.

The U.S. Federal Crop Insurance Corporation (FCIC) converted a 1995 pilot program into a permanent blueberry crop insurance program in 2005. Our four study states were covered beginning with the 2000 pilot expansion, which informed the survey question related to respondent crop insurance purchases in the previous ten years. In the United States, market penetration for fruit and nut crop insurance coverage held steady from 2000 to 2011 at 73% coverage of commercial acreage. Blueberry crop insurance participation rates were 80% nationwide, and more than 30% of insured acres purchased buy-up insurance in 2011 (USDA, 2013c).

Empirical Model

We model the producer's continuous decision of land allocation using the following empirical model:

$$\begin{aligned}L_{1i} = {} & \beta_0 + \beta_1 PRATIO_i + \beta_2 SIZE_i + \beta_3 SIZE_i * RBBT_i + \beta_4 AVGWAGE_i \\ & + \beta_5 WAGESTD_i + \beta_6 WAGESTD_i * RBBT_i + \beta_7 INS_i \\ & + \beta_8 CONCERN\_AVG\_PRICE_i + \beta_9 CONCERN\_STAB\_PRICE_7 \\ & + \beta_{10} EXP_i + \beta_{11} EXPSQ_i + \beta_{12} OFF\_FARM\_INC_i \\ & + \beta_{13} FINANCED\_LAND_i + \beta_{14} TRANSFER\_OWN_i + \beta_{15} FAMILY_i \\ & + \sum_{l=1}^{2} \beta_{15+l} STATE_{li} + \varepsilon_i\end{aligned} \tag{2}$$

where L_{1i} is the percentage of land harvested using machine harvesting by the ith producer, $PRATIO$ is the ratio of the price for blueberries destined for the fresh market and the price for blueberries destined for the processed market,[3] $SIZE$ is a measure of farm size using production,[4] and $RBBT$ is an indicator variable that takes the value of 1 if the producer grows the Rabbiteye

[3] The price ratio was calculated using prices reported by survey respondents. Additionally, there is little to no variation in the cost of machine harvesters given that there are only two types of blueberry harvesters available. Other costs related to blueberry production are identical for the two technologies.
[4] Using acres as a measure of farm size produced similar results.

variety,[5] $AVGWAGE$ is the average of the county agricultural wage rate estimated using the last ten years of monthly wage rates, $WAGESTD$ is the standard deviation of the county agricultural wage rate estimated using the last ten years of monthly wage rates, which is used to capture the relative riskiness of two technologies serving as a proxy for labor uncertainty possibly due to,[6] among other things, immigration legislation and enforcement (Kostandini, Mykerezi, and Escalante, 2014).

To obtain a measure of producer risk preferences, the survey included a question about the number of times blueberry crop insurance had been purchased in the last ten years.[7] Indicator variables were used to model the responses from this question. INS is an indicator variable that takes the value of 1 if the producer has made four or more blueberry insurance purchases in the last ten years, which was used as a measure of producer level of risk aversion.[8] $CONCERN\_AVG\_PRICE$ is an indicator variable that takes the value of 1 if the producer expresses concern over the average price for the next year, used as a measure of producer concern over the level of returns he/she may obtain in the future. $CONCERN\_STAB\_PRICE$ is an indicator variable that takes the value of 1 if the producer expresses much concern over the stability of the price for the next year, used as a measure of producer concern over the variability of returns. EXP and $EXPSQ$ are the producer experience in growing blueberries and its square (to capture any nonlinearity), OFF_FARM_INC is the percent of producer income from other non-farm sources, $FINANCED\_LAND$ is the percentage of land and establishment costs that are financed, $TRANSFER\_OWN$ is an indicator variable that takes the value of 1 if the producer plans to transfer ownership, $FAMILY$ is the number of family members employed in the blueberry operation, $STATE_1$ and $STATE_2$ are indicator variables for Georgia and North Carolina, respectively, and control for possible regional differences in adoption patterns, and β_0 through β_{17} are the parameters to be estimated.[9]

Given that L_{1i} is potentially bounded by 0 and 1, we use the tobit model (Tobin, 1958) to estimate the regression model specified in equation (2). The log-likelihood and the partial effects (Greene, 2012) are

$$(3) \qquad ln\, l = \sum\nolimits_{L_i>0} -\frac{1}{2}\left[ln(2\pi) + ln\sigma_\varepsilon^2 + \frac{(L_i - \boldsymbol{x}_i'\boldsymbol{\beta})^2}{\sigma_\varepsilon^2}\right] + \sum\nolimits_{L_i=0}\left[1 - \Phi\left(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\sigma_\varepsilon}\right)\right]$$

$$(4) \qquad \frac{\partial E[L_i|\boldsymbol{x}_i]}{\partial \boldsymbol{x}_i} = \boldsymbol{\beta\Phi}\left(\frac{\boldsymbol{x}_i\boldsymbol{\beta}}{\sigma_\varepsilon}\right)$$

where the $\boldsymbol{x}$ variables in equations (3) and (4) are as defined in equation (2), σ_ε^2 is the variance of the error term, and $\Phi(\cdot)$ denotes the cumulative density. Marginal effects for discrete explanatory

[5] Most Rabbiteye blueberry varieties have firmer skins and fruit than the Southern Highbush varieties planted in the study region; therefore, they tend to have longer shelf-life and are more commonly mechanically harvested (Braswell, et al., 2009).
[6] We assume constant temporal variation in the cost of machine harvesters for every producer.
[7] The survey also asked producers to rank their willingness to accept risk relative to other blueberry producers. However, using this measure of risk preferences in the regression resulted in reduced model fit as measured by AIC and BIC criteria.
[8] Other indicator variables were not significant.
[9] Nearly all respondents were white males, thus race and sex are not included as socioeconomic variables.

variables and for interaction variables between one continuous variable and one dummy variable are calculated using

(5) $$\frac{\partial E[L_i|\boldsymbol{x}_i]}{\partial \boldsymbol{x}_i} = E\left[L_i\middle|\boldsymbol{x}_{ij(d)}, d = 1\right] - E\left[L_i\middle|\boldsymbol{x}_{ij(d)}, d = 0\right],$$

where d is the discrete variable and $\partial E[L_i|\boldsymbol{x}_i] = \boldsymbol{\Phi}\left(\frac{\boldsymbol{x}_i\boldsymbol{\beta}}{\sigma_\varepsilon}\right)\left(\boldsymbol{x}_i\boldsymbol{\beta} + \sigma_\varepsilon \frac{\boldsymbol{\phi}(\boldsymbol{x}_i\boldsymbol{\beta}/\sigma_\varepsilon)}{\boldsymbol{\Phi}(\boldsymbol{x}_i\boldsymbol{\beta}/\sigma_\varepsilon)}\right)$ is calculated at d=1 and d=0 for each observation. The two series of $\partial E[L_i|\boldsymbol{x}_i]$ are then averaged and the marginal effect for the discrete variable is calculated as the difference between the averages. Marginal effects for variables that have a quadratic term were calculated using

(6) $$\frac{\partial E[L_i|\boldsymbol{x}_i]}{\partial \boldsymbol{x}_i} = \left(\beta_l + 2\beta_q x_{ij}\right)\boldsymbol{\Phi}\left(\frac{\boldsymbol{x}_i\boldsymbol{\beta}}{\sigma_\varepsilon}\right),$$

where β_l is the coefficient for the linear term and β_q is the coefficient for the quadratic term. The marginal effects for these variables are calculated as the mean of the marginal effect for each observation.

The tobit model in equation (3) is considered a special case of the more general two-step model (Greene, 2012), where the first step models the probability of adoption, which is also independent of the intensity of use of the technology modeled in the second step. We test this restriction using the Lagrange multiplier (LM) test discussed in Greene (2012). The test statistic calculated as LM = 2*(lnL_{tobit} – (lnL_{probit} + $lnL_{truncated}$)) has a Chi-square distribution, and lnL_{tobit}, lnL_{probit}, and $lnL_{truncated}$ are, respectively, the log likelihood values from the tobit model, the probit model of the adoption decision, and the truncated regression model using only observations with positive number of acres that are machine harvested.

In addition to the tobit model, we also estimate the fractional response regression proposed by Papke and Wooldridge (1996).[10] In this model, the dependent variable is bounded between 0 and 1 by imposing a link function $G(\cdot)$, such as a logit or log-log transformation function:

(7) $$E[L_i|\boldsymbol{x}_i] = G(\boldsymbol{x}_i\boldsymbol{\beta}).$$

The quasi-likelihood estimator of $\boldsymbol{\beta}$ is obtained by maximizing the log-likelihood function as given by

(8) $$lnl = \sum_i (L_i logG(\boldsymbol{x}_i\boldsymbol{\beta}) + (1 - L_i)log(1 - logG(\boldsymbol{x}_i\boldsymbol{\beta}))).$$

Results

Using the LM statistic to test the tobit restriction against the two-step model that considers the probability of adoption as independent of the intensity of use of the technology, we obtain LM

[10] Results for the fractional response regression are available from the authors upon request. The results are similar to the results from the tobit regression. We do not report these results here as they are generally inferior to the tobit regression results in terms of model fit as measured by the AIC/BIC criteria.

19.86 and a respective probability for a Chi-square distribution with 17 degrees of freedom of 0.282. Therefore, we fail to reject the tobit restriction.[11]

Regression coefficients of the tobit model, associated standard errors, and significance levels are presented in Table 3, along with the marginal effects and standard errors derived using the delta method. Table 3 reports results for both non-weighted and weighted regression models. The weighted regression uses the post-stratified weights (ω) described earlier and provides a better fit as indicated by the log-likelihood value. The signs and magnitudes of the marginal effects are similar across the non-weighted and the weighted regression models. The price ratio (fresh price/processed price) negatively affects the use of machine harvesting. Since blueberries from machine harvesting are primarily destined for processing, a higher price for fresh blueberries relative to the price for blueberries for processing would result in reduced or no use of machine harvesting. The effect of farm size for producers of both Highbush and Rabbiteye varieties is not statistically significant in the non-weighted regression but becomes significant when post-stratified weights are applied. Given that larger producers are more likely to respond to technology adoption surveys,[12] it is important to account for this sample bias by using post-stratified survey weights.

The average wage rate and the standard deviation of wage rate also have no statistically significant effect on the use of machine harvesting.[13] However, when interacted with a dummy variable for Rabbiteye production, the standard deviation of wage rate has a significant positive effect on the use of machine harvesting. The marginal effect implies that a one dollar increase in the standard deviation of the weekly wage increases the percentage of land under machine harvesting for Rabbiteye production by 0.0043 percentage points (0.0098 percentage points based on the weighted regression results). This finding supports the hypothesis that the effect of increasing farm labor uncertainty due to recent legislative initiatives in the Southeast may have led blueberry producers to view the current labor-harvesting technology as the riskier option and the new machine-harvesting technology as a risk-reducing option.

Frequency of blueberry insurance purchases and concern about the stability of price serve as measures of producers' risk preferences. Producers who more frequently buy crop insurance and have higher concerns about price stability, indicating higher levels of risk aversion, are more likely to use machine harvesting at higher intensity. These effects are as expected under the hypothesis that the machine-harvesting technology is considered the safer (less risky) option. Concern about the average price for the season measures producers' attitude toward the profitability of their operation. Producers who have higher concerns about average price are

[11] We report the results of the probit regression modeling the decision to adopt machine harvesting and the truncated regression modeling the intensity of use of machine harvesting in Appendix Tables A1 and A2. Results of Tables A1 and A2 are consistent with the tobit results reported in Table 3 and the tobit restriction, in the sense that the direction of the effect for each regressor on both, the decision to adopt, and the intensity of use of machine harvesting are the same. One result to highlight is that farm size has a positive and significant effect on the intensity of use of machine harvesting, particularly for producers that grow Rabbiteye varieties. This finding is similar to the tobit results based on the weighted sample that adjusts for the bias in the higher response rate from larger producers. Additionally, farm size has a positive and significant effect on the decision to adopt machine harvesting, but only among producers that grow Rabbiteye varieties. Finally, plans to transfer ownership have a significant negative effect on the decision to adopt machine harvesting.

[12] The authors appreciate the suggestions of one of the anonymous reviewers.

[13] We investigated using wages for the last available year (2009) and obtained similar results.

Table 3. Tobit Model Results of Machine Harvest Adoption and Intensity of Use for the Non-Weighted and Weighted Sample

	Non-Weighted Sample			Weighted Sample		
Variable	**Coeff.**	**Std. Err.**	**Marginal Effect**	**Coeff.**	**Std. Err.**	**Marginal Effect**
INTERCEPT	-0.413	0.334		-0.443	0.708	
PRATIO	-0.128***	0.035	-0.0613***	-0.102**	0.049	-0.0495**
SIZE	0.160	0.214	0.0763	1.029**	0.564	0.3956**
SIZE*RBBT	-0.168	0.213	-0.0804	0.728**	0.357	0.2875**
AVGWAGE	-0.0004	0.0005	-0.0002	-0.0004	0.001	-0.0002
WAGESTD	-0.004	0.003	-0.0018	-0.003	0.008	-0.0011
WAGESTD*RBBT	0.009***	0.002	0.0043***	0.025***	0.007	0.0098***
INS	0.187**	0.099	0.0893*	0.263*	0.173	0.1017*
CONCERN_AVG_PRICE	0.285*	0.175	0.1361*	0.414*	0.216	0.1601*
CONCERN_STAB_PRICE	0.230**	0.107	0.1096**	0.404**	0.189	0.1606**
EXP	0.019**	0.009	0.0093**	0.004	0.017	0.0015
EXPSQ	-0.0002*	0.000		-0.000	0.000	
OFF_FARM_INCOME	-0.244**	0.122	-0.1164*	-0.160	0.254	-0.0620
FINANCED_LAND	-0.055	0.133	-0.0264	-0.021	0.217	-0.0083
TRANSFER_OWN	-0.106	0.112	-0.0508	-0.263	0.196	-0.1018
FAMILY	0.0003	0.011	0.0001	0.002	0.019	0.0009
GA	0.711***	0.116	0.3394***	0.981***	0.272	0.3791***
NC	0.485***	0.178	0.2315***	0.605*	0.383	0.2340*
SIGMA	0.365***	0.035		0.434***	0.071	
Number of Observations	133			133		
Log Likelihood	-42.69			-22.37		

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

more likely to use machine harvesting at higher intensity. This finding can be explained by the fact that once northern states hit peak production in the summer months, supplies overwhelm the fresh market, average grower prices received decrease, and the cost of hand-picking is too high to justify continued labor harvesting. While nominal grower fresh prices increased during the study period, nearly 5% of 2013 fruit volume was either unharvested or unsold, perhaps as a result of pressure on labor availability and increased fruit volumes due to nationwide doubling of blueberry acreage that reached 2013 markets. Producers see adoption of machine harvesting as a way to reduce variable costs and minimize the problems associated with finding pickers.

The coefficient for number of years' experience with blueberry production shows increased intensity of use of machine harvesting with more experience. However, the negative sign of the quadratic term reveals that the rate of use decreases as the producer reaches a certain number of years of experience. The inflection point was calculated to be 43 years. Higher levels of off-farm income, implying reduced importance of blueberry production to the producer's financial well-being, result in lower intensity machine harvesting use. Producers in Georgia and North Carolina have higher intensity of use of machine harvesting compared to producers in Florida and Mississippi. One reason for this may be recent developments with respect to immigration, like the signing into law in 2006 of the Georgia Security and Immigration Compliance Act (SB 529) which created the Southeast's strictest state-led immigration enforcement legislation.

It is possible that the inclusion of some decision variables — like farm size and off-farm income —as explanatory variables may lead to an endogeneity problem. We believe that the decision on farm size and off-farm employment is not simultaneous with the decision to adopt and use machine harvesting. However, to provide a robustness check, we perform the two-step endogeneity test proposed by Smith and Blundell (1986) and described in Wooldridge (2010). In the first step, OLS regressions are estimated by regressing the possible endogenous variables, farm size and off-farm income, against all other exogenous variables. Additional exogenous variables included in the OLS regressions were an indicator variable for Florida, education, and age of the producer. In the second step, residuals for size and off-farm income from the first-step OLS regressions are included as additional explanatory variables in the tobit regression. The t statistic on the residuals reported by the tobit model provides a simple test of the null hypothesis that size and off-farm income are exogenous (Wooldridge, 2010). Results of the endogeneity test in the second-step tobit estimation are reported in Appendix Table A3. The coefficients for both residuals are not significant, indicating that endogeneity may not be an issue in this case.

Conclusions

This research adds to the empirical work dedicated to measuring the effect of producers' risk preferences in the adoption and use of a new technology. We employ the theoretical work of Feder (1980), Feder and O'Mara (1981), and Just and Zilberman (1983) to model the decision of blueberry producers in the Southeastern United States to adopt machine harvesting and the extent of land allocated to machine harvesting as a function of risk attitudes, the stochastic relationship between the returns of the new and existing technology, and other factors such as wealth, farm size, and sources of income.

Given recent legislative developments with regard to immigration status and enforcement in the largest blueberry-producing Southeastern states of North Carolina, Georgia, Florida, and Mississippi and the resulting labor shortages and wage volatility, we also investigate the effect of labor uncertainty in the adoption and use of machine harvesting among blueberry producers. While technology adoption literature assumes that risk aversion leads to a decreased likelihood of adoption of a new technology, our analysis reveals that Southeastern blueberry growers who exhibit higher levels of risk aversion are more likely to adopt and use machine harvesting. One explanation for this discrepancy between our analysis and previous technology adoption literature is that our analysis assumes that there are risks in both forms of harvest technology. The status quo technology for blueberry harvesting is manual labor; due to the current state of patchwork immigration policy and enforcement, labor availability is becoming more volatile. Conversely, new machine-harvesting technology is still economically unproven for many of the premium price Southeastern blueberry cultivars.

We find that increased labor uncertainty has a positive effect on the likelihood of adopting machine harvesting and on its intensity of use. This finding supports the hypothesis that Southeastern blueberry producers may view the machine-harvesting technology as a risk-reducing technology compared to the current technology of labor harvesting. We also find that blueberry producers who express higher levels of concern regarding both the average grower price received and the stability of grower prices received are more likely to adopt machine harvesting and use it at a higher intensity. Our results regarding the factors that affect the adoption and use of machine harvesting have implications for both blueberry producers and policymakers in states that produce blueberries and other specialty crops.

Our findings may be useful to machine harvester dealers looking to expand market coverage in the Southeastern blueberry production regions given the large increase in acreage and continued uncertainty surrounding farm labor access and availability. Producers are encouraged to consider the financial implications of investment in machine harvest equipment relative to labor costs as a risk management option, viewed through the lens of individual operation scale, labor access situation, blueberry variety and planting arrangements, and current farm financial conditions. For many mid- to large-size Southeastern perennial fruit operations, federal, state, and local policies related to farm labor wages and other key employment conditions have resulted in grower adoption of innovative technological advantages. This research may be used to inform policymakers of the impact of restrictive immigrant farm labor policies on the blueberry industry and related market supply conditions.

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Appendix

Table A1. Probit Model Results of Decision to Adopt Machine Harvesting

Variable	Coefficient	Std. Error	Marginal Effect
INTERCEPT	-2.490	1.784	
PRATIO	-0.395**	0.199	-0.0374
SIZE	0.777	1.290	0.0856
SIZE*RBBT	17.670***	6.621	0.236***
AVGWAGE	0.007	0.004	0.0008
WAGESTD	-0.030	0.028	-0.0033
WAGESTD*RBBT	0.018**	0.009	0.0020*
INS	1.879**	0.119	0.2068**
CONCERN_AVG_PRICE	1.797**	1.129	0.1980**
CONCERN_STAB_PRICE	1.308***	0.677	0.1440***
EXP	0.574***	0.229	0.0637**
EXPSQ	-0.021***	0.008	
OFF_FARM_INCOME	-1.070	0.756	-0.1177
FINANCED_LAND	-1.278	0.878	-0.0407
TRANSFER_OWN	-1.798***	0.635	-0.1979**
FAMILY	0.041	0.066	0.0045
GA	2.136***	0.731	0.2351***
NC	2.865**	1.118	0.2517**
Number of Observations	133		
Log Likelihood	-24.23		

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Table A2. Truncated Regression Results for Intensity of Use of Machine Harvesting

Variable	Coefficient	Std. Error	Marginal Effect
INTERCEPT	0.276	0.279	
PRATIO	-0.034*	0.021	-0.0322*
SIZE	0.744***	0.269	0.7054***
SIZE*RBBT	0.695***	0.245	0.659***
AVGWAGE	-0.0005	0.0003	-0.0004
WAGESTD	0.010***	0.003	0.0092**
WAGESTD*RBBT	0.006**	0.003	0.0059*
INS	0.048*	0.034	0.0461*
CONCERN_AVG_PRICE	0.070	0.181	0.0664
CONCERN_STAB_PRICE	0.011	0.088	0.0105
EXP	0.009*	0.005	0.0080*
EXPSQ	-0.001	0.008	
OFF_FARM_INCOME	-0.036	0.094	-0.0337
FINANCED_LAND	0.037	0.105	0.0352
TRANSFER_OWN	0.047	0.098	0.0455
FAMILY	0.006	0.009	0.0062
GA	0.332***	0.108	0.3158***
NC	0.104	0.168	0.0983
SIGMA	0.238***	0.023	
Number of Observations	61		
Log Likelihood	-8.53		

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Table A3. Robustness Check of the Regression Results for Possible Endogeneity

Variable	Coefficient	Std. Error
INTERCEPT	-0.501	0.676
PRATIO	-0.134***	0.035
SIZE	0.082	0.624
SIZE*RBBT	-0.223	0.209
AVGWAGE	-0.0005	0.0005
WAGESTD	-0.004	0.003
WAGESTD*RBBT	0.009***	0.002
INS	0.184**	0.120
CONCERN_AVG_PRICE	0.308*	0.185
CONCERN_STAB_PRICE	0.203**	0.107
EXP	0.014**	0.009
EXPSQ	-0.0001	0.009
OFF_FARM_INCOME	-0.307**	0.154
FINANCED_LAND	-0.118	0.136
TRANSFER_OWN	-0.126	0.139
FAMILY	0.000	0.011
GA	0.765***	0.147
NC	0.448***	0.213
SIZE_RESIDUALS	-0.216	0.348
OFFFARM_RESIDUALS	1.098	0.796
SIGMA	0.356***	0.034
Number of Observations	133	
Log Likelihood	-40.98	

Notes: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level.

Who Buys More Directly from Producers in the Southeastern United States? A Research Note

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Abstract

This paper examines factors affecting how much consumers spend when purchasing directly from producers. A joint decision framework models two decisions: 1) whether to purchase directly and 2) how much to spend. Consumers with a greater incidence of family disease or who are immigrants, prepare more meals at home, and are more concerned with U.S. food safety also spend more on food purchased directly from producers. Results suggest that farmers should develop a three-pronged marketing strategy by attracting new consumers, adopting sales promotion tools that encourage existing customers to purchase more frequently, and encouraging consumers to spend more per visit.

Keywords: consumer behavior, direct marketing, food safety, health motivation

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Introduction

A recent study by Key (2016) compared 2007 and 2012 USDA-NASS Census of Agriculture data and found that farms that sell direct to consumers had higher rates of business survival. In 2008, local food market sales in the United States totaled $4.8 billion, of which 18.3% were direct-to-consumer food sales (Low and Vogel, 2011). Direct-to-consumer transactions can occur through community supported agriculture, farmers' markets, U-pick operations, roadside stands, and online sales. By 2012, U.S. local food sales were estimated at $6.2 billion, which may underestimate actual sales since the U.S. Census of Agriculture did not include the value of intermediated local foods sales made through grocery stores or institutions (Low et al., 2015). The number of farmers' markets across the nation jumped to 8,628 in 2014, a 180% increase over 2006 numbers (Key, 2016).

The majority of direct-to-consumer sales consist of locally produced food, and several studies have shown that consumers are willing to pay a higher price for locally grown food, which is commonly perceived to be fresh and have lower environmental impact, increased food safety, and support local agriculture (Scarpa, Philippidis, and Spalatro, 2005; Darby et al., 2008; Thilmany, Bond, and Bond, 2008, Maples et al., 2013; Martinez et al., 2010; Zepeda and Li, 2006). While these documented factors may influence a consumer's initial decision to purchase food products directly from producers, marketing theories reveal that the cost-effectiveness of promotional efforts to influence expenditure levels of existing customers are related to consumer willingness to engage with the product (Kotler and Keller, 2016). For example, sales promotion tools, such as recipe cards and cooking demonstrations, return higher margins when aimed at current buyers who may then decide to increase per visit expenditures.

This research examines the factors that significantly impact the expenditure levels of consumers who elect to purchase food items directly from producers. Producers who adopt sales promotion strategies focused on communicating the benefits of direct-marketed food and food products are expected to be effective at recruiting new consumers to the market, increasing the frequency of visits among existing customers, and increasing average expenditures per customer.

Review of Literature

While recent studies have revealed the relative importance of consumer purchase of local foods that is motivated by "proven health benefits" (Onozaka, Nurse, and Thilmany, 2010) and the growing scientific evidence linking food choices to health (Variyam and Golan, 2002), there exists a gap in understanding the relationship, if any, between consumer health outcomes and re-localization of food systems (McFadden and Low, 2012). This information is of particular importance in the Southeastern United States, where evidence from the 2012 Prevalence and Trends Data (CDC, 2017) revealed that residents in Mississippi, Arkansas, Tennessee, Texas, and Louisiana reported lower participation levels in physical activities, were less likely to describe themselves as in "excellent" or "very good" general health, and were more likely to indicate "fair or poor health" status when compared to nationwide averages.

To adequately capture the presence of culturally driven impacts of health conditions and food safety concerns on consumer decisions to purchase foods directly from producers, a clearer understanding of eating habits and community composition is needed. The prevalence of obesity is higher among Hispanic children of all ages relative to non-Hispanic white children (Cunningham, Kramer, and Venkat Narayan, 2014). Furthermore, Hispanic immigrants who had lived in the United States more than 15 years experienced a four-fold increase in obesity rates relative to newer immigrants (Kaplan et al., 2004). Tovar et al. (2013) used a focus group approach to interview Spanish-speaking female immigrants from Brazil, Latin America, and Haiti about changes in their lifestyle that might be linked to obesity. In the resulting response themes, participants indicated that food was “more natural” in their home country and that they had had more time for shopping and food preparation compared to when they lived in the United States.

Major findings from a qualitative meta-analysis of U.S. Latina food consumption patterns (Gerchow et al., 2014) revealed that dietary habits in terms of frequency of meals, scheduling, and snacking changed post-immigration as they adjusted to new employment schedules and had limited time to prepare and enjoy more traditional, multi-course, leisurely family meals, resulting in poor dietary choices and overeating. They also found that some Latinas attributed weight gain after immigration to the presence of “chemicals” and “harmful additives” in “poor-quality foods” available in the United States.

An important tenet of consumer purchase decisions under conditions of uncertainty is that observed selections are made subject to a rule of thumb that is used to sort purchase alternatives, motivating the need to understand those behaviors which are subject to this bounded rationality assumption. Marketing and economics literature reveals that, while a consumer may demand or require all the factual details related to a food item, the rational choice is not always selected in the presence of objective information (Verbeke, 2005; Tellis and Gaeth, 1990). In fact, Verbeke (2005) concluded that adding more information often resulted in information overload, and frustrated consumers became indifferent and bored, losing confidence in their decisions. A primary goal of attaching educational information to direct-to-consumer marketed food products is to help distinguish these items from similar choices to better inform consumer decisions. Based on these concerns, it appears there is a need to understand the degree to which consumers’ current knowledge of the U.S. agricultural industry might impact their purchase decisions and how much they decide to spend per visit.

Most studies on consumer preferences for locally grown food have been conducted in either the western United States or on the East Coast (Giraud, Bond, and Bond, 2005; Hardesty, 2008), where 52% of the total value of U.S. direct-to-consumer sales were reported in 2015 (USDA, 2016). However, 29% of U.S. farms that offer community supported agriculture programs were located in the Southeast in 2012 (USDA, 2013), and direct-to-consumer sales conducted by 30,014 operations in the Southeast were valued at $602.6 million in 2015 (USDA, 2016) The Southeast is, therefore, no exception to the trend of increased direct-to-consumer food transactions.

In this paper, we examine the factors that affect how much Southeastern consumers spend when purchasing food directly from producers. We model the two decisions—whether to purchase directly from a producer and, if so, how much to spend per trip—in a joint decision framework, the parameters of which are estimated jointly via maximum likelihood. We find that consumers with a greater incidence of disease in their families have higher expenditures on food purchased directly from producers. We also find that immigrants, those who prepare more meals at home, and those who are relatively more concerned with the safety of food produced in the United States spend more on food purchased directly from producers. We expect our findings to help farmers develop a three-pronged marketing strategy that 1) brings new direct-from-producer consumers into the market, 2) retains existing customers and encourages more frequent purchases, and 3) induces current customers to spend more per visit through the use of sales promotion tools aimed at improving sales per dollar (or time) expended on marketing communications.

Survey and Data

To better understand consumer decisions about increasing the frequency of their purchases directly from growers, Research Now® (Plano, Texas) administered an online survey that collected two hundred observations from adults in five Southeastern cities: Atlanta, Georgia; Austin and Houston, Texas; Birmingham, Alabama; and Nashville, Tennessee. The sample was constructed to be demographically representative, and respondents were pre-screened to ensure that the respondent was the primary food shopper for the household. Further details on the survey and sampling methodology can be found in Maples et al. (2013).

Variables used in the model are described in Table 1. The two dependent variables are c, indicating whether the person has purchased food directly from a producer, and y, indicating average expenditures per direct food purchase. Thirty-six percent of respondents had purchased directly from a producer; of those, the average expenditure per trip was almost $8.00. We wanted to test whether purchasing directly from a producer was influenced by the respondent's knowledge about the agricultural sector, so the survey included an eight-question true/false survey about agriculture (see Appendix A.1). Respondents' scores on this questionnaire were included as an independent variable. We also hypothesized that respondents' perceptions of the health risk of various food sources affect purchasing decisions. We asked, relative to their friends and family, how concerned respondents were about the safety of food produced in the United States and how concerned they were about imported food. We also asked them to indicate whether they, or members of their family, had been treated for cancer, heart disease, diabetes, back or joint pain, Alzheimer's disease or dementia, and obesity (see Appendix A.2). Their levels of concern about food safety and the incidence of family health issues were included as independent variables. Finally, respondents were asked to indicate whether they were born in the United States.

Conceptual Framework

We model the consumer problem as a joint decision of (1) whether or not the consumer decides to purchase directly from the producer and, if so, (2) how much to spend. The consumer has a set of characteristics, $\mathbf{x_i} = [\mathbf{x_i^0}\ \mathbf{x_i^1}\ \mathbf{x_i^2}]$, a subset of which ($\mathbf{x_i^1}$) affects the first decision, a subset of which ($\mathbf{x_i^2}$) affects the second decision, and a subset of which ($\mathbf{x_i^0}$) affects both decisions.

We assume that when deciding whether to purchase directly from a producer (for example, whether to visit a farmers' market) the participant compares his utility from the purchase to his

Table 1. Variable Definitions and Descriptive Statistics

Variable Descriptions	Type[a]	Mean	S.D.	Min	Max
Dependent Variables					
Over the past six months, have you purchased any food or food products directly from a grower/rancher/farmer/fisherman?	Binary	0.365	0.481	0	1
On average, how much did you spend per trip on food/food products purchased directly from a grower/rancher/farmer/fisherman?	Continuous	7.905	14.432	0	99
Independent Variables					
Atlanta resident[b]	Binary	0.201	0.401	0	1
Nashville resident	Binary	0.197	0.398	0	1
Houston resident	Binary	0.200	0.401	0	1
Birmingham resident	Binary	0.197	0.398	0	1
Austin resident	Binary	0.203	0.403	0	1
Female	Binary	0.680	0.467	0	1
Income (1 = < $10000, 15 = > $500,000)	Continuous	7.000	2.550	1	15
Associate's degree or greater education	Binary	0.749	0.434	0	1
Number of residents per household in previous six months	Continuous	2.399	1.234	1	9
Number of meals prepared at home each week (reported in seven, 3-meal increments)	Continuous	4.016	1.754	1	7
Score on 8-question true/false quiz	Continuous	3.93	1.82	0	8
Concern about average US food prices in next six months, relative to friends and family (0 = much less concerned, 4 = much more concerned)	Continuous	2.643	0.928	0	4
Concern about safety of food produced within the US (0 = much less concerned, 4 = much more concerned)	Continuous	2.457	1.084	0	4
Concern about safety of food produced outside the US (0 = much less concerned, 4 = much more concerned)	Continuous	2.891	1.015	0	4
Number of days traveled per month (6 categories)	Continuous	2.083	1.548	1	6
One-way commute time (15-minute increments)	Continuous	1.838	1.053	1	5
Less than 1.5 miles brisk walking per day[c]	Binary	0.434	0.496	0	1
More than 3 miles brisk walking per day	Binary	0.117	0.322	0	1
Number of disease incidences in family	Continuous	3.979	2.848	0	19
Number of times purchased health insurance in past 10 yrs. (1 = never, 5 = 10 times)	Continuous	2.686	1.561	1	5
Born in the United States	Binary	0.925	0.264	0	1

[a] All binary variables equal 1 if the description is true, 0 otherwise.
[b] Atlanta is the omitted base city.
[c] Active (equivalent of 1.5–3 miles brisk walking daily) is the omitted activity level.

utility from not making the purchase. The utility of representative consumer i is a linear-in-parameters function of a vector of consumer characteristics:

$$(1) \qquad u_{ic} = \beta^c + \boldsymbol{\beta}_0^{c\prime}\mathbf{x}_i^0 + \boldsymbol{\beta}_1^{c\prime}\mathbf{x}_i^1 + \varepsilon_i^c,$$

where i indexes the individual, $c \in \{1,0\}$ indicates the choice of buying directly from the producer (1) or not (0), β^c, $\boldsymbol{\beta}_0^c$, and $\boldsymbol{\beta}_1^c$ are parameters to be estimated, and ε_i^c is an independent and identically distributed (i.i.d.) error term with a mean of 0.

If the consumer decides to purchase directly from the producer, we assume s/he then decides how much to spend. Her/his average total expenditures per direct-from-producer shopping experience, y_i, are also a function of personal characteristics:

$$(2) \qquad y_i = \alpha^c + \boldsymbol{\alpha}_0'\mathbf{x}_i^0 + \boldsymbol{\alpha}_2'\mathbf{x}_i^2 + v_i,$$

where α^c, $\boldsymbol{\alpha}_0$, and $\boldsymbol{\alpha}_2$ are parameters to be estimated and v_i is an i.i.d. error term with a mean of 0.

We have observations on y_i only for the subset of consumers who have actually purchased directly from producers. Hence, the model specified in equations (1) and (2) is a natural candidate for a sample selection model. One approach to estimating a sample selection model is to use a two-step process in which equation (1) is estimated using a probit model, the estimates from which are then used to estimate the inverse Mills ratio, which itself is included as a regressor in equation (2) (Heckman, 1979). However, this approach is known to have several drawbacks including intrinsic heteroskedasticity, and it is no more consistent than the full information maximum likelihood (FIML) estimator (see Puhani, 2000). Therefore, we estimate the system using a FIML estimator.

Results

The sample selection model specified in equations (1) and (2) was estimated using SAS software, Version 9, of the SAS System for PC. (Copyright © 2002-04. SAS Institute, Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA.) The variables, $\mathbf{x}_i^0$, common to both equations are the number of household residents, the number of meals prepared at home each week, the respondent's score on the true/false quiz, level of concern for the safety of food produced in the United States, the average number of days the respondent travels per month, her/his activity level (whether s/he walks less than 1.5 miles per day and whether s/he walks more than 3 miles per day), and the number of family health issues. The variable $\mathbf{x}_i^2$, which appears only in the expenditure equation (2), are respondent income and whether the respondent was born in the United States. All other variables listed in Table 1 appear only in equation (1). Note that the full set of variables included in equation (1), $\{\mathbf{x}_i^0, \mathbf{x}_i^1\}$, are the same as those used in Maples et al. (2013). We restricted the set of variables in equation (1) to match that used in Maples et al. (2013) in order to examine how the model choice—whether to estimate the decision to purchase directly from a producer as an independent decision or as a joint decision with how much to spend—affects parameter estimates for equation (1).

Table 2. Parameter Estimates

Dependent Variable:	**Direct Purchase (Equation 1) N = 1,023**		**Expenditures (Equation 2) N = 373**	
Variable	**Est.**	**S.E.**	**Est.**	**S.E.**
Nashville resident	0.047	0.059	—	
Houston resident	-0.081	0.126	—	
Birmingham resident	-0.056	0.053	—	
Austin resident	-0.102	0.062*	—	
Female	0.010	0.066	—	
Income (1 = < $10000, 15 = > $500,000)	—		0.367	0.287
Associate's degree or greater education	0.060	0.045	—	
Number of household residents in previous six months	0.087	0.033***	2.128	0.790***
Number of meals prepared at home each week (reported in seven, 3-meal increments)	0.047	0.023**	1.279	0.563**
Score on 8-question true/false quiz	0.069	0.022***	1.567	0.562**
Concern about average US food prices in next six months, relative to friends and family (0 = much less concerned, 4 = much more concerned)	-0.024	0.023	—	
Concern about safety of food produced within US (0 = much less concerned, 4 = much more concerned)	0.143	0.042***	3.588	0.926***
Concern about safety of food produced outside the US (0 = much less concerned, 4 = much more concerned)	0.003	0.025	—	
Number of days traveled per month (6 categories)	0.088	0.025***	1.870	0.639***
One-way commute time (15-minute increments)	0.009	0.017	—	
Less than 1.5 miles brisk walking per day	-0.302	0.089***	-7.591	2.562***
More than 3 miles brisk walking per day	0.256	0.126**	6.575	2.928**
Disease incidence in family	0.031	0.014**	0.650	0.344*
Number of times purchased health insurance in past 10 yrs. (1 = never, 5 = 10 times)	0.009	0.011	—	
Born in the United States	—		-3.667	1.763**
Intercept	-1.620	0.215***	-33.018	5.529***
Rho		0.998		
Log-Likelihood		-2,081		

Note: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels.

The parameter estimates and standard errors for equation (1) are presented in Table 2. We see that the decision of whether to purchase directly from a producer depends positively on the respondent's knowledge of the agricultural sector, food safety concerns, number of meals prepared at home each week, number of days spent traveling per month, whether the respondent exercises the equivalent of 3 miles of brisk walking per day, and family health history. In terms of geographic differences, Austin residents are less likely to make direct-from-producer purchases compared to Atlanta residents (omitted base category), as are those who exercise less than the equivalent of 1.5 miles of brisk walking per day.[1]

The estimates and standard errors of equation (2)—factors affecting total expenditures—are presented in Table 2. Of the variables common to both the decision to purchase directly from the producer (equation 1) and how much to spend (equation 2), those with significant parameters in equation (1) have the same sign and are significant in equation (2). This indicates that respondent characteristics that increase the likelihood of purchasing directly from a producer also increase expenditures, when the respondent makes such purchases. In particular, respondents who are more concerned about the safety of food produced in the United States spend \$0.14 per trip and average total expenditures are \$3.59 more than those who indicated lower levels of concern. A greater incidence of family health issues results in significant increases of \$0.65 in average total expenditures on food purchased directly from producers. Respondents who performed better on the true/false quiz, and who were, therefore, assumed to have greater knowledge of agriculture, also spend \$0.07 more and increase average total expenditures by \$1.57 per trip. We find that more physically active consumers are significantly more likely to spend more. For example, those respondents who perform the equivalent of more than 3 miles of brisk walking daily spend \$0.26 more per trip, whereas those who completed fewer than 1.5 miles of brisk walking daily spend \$0.30 less per trip.

The two variables that appear only in the expenditure function are income and whether the respondent was born in the United States. Kolodinsky and Pelch (1997) and Onianwa, Wheelock, and Mojica (2005) find that income does not affect purchases of local foods. This study also shows that income does not affect expenditures on food purchased directly from the producer. A new finding, however, is that average total expenditures for respondents who were not born in the United States are \$3.67 higher than those of respondents who were born in the United States. Although we are unable to separate our "born in the United States" variable into respondent country of birth or year of immigration to further investigate any underlying cultural influences on this finding, we do propose two hypotheses for future exploration. First, immigrants may have their own perceptions of the quality, safety, or health impacts of food purchased directly from producers. However, an examination of Pearson correlation coefficients indicates that the correlations are quite weak between being born in the United States and either concern for safety of domestically produced or imported food or total family incidence of health issues. Second, it is possible that purchasing directly from producers is more common in other countries, motivating immigrants to continue this practice in the United States.

[1] The signs and significance of parameters in our model match very closely with those of Maples et al. (2013) for the behavioral variables, but not as well for some demographic variables. For example, Maples et al. find that Nashville and Houston residency as well as gender and education significantly affect the decision to purchase directly from the producer, whereas we do not find significance for those parameters.

Conclusions

There is no indication that growing consumer interest in niche food markets, such as organic and local, is waning, and food producers would be remiss not to differentiate among consumers and the products for which they can potentially charge a price premium. The joint model estimated in this paper provides insight for producers about (1) factors that affect whether or not consumers buy food directly from producers and (2) factors that affect how much consumers spend on food purchased directly from producers.

We find that all the factors increasing the likelihood of direct-from-producer purchases also increase expenditure levels. Consumers are more likely to purchase directly from the producer and spend more on these purchases when they (1) have a more accurate knowledge about agriculture, (2) are more concerned with the safety of food produced in the United States, (3) are more physically active, and (4) have a greater incidence of family health issues. A producer marketing strategy that focuses specifically on the health benefits of fresh produce could, therefore, be effective in recruiting new consumers to the market, increasing the frequency of visits among existing customers, and increasing average expenditures per customer.

In addition, immigrants spend significantly more than U.S.-born respondents, so an effective marketing strategy could target that population. As noted in our review of the literature, eating habits and the cultural composition of immigrant communities are significant factors for food purchase decisions, particularly among U.S. Latina and Spanish-speaking populations. Producers who market directly to consumers are encouraged to explore buyer characteristics, such as cultural food preferences, food preparation methods, shopping habits, and primary language spoken in their customers' households. Armed with this information, producers are encouraged to offer promotional materials (recipes, coupons, product descriptions, and pricing guides) that recognize the cultural and language variations of their client base, better communicate the value of their product offerings to those clients, and secure long-term relationships with them.

In particular, our examination of a respondent's family health history and knowledge of agriculture add to the existing literature exploring characteristics of those consumers who are motivated to spend time and other personal resources to purchase directly from producers on a regular basis. In sum, consumers who are highly motivated to secure food of a known origin, in an effort to control for both the safety of the food and the perceived positive health benefits, appear willing to incur the associated temporal and search costs. Future research might investigate whether these consumer characteristics are important to a larger population, beyond urban consumers in the Southeastern United States.

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Appendix

A.1 Eight-Question True-False Quiz

You will now see a series of statements and will be asked if, in your opinion, they are true or false. There are no wrong answers.

There are more farmers in the U.S. than there were 10 years ago.
True
False
Not Sure

Less than 3 percent of the U.S. gross national product is from agriculture
True
False
Not Sure

For every $1.00 consumers spend on food in the U.S. the actual farmer/rancher receives less than 25 percent of that dollar.
True
False
Not Sure

One of every five jobs in the U.S. is related to agriculture.
True
False
Not Sure

The average U.S. farm is larger than 500 acres.
True
False
Not Sure

Several countries depend on U.S. agriculture exports for food and fiber.
True
False
Not Sure

The average U.S. farmer feeds about 155 people.
True
False
Not Sure

In the U.S., the agricultural industry has a trade surplus.
True
False
Not Sure

A.2 Family Health History Question

Please check if you or your relatives have been treated for any of the following health issues (check all that apply)

	Me	Siblings	Father	Mother	Children	Grandparents
Cancer						
Heart Disease						
Diabetes						
Back/Joint Pain						
Alzheimer's/Dementia						
Obesity						
None of the above						

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Farm Diversification through Farm Shop Entrepreneurship in the UK

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Abstract

Declining real farm income, increased development, and loss of government agricultural programs have created pressure for smaller-scale farms to enhance farm income, often through diversification into agritourism. This study examines farm shops as a farm diversification strategy by investigating farm shop managers as entrepreneurs and highlighting the strategies and skills required for success through interviews with farm shop owners in the UK. Results of the qualitative analysis show that agricultural entrepreneurs must create a unique identity or brand for their operation, build networks, develop knowledge and talent, and build business acumen in order to creatively overcome obstacles and manage diverse operations.

Keywords: agritourism, direct marketing, diversification, entrepreneurship, farm shops, foodies, local sourcing, UK

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Introduction

Multiple factors have placed smaller-scale family farms under increased pressure to cut costs and enhance income, often through diversifying and generating off-farm income. These factors include the decline in real farm income since the 1980s, increased development pressure, loss of government agricultural programs and subsidies, and farm consolidation into large corporate farms worldwide to take advantage of economies of scale (Strevens, 1994; Evans and Ilbery, 1989). For many, diversification has meant providing leisure or recreational opportunities, often referred to as agritourism or agritainment on their farm or ranch (Nickerson, Black, and McCool, 2001). The motivations for and the benefits of diversification into agritourism, a subsector of food tourism, have grown in popularity as a research subject over the past decade. It has been suggested, in fact, that agritourism has preserved traditional family farming, maintained agricultural land and open space, improved the productivity of farm resources, and enhanced the overall economic situation in rural areas (Tew and Barbieri, 2012; Wilson, Thilmany, and Watson, 2006).

The literature has highlighted the farm and operator characteristics—such as farm size, operator gender, education level, age, and family economic dependence on the farming operation—that influence agritourism success (Barbieri and Mshenga, 2008). Additionally, the literature has considered the entrepreneurial motivations for diversification into agritourism, highlighting the need for additional income, employment for family members, tax incentives, and other factors (Nickerson, Black, and McCool, 2001; McGehee and Kim, 2004; Schilling, Sullivan, and Komar, 2012). The benefits of increased agritourism offerings for their operators, their communities, and consumers in general have also been detailed (Mitchell and Turner, 2010; Yoon and Uysal, 2005; Renko, Renko, and Polonijo, 2010).

Few studies, however, have considered the wide range of entrepreneurial skills and strategies required for success in multi-faceted agricultural enterprises. Little is known about the range of competencies needed for an entrepreneur to move from a traditional production-oriented farming operation to a diversified, highly experience-based operation, such as a food or agritourism destination (Slocum, 2015). Solvoll, Alsos, and Bulanova (2015) write, “the structural change and transition to more experience-based products in tourism demand entrepreneurial behavior in order to implement needed innovations” (p. 120). Small business development and entrepreneurship are important components of diversification into agritourism and its success as a development strategy (Koh, 2002).

Studies addressing the entrepreneurial skills of agritourism operators have focused primarily on traditional agritourism venues (hay rides, corn mazes, u-picks) or agritourism operations in general (Phelan and Sharpley, 2011; Tew and Barbieri, 2012) rather than on the fast-growing segment devoted to food and culinary experiences such as tasting areas, bed and breakfasts, bakeries, creameries, cafes, and farm shops. Akbaba (2012) reminds us that “although many common characteristics exist between small businesses in general, the milieu, and the sub sector in which they operate should be taken into consideration when analyzing business performance, characteristics, or managerial issues of small tourism businesses” (p. 178).

This study examines the role of farm shops, under various organizational structures and offerings, as a farm diversification strategy focused on developing food-based tourism operations. A farm shop or store, also referred to as a roadside farm market, is a permanent or semi-permanent structure where farm products from a specific farm or multiple farms, both fresh and processed (such as jams, honey and cheese) are offered for direct sale to consumers. Shops are normally open to the public year-round and often provide snacks, a bakery or butchery, and a small café. Shops may be located on a farm or in nearby towns or cities, and they are frequently operated or controlled by the farmer. Farm shops are a unique food tourism opportunity—currently more common in Europe and New Zealand than in the United States—that create expanded benefits to operators in terms of consistent revenue generation, an outlet for new product offerings, and employment for family members. They are especially popular with the ever-growing "foodie" market.

In particular, this study investigates farm shop operators as entrepreneurs and highlights the strategies and skills required for success in such a highly diversified operation, as evidenced through interviews with farm shop entrepreneurs in the United Kingdom (UK). While the business environment and operations in the UK are somewhat different from the United States and other countries, study results provide a solid foundation upon which current agricultural operations can build to successfully diversify their operations into food tourism and, specifically, farm shops. This is especially important in regions with few successful models to emulate.

Literature Review

The rising social movement known as the foodie movement provides new and innovative opportunities for agricultural and food-based tourism. A foodie is defined as "a food lover, one whose personal and social identity encompasses food quality, cooking, sharing meals and food experiences" (Getz et al., 2014, p. 6). Foodie identity is expressed through one's behavior, including food-related travel experiences, as well as opportunities for self-identity and social identity. Foodies often seek out quality food experiences as a lifestyle choice (Santich, 1996). These internal "push" strategies have facilitated growth in food tourism (Kivela and Crotts, 2006), which allows foodies to experience culture through culinary consumption. Slocum (2015) argues that this social movement is also driven by sustainable consumption values, in that consumers are increasingly aware of the negative environmental, cultural, and social impacts posed by increasingly globalized food systems. Therefore, foodies seek foods they view as "sustainable" as well as experiential food-related opportunities, which have become a key travel motivation in certain markets (Heldke, 2003) and provide opportunities for entrepreneurial activity.

As travelers seek unique travel experiences, agricultural entrepreneurs can use flexibility and creativity to promote new and innovative consumer experiences (Ateljevic and Doorne, 2000), creating regional economic growth and development. Small firms provide opportunities for job creation, increase the variety of tourism offerings with comparatively less investment than larger firms, possess greater flexibility in adopting technology, encourage personal savings and reinvestment, and provide flexible innovations within economies (Thomas, Shaw, and Page, 2011).

Small firms also possess greater flexibility to support sustainability initiatives as their committed entrepreneurs often lead the charge toward more sustainable development (Dixon and Clifford, 2007). The flexibility inherent in small firms—especially those in agriculture—may be due, in part, to agricultural entrepreneurs' emphasis on lifestyle preferences, such as maintaining traditional ways of life and economic independence, rather than profitability (Bosworth and Farrell, 2011; McGehee and Kim, 2004). Ateljevic and Doorne (2000) reason, "Whilst there has been extensive research into the 'greening' of consumers in which numerous 'shades of green' can be identified, the value positions underlying the corresponding small scale entrepreneurial activity remains comparatively under theorized" (p. 378).

Almost twenty years later, entrepreneurship and the role that small family farms can play in uniting food and tourism to create the foodie experience that consumer seek are still under-investigated. The term agritourism embraces a variety of organizational structures and ownership types. Everett and Slocum (2013) provide a general overview of the various business types and structures across the spectrum of food tourism, but on the whole very few studies provide further insight into the entrepreneurial skills and strategies required for successful outcomes for these business structures.

Using interviews conducted with farm shop operators in the UK in 2014, this study finds that agricultural entrepreneurs must create a unique identity or brand for their operations, build networks to take advantage of marketing partnerships and supplier relationships, focus on developing their own knowledge and skills as well as those of others (especially to enhance local sourcing and mentoring of local providers), and build business acumen in order to creatively overcome obstacles and manage diverse operations with competing time commitments. These results are consistent with those described by Hall, Mitchell, and Sharples (2003) that reference the critical need to develop intangible capital to ensure success for food tourism businesses.

Data and Methods

In August 2014, semi-structured one-on-one interviews were conducted with nine farm shop operators as well as representatives from two UK food tourism organizations. The initial 38 subjects were identified through the UK Farm Shop Directory in the study area, defined as no more than 150 miles from London. Once interviews commenced, snowball sampling was added, in which one interviewee would suggest another interview site. Table 1 lists the research sites and location information. All of the interviews were recorded and later transcribed. An interview guide was developed to ensure that participants answered a similar set of questions, allowing comparison between participants (Bernard and Ryan, 2010). The research team developed the questions collaboratively and drew from themes in the food tourism and agricultural marketing literature. All questions were open-ended and pertained to farm shop marketing methods, networking and cooperative organizations, tourism authority services, shop ownership structures, types of products and activities offered, clientele, regulatory and licensing requirements, product origin labeling and sourcing strategies, resources in terms of governmental or non-profit educational opportunities, tax benefits and financial incentives, operator professional background and education, and participation in local events or festivals.

Table 1. Research Sites

Name	Location
Boycott Farm Shop	Stowe, Buckinghamshire
Chilterns Tourism Network	High Wickam, Buckinghamshire
Farndon Fields Farm Shop	Market Harborough, Leicestershire
Manor Organic Farm	Long Whatton, Loughborough
King Farms	Aylesbury, Buckinghamshire
Leicestershire Local Enterprise Partnership (Government)	Leicester, Leicestershire
Middle Farm	Lewes, East Sussex
Northfields Farm	Oakham, Leicestershire
Park Farm Shop	Brighton, East Sussex
Peterley Manor Farm	Great Missenden, Buckinghamshire
Summerhill	Cardington, Bedfordshire

All interview data were combined and then hand-coded into topics. These topics were then pooled to develop a series of themes, defined as common plots or ideas that ran through the data (Richards and Morse, 2007). The subjectivity of qualitative analysis can result in an overwhelming number of hypotheses; consequently, researchers must use theory to guide them to determine the research focus and define a complete and appropriate description of the evidence (Slocum, Backman, and Baldwin, 2012). Therefore, the data were evaluated in three stages for this analysis: 1) each team member reviewed and coded the data independently to identify emergent themes; 2) team members discussed the interpretation of findings and potential data topics in relation to the theoretical underpinnings within the literature; and 3) a second round of theme development was conducted jointly.

Each farm shop varied, not only in the services offered, but also in their clientele, marketing strategies, and inventory. Each individual farm shop owner or manager interviewed represented a mix of formal and informal training as well as personal and professional characteristics and values. The most notable and common characteristic was their interest in local sourcing and the heritage they perceived their farm shops to represent. The oldest farm shop was established in 1922 and was owned by a third-generation member of the founding family. The newest farm shop opened in 2010, while the majority were established between 1977 and 1990.

Results

Four central themes were identified from the interviews: 1) creating a unique identity or brand; 2) developing knowledge and talent; 3) building networks; and 4) overcoming obstacles. Within each theme, several additional topics were identified. Table 2 lists the themes and their corresponding topics. Interestingly, three of the four themes fall within the intangible capital categories (networks, brand, talent) identified by Hall, Mitchell, and Sharples (2003) as critical to the success of regional business strategies, while the fourth (overcoming obstacles) falls under the intangible category of business management skill and acumen, or intellectual property. The results of each theme are discussed below.

Creating a Unique Identity or Brand

Branding, or creating a unique identity through products and services offered, is key to differentiating a business or product in the marketplace and earning higher returns (Tronstad et al., 2005). The branding theme emerging from the study addresses complex issues, such as the varying definitions of "local," the marketing and merchandizing of products and services that reinforce the image or brand of the farm shop, and the importance of differentiating the shop from its competition by providing unique products and/or experiences.

Table 2. Themes and Topics

Themes	Topics
Creating a Unique Identity or Brand	Local sourcing Product variety Experiential activities
Developing Knowledge and Talent	Discerning talent Developing knowledge/skills Mentoring
Building Networks	Supply relationships Marketing partnerships Educational opportunities
Overcoming Obstacles	Federal regulation Local politics Capital investment Tourism infrastructure

While local sourcing was very important to all farm shop operators interviewed, study participants did not share a clear definition of "local." Instead, farm shops tended to source from producers as close to the farm as possible, then worked outward geographically to find high-quality products. One common perception held by farm shop operators was that local food should be British, but specialty items from Europe were also included in certain inventories depending on the clientele that frequented the shop and the availability of local merchandise.

> *"So it was all about sourcing within a 30-mile radius, because I think, within England, that's sort of the standard set by the farmers' market association. We're something like a 100-mile radius, but a lot of it is sourced within 10 miles. In the end, it's about sourcing from individual farmers and producers rather than just saying it was British. Even small distances seem really big to people because it's all relative."*

Each area faced unique farming conditions, soil fertility, and urban development patterns, all of which influenced their definitions of local. More urban areas, such as the London suburbs and densely populated areas of Leicestershire, did not have available grazing land in the immediate area from which to source meats and cheeses. Instead, the farm shop operators encouraged local artisans to process these items locally.

> *"I mean the vast majority is not from our farm actually. Certainly, from here out East it's very fertile, alluvial soil, and you can see over there is onions. So, if farmers just sourced from this field all we'd sell is onions. So, sourcing locally for us is not necessarily only what's in our field, it's about looking at artisan producers, people who are doing stuff in the local area."*

The farm shops carried a very diverse selection of products. Some specialized in rare breed meats, others in English wine. Many carried staple foods, such as bread, butter, and spices, so that customers could shop for an entire meal on the premises. Additionally, value-added products were highly sought after, including jams, cheeses, and sauces. A few of the farm shops sold prepared foods that could be put directly in the oven for meals at home. Others operated as a butcher, bakery, or cheese shop, selling items that complemented their main brand. For example, a butcher might carry a variety of locally made barbeque sauces or make coleslaw to sell as a complement to a Sunday barbeque purchase.

> *"The idea is to keep it grounded really. It's not an individual enterprise; it is part of the farm. So even though the shop that's here and the bakery run as a separate part of the company, it is all part of the whole farm."*

> *"The animals we have on the farm, we have llamas, we have cattle which are raised in Leicestershire, and we have funny sheep which are raised in Leicestershire. So, the whole thing is related to the shop."*

Additionally, each farm shop offered products and services beyond the food items they produced or sourced. Catering and cafés, or teashops, were common, as were on-site picnic areas. Children's activities, such as petting zoos, were important, especially on farms that offered restaurants where parents could relax. One farm shop was frequently used as a wedding venue. Many of the farm shops additionally sold products at local farmers' markets, offered community supported agriculture (CSAs) programs for residents, and showcased their merchandise (such as award-winning premium sausages or lamb) at national shows and competitions. One shop offered pottery classes hosted by a local artist, while another offered a paintball course.

> *"The food is what started it. But then you have someone who wants coffee and spends the whole day here with some staff looking after them and you're not making much money. But there are farms that go that way…There's a big birds of prey center where they fly these hawks and owls and they're going to come down and do a display in the car park for us. So, that kind of stuff we try and do as add-ons. About once a month we'll have a cheese and wine evening."*

In the end, all of the merchandise and special events were part of a complex branding strategy to differentiate each farm shop from its competition. Personal relationships with customers were very important, and promoting the history and personalities behind the farm shop was essential to their marketing strategy. All participants used social media (for example, Facebook and

Twitter) to keep customers updated on inventory items, special events, and news. Constant reassessment of each company's brand was important to its continued success.

> *"When I started a lot of it wasn't local. I decided to bring kind of a local focus. It made sense of what the history of the place was. It's having a balance between not looking like every other farm shop in the Chilterns, but also having the things that people accept and what they like."*

The increased competition in the farm shop industry has resulted in several different marketing strategies. No two farm shops were alike, and no common organizational or ownership structure was apparent. Instead, farm shops were diverse, catering to a variety of target markets. Shop inventories were derived from guesswork and an attempt to keep the shop new and exciting. Participants noted several failed attempts to diversify, but each endeavor had been a learning experience for the shop operator.

Developing Knowledge and Talent

Hall, Mitchell, and Sharples (2003) state that talent—in addition to knowledge development and retention—is key to successful business innovation. The participants in this study embodied this theme by cultivating high-quality suppliers, mentoring and supporting local providers, and creating intellectual capital and management skills in themselves and others.

The majority of farm shop operators worked with outside vendors to ensure adequate supply and product variety, even when the farm shop was located on a working farm. While local origin was important, quality was the most important consideration when choosing vendors. Discerning and developing talent in potential vendors was a primary focus. To that end, all shop operators visited the farms and food producers from which they sourced, provided advice on product development and potential improvements, and conducted basic, unofficial health and safety inspections.

> *"It's just a different kind of buying. Whereas with most shops, a lot of buyers will just sit there with their catalogues and buy stuff. For us it was literally running out and meeting people and getting the story behind it, and then testing the product and saying okay is this something that we can sell. Not just is it good, but you've got to think about is it local and can we sell it?"*

Farm shop operators were also proponents of and leaders in encouraging new entrants to the local food movement. They were generally supportive of community development and wanted as many of their suppliers as possible to be local. While they were, in fact, mentoring others, study participants recognized that they had acquired a wealth of knowledge about food production and therefore were cautious with whom they shared that knowledge.

> *"So the lady who's doing the pickled garlic, she gets her garlic from the UK which is good enough for us. Whereas before we were getting it from a different garlic supplier, and he was getting all his garlic from China because it was cheaper and we backed out. We stopped selling that product."*

> *"We get people coming and I tend to be fairly ruthless because it's taken me nearly 20 years, a lot of sweat and tears (literally) to build up huge debt of expertise and knowledge and I can't just give that away for nothing. Because it's the intellectual capital of my business really."*

The farm shop operators interviewed had developed an immense amount of intellectual capital and skill and were well versed in a variety of different activities, from blogging to inoculating cattle and from customer service to federal safety standards. Their roles were diverse and they wore several hats, including buyer, manager, accountant, event coordinator, chef, butcher, baker, farmer, community advisor, teacher, and safety inspector. Hence, time management was a great challenge. Customers arrived throughout the day and late into the evening, and they also needed to complete off-site visits, special events, and marketing. In other words, the farm shop operators were really running two businesses simultaneously—a farm and a retail operation.

> *"But it's like having another branch. How do you know your accounts are packaged, that you're paying your bills and you're dealing with someone stealing money from you? You go through the whole day and then you have to have creative input into this, that, and the other. And then going down to London on a Monday and another meeting on a Thursday. You just don't get it all done."*

While each farm shop provided a unique experience to visitors, operators shared common philosophies related to regional development, including supporting the local food movement and assisting fellow food producers and farmers. Developing their own knowledge and skills, as well as assisting in the creation of intellectual capital in others through mentoring, was clearly important to them.

Building Networks

Networking can be defined as cooperation between potentially competing firms and other organizations connected through economic or social relationships (Hall, Mitchell, and Sharples, 2003). Networks create advantages to participating entities through shared access to information, market intelligence, supplier networks, and cooperative arrangements. The networking theme in this study focused on competition between farm shops and the government or industry partnerships available. The most common form of organized partnership consisted of marketing cooperatives, although informal partnerships between farms to improve the depth and variety of products offered were also a common rationale for networking.

Local food networks are growing in the UK, and many of the farm shops worked with regional promotional organizations. The interviews with the Local Enterprise Partnership (government) and the Chilterns Tourism Network provided valuable insight into the networking opportunities available to farm shops. In particular, marketing partnerships and educational opportunities were key advantages. UK and EU grants were also available through these organizations.

> *"They charge a fee for all the producers who want to join, but they offer lots in the way of training and capacity building. They'll do product photography or help you with marketing if you want them to. I think not just in terms of the*

passion and it looking nice, but I think they genuinely help producers totally access the different marketplace. I think they're a great asset."

Local universities, regional conferences, and local farmers' markets provided avenues to develop partnerships. However, farmers tend to be isolationists, and neighboring farm shops are seen as competitors rather than partners. Therefore, the conversation of partnerships revolved around regional governing agencies and membership (tourism) organizations.

"They're thinking about doing a Foodie Group. Which I think would be the best thing they could do which would be a set group around Beds with little signs telling which way to drive and you can visit. You know you've got the microbrewery and then a farm shop and then you know there's a really good flour mill."

"I wouldn't say we worked… well I wouldn't say we even speak to each other. In terms of farm shops. Because we are in competition with them so I will chat with them occasionally. If we've had a dodgy, somebody who's come in and tried to shoplift, then I might give them a ring and say, "you know likewise, you might do the same for us". But that'd be about the limit of our cooperation."

It can be argued that farm shop operators had little time to facilitate partnerships, although all shops recognized the value inherent in networking opportunities. In the end, they work with potential suppliers to find quality merchandise, but partnerships between farm shops and complementary businesses to promote local food and take advantage of destination branding are currently underutilized. The economic advantages of creating clusters, or linkages among businesses in the value chain, could greatly enhance the economic sustainability of farm shops by creating shared access to markets, market intelligence, supplier networks, etc. (Hall, Mitchell, and Sharples, 2003).

Overcoming Obstacles

Farm shop operators encountered several common obstacles—including governmental regulations, local political environment and support, and a lack of infrastructure and resources for visitors (especially for overnight tourists) and access to capital financing. These obstacles or constraints required farm shop operators to sharpen their business management skills and acumen to increase their potential for success.

The farm shops faced a number of regulations, at both the national and the local level. National regulation was frequently referred to by participants as "common sense," "relatively easy," and "not too onerous." For example, the Food Standards Agency conducts HACCP (Hazard Analysis and Critical Control Point) inspections every six months.

"We've always been absolutely on top. We've got insurance coming out our ears. We've got scotch certificates; we've got all that. So, it is really important. It's not rocket science though. We're audited at the market, regularly, by an internal auditor."

In exchange, the national government has implemented several grant options and tax incentives for farm shop businesses.

> *"So we don't pay as much as others because we got a lot of small business grants that pay some of the rates, because we employ less than nine people. We're an expanding small business so we got a bit more release. So, after all these, we actually don't pay any business rates at all. It really does help. I think the UK government is for the first time in a long time actually focusing on small business and trying to help them keep going."*

> *"The landlady put (solar) panels so she gets the subsidies from the government. We get free electricity when the sun shines while she gets the government subsidy, which is awesome. She gets the money back while I get electricity for nothing."*

Local regulations appeared to be much more burdensome. Local planning and zoning regulations were the most cumbersome for farm shops, many of which were located in historical buildings or on historical farmland. Making building improvements or converting farm buildings into cafés or restaurants was very frustrating.

> *"So you have to have enough parking spaces because you're not allowed to let people park in the roadside and disturb the traffic flow. If we wanted it to go from our café and extend it to the end of the building, we have to keep that in exactly the same external look. They're about offering products locally in Bedfordshire, so we've got to get local bricks and black timber web or knotted clay. It has to look exactly the same from the outside."*

In particular, signage was a contentious topic at most research sites. Many farm shop operators acknowledged that their signs were illegal, and several shops often had their signs removed without warning.

> *"We're an enlisted building spot which is just a nightmare. So, anything to do with planning. And because we're in a conservation area, they then get excited about what it looks like from the road. So, when someone comes down what they think will make a difference to their view, then it won't do. The sign across from the drive is illegal. It shouldn't be bigger than four foot, literally. So, things like that just drive me nuts. "*

While farm shops appear to be well integrated into their communities and support many of the local farmers and food producers, there appeared to be little reciprocal support at the local level. The UK has adopted food tourism policies to promote regional development; however, many local councils continue to prioritize zoning and signage regulations that conflict with the national goals of encouraging visitation to these enterprises.

Study participants indicated that the lack of signage was a major barrier to taking advantage of the tourism market. Tourists couldn't find the farm shops unless they were directed there by hotels, local businesses, residents, or internet sites. Inadequate tourism infrastructure also seemed to reduce tourism visits. For example, a lack of accommodations along hiking and biking trails limited the opportunity for farm shops to cash in on the tourism industry. Participants felt that the farm shop's proximity to tourist attractions was the most important factor in tourism volume. Some of the farm shops were located near National Trust properties or within conservation districts.[1]

All farm shop operators interviewed acknowledged that locals were the main revenue source for their shop, not recognizing these customers as local tourists. This aligns with Hall, Mitchell, and Sharples (2003), who state that farmers do not see themselves in the tourist business, although their clientele fit the definition of tourists or excursionists (day-trippers). Indeed, excursionists on a day or afternoon visit to the shop—to have coffee or lunch, purchase food items, allow children to play, or pick fruit and vegetables—were very much a part of the farm shops' core business strategy.

> *"But to have things for the tourism industry. It's all about margin and the smaller you are the more important it is, you have to create big margins, and add some substantial value. There's a high margin in tourism. And you can really make a killing."*

Additionally, restricted partnerships with tourism providers (such as hotels and tour operators) seemed to limit tourism numbers. Organizations like the Chilterns Tourism Network were viewed as positive advancements in accessing tourists.

> *"As a country, we're doing a better job of helping areas for tourism. I mean they're making more use of perhaps natural resources though in the Chilterns. There's a very long distance national walking path, The Ridgeway, which they started to promote more. (However) there's nowhere to stay after about 25 miles on the first day. Nowhere to stay after 50 miles on the second day. Now these guys are starting to get more clued up. And the government and local authorities are promoting that kind of stuff to help local businesses more."*

Special events were another way to access tourism markets. Most of the participants were actively involved in special events, both nationally and locally.

> *"So we have Borough Markets which is pretty much 5-6 days a week, we have a little market in Hattney which we were also in right at the beginning and Broadway Market which is a lovely old street market. Then we have two of these catering trailers. There's one that's smaller and we have a much larger one which just started today at the Cambridge Folk Festival which is one of the most famous folk festivals in the world. We've been trading there for about 5-6 years. And then we do smaller local events and a few other large events with that and we do our bacon, our sausages, our burgers, steaks perhaps, chips."*

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[1]The National Trust is a charity that protects and manages over 350 historic properties and makes them available for visitation by the general public.

Capital investment and profitability weighed heavily on the minds of all interviewees. Many of the farm shops operated on tenant farms, as the cost to purchase their own farmland was outside their reach. Once in operation, they spent a lot of time analyzing margins and planning for potential investments and growth. As retail operations, most operators recognized that they, rather than the producers from whom they source, are bearing the risk. They claimed that success lies in the details.

> *"You know we've got spreadsheets coming out of our ears. When I was making burgers with a hand press and I had an order for a thousand burgers, we were very clear to price ourselves at the top of the market. You know that you have to go from a hand press, which might cost you 300 pounds, to an automated press that may cost you 4-5,000 pounds. And if you're still selling for 2.50, not only are you not paying for your time, you're probably not paying for the machine. And then once you get the machine, then you've got to hire someone to operate the machine. And then if you're still selling at 2.50 or 2.75, you're not going to be able to afford that person."*

While many of the farm shop operators interviewed encountered the obstacles or constraints mentioned throughout this theme, these entrepreneurs found creative ways to overcome them. They had to sharpen their business management skills across a wide range of managerial and entrepreneurial dimensions (Phelan and Sharpley, 2011), building the intellectual capital required for success.

Discussion and Conclusions

This study provides a more detailed understanding of the entrepreneurial skills and strategies required to increase success in agritourism, specifically farm shop management, based on interviews of farm shop operators in the UK conducted in 2014.

Results show that study participants considered the most important component of success to be the ability to differentiate their businesses from their competitors and reach financial sustainability. The farm shop industry in the UK is very competitive, requiring niche strategies to distinguish product offerings, develop promotional strategies, and create a unique brand or image in the mind of the consumers (Koh, 2002). Specific areas of importance included providing innovative experiential components to their operations—such as tearooms or cafés, children's activities, events, and artisan opportunities to build customer loyalty—for both local residents and visitors to enhance income generation (Thomas, Shaw, and Page, 2011). It appears that these farm shop entrepreneurs have the flexibility, as described by Ateljevic and Doorne (2000), to quickly adjust the focus of their business, experiment with new product and service offerings, and adjust their business model to accommodate changes according to the needs of their clientele.

As was the case for Kaaristo and Bardone's (2013) tourism farms, the experience of "local" can be crafted by these farm shops. Hence, it is imperative that shop operators communicate how their values and branding strategies (such as sustainable, local and/or organic) align with those of their customers. Tourists—both day-trippers and overnight visitors—seek new and innovative consumer experiences that involve cultural immersion (Ateljevic and Doorne, 2000). Foodies, in particular, often use food-related experiences to express self-identity and social identity, looking for destinations that provide participatory culinary delights (Getz et al., 2014). Therefore, branding comparisons can distinguish the shop from other food tourism options and create the atmosphere, in addition to food products and experiences, that their specific foodie clients seek.

Another area of importance included developing partnerships with local producers to ensure product variety and value-added food availability, especially given the importance of local sourcing. As a lifestyle business, much of the reward comes from discovering new products and experimenting with new activities to promote value in the local food experience through cooperation (Bosworth and Farrell, 2011). These partnerships appear to closely resemble mentorships (Dixon and Clifford, 2007), as farm shop entrepreneurs often possess important intellectual capital encompassing market trends, production processes, and regulatory issues.

As Thomas, Shaw, and Page (2011) claim, these entrepreneurs have the flexibility and the drive to increase the variety of their offerings without large-scale investment and provide flexible innovations in regional economies. However, networking between farm shops is rare since competition is fierce. Farm shop entrepreneurs do partner with non-food businesses—such as artisans, tourist attractions, and festivals—to support local development and diversify their product offerings. Improved communication, networking, and partnerships between farm shops to establish destination branding, achieve economic synergies, and structure shop-specific branding strategies would be advantageous to farm shop operators. Offering a unique destination would reduce competition between shops and provide an improved experience for customers seeking a specific niche. Regional planning organizations or tourism-specific organizations could foster communication and discussion between farm shop operators and assist with synergies related to sourcing, marketing, brand establishment, and governmental regulations. Farm shop operators also value access to resources, such as small business development grants, as well as help educating local governments on the impact of zoning and signage regulations. These are areas where cooperation between farm shops could potentially build social capital, facilitate influence, and reduce the competitive nature of the industry (Everett and Slocum, 2013).

The use of regional partnership organizations (primarily for tourism promotion) is already valued highly, and policy support at the federal level is a big advantage for farm shops. These supports include tax incentives, access to UK and EU loans and grants for small businesses, and marketing support. The EU spent $2 billion in the 1990s helping farmers diversify into agritourism, such as converting barns into accommodations (Saunders, 1998). Incorporating joint promotional activities with tourism and hospitality providers may serve to increase the market and associated revenue streams as the UK promotes tourist visits to new areas of England.

One potential detriment to diversity among farm shops is the lack of destination image that may result from differing interpretations of the role of farm shops in local food marketing. While all research participants attempted to source their products as locally as possible, the common idea that "British themed" constituted local food contradicts regional variety and identity as promoted through food tourism marketing (Renko, Renko, and Polonijo, 2010). Increasing competition and the lack of shop-to-shop networking creates a diverse image of farm shops as direct market outlets. For example, farm shop operators may agree that selling items such as British beef is adequate, but visitors may prefer regional or rare breeds that they cannot obtain in other parts of the county. Regional distinctiveness and cultural exploration are key components of food tourism and foodie culture (Everett and Aitchison, 2008).

To secure "local" inventory and keep product offerings variable, farm shop operators are central to finding and training local residents to participate in food production. These activities also play into opportunity-based entrepreneurship, as they create new products and services not currently available in their local communities. As middlemen, they are keenly aware of the needs of customers (locals and tourists) while understanding the personalities and talents within their community (Ateljevic and Doorne, 2000). This also transfers to business formation activities that support business development opportunities in their region. When these opportunities are not available, they encourage new business entrants. Moreover, many farm shops have refurbished historical buildings, having found new uses to justify the expense of refurbishment while simultaneously protecting regional heritage. They also seek outside funding through their networks to make renovations possible. This supports opportunity-based entrepreneurship, where new infrastructure is added to the set of tourism offerings.

Lastly, the innovation and entrepreneurial spirit of farm shop operators is highlighted. While their primary motivation is a for-profit enterprise, these actors also enhance regional food opportunities, encouraging new entrants into the industry, and expanding above and beyond simple retail operations. In particular, they support enhanced food-related experiences for both residents and visitors alike. Much can be learned from these British entrepreneurs that could be applied to other communities promoting local food as a vehicle to support regional economic development.

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A First Step to Identifying Underserved Foreign Markets

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Abstract

We describe a first step for identifying foreign markets that may be candidates for export expansion. The method compares export data to the amount of exports predicted by the gravity equation. We estimate four sets of gravity equation coefficients and use both in-sample and out-of-sample predictions. To illustrate our method, we use data from Washington agricultural industrial groups. We find many markets, particularly those in Europe, that are currently underserved by Washington agricultural exports, often by large amounts. We also identify overserved markets that can be further studied to provide lessons on what works for increasing exports.

Keywords: agriculture, exports, gravity

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Introduction

This paper describes a method for identifying foreign markets whose imports greatly deviate from simple trade model predictions. Finding these markets is a time-saving first step to identifying foreign markets that may be candidates for expanded exports. Unlike beginning with a list of markets ordered by trade flows, our approach controls for the basic explanatory variables of trade (distance, market size, and industry group), thus allowing an analyst to focus on more promising markets for export expansion by subsequently determining whether those markets have idiosyncratic or explanatory variables not in our model that drive the observed trade pattern. Identifying underserved markets has the potential to create significant economic benefits from targeted expansion of exports.

Our method compares export predictions from the gravity model of trade parameterized with four different sets of coefficient estimates to the actual export data and then ranks markets by the amount by which the export data differ from the models' predictions. We define markets with the biggest difference between actual exports and the models' export predictions as “underserved” markets. Our method also identifies “overserved” markets, those that have the greatest difference between actual exports and those predicted by the models. Overserved markets could be studied further to understand their success as export destinations. We do not construct a complicated trade model with many variables to fully account for the trade pattern observed in the data. Rather, we describe a method to identify markets and industry groups whose pattern of trade most deviates from a simple trade model so that those markets can be further analyzed for economically meaningful but potentially idiosyncratic factors.

There is a large existing literature on “international market selection.” This literature, typically found in marketing journals, presents models with many different variables that try to assess the potential of foreign markets. The fundamental dichotomy in the many models in this literature is between (1) simplicity, so that the data required to assess markets are not too expensive, versus (2) the inclusion of speculative market potential variables, such as predictions of future market growth and cultural similarities. Good examples of this literature are Brouthers et al. (2009); Sakarya, Eckman, and Hylledard (2007); and Papadopoulos, Chen, and Thomas (2002). What these models often lack, however, is a foundation in international trade theory and empirics. Thus our goal is to present a method of international market selection that is simple in terms of data requirements, yet grounded in the economics of international trade and that quickly yields the most promising foreign markets for each industry group. Subsequent to applying our method is the more time-consuming idiosyncratic analysis of those markets that our first-step method has identified.

The gravity model is an immensely popular tool for analyzing international trade flows, though it has not typically been the basis for international market selection models. The empirical gravity model was first described by Tinbergen (1962) and has since been theoretically justified by Anderson (1979) and Anderson and van Wincoop (2003). The gravity model relates the economic size of the destination market, the economic size of the exporting market, and the physical distance between the two. It is widely applied to study trade flow patterns such as assessing the impact of trade agreements, currency unions, the border effect, and common language. For example, Hanson and Xiang (2002) use a gravity model to assess the importance of barriers to trade. In another example, Subramanian and Wei (2007) use the gravity model to find a positive effect of the World Trade Organization on exports.

To illustrate our method, we study the case of the 24 Washington State agricultural industry groups.[1] We choose this case to study because agriculture and international sales are two important components of the Washington State economy. In 2013, GDP from food and agricultural sectors was $49.0 billion or 13% of the state's economy. In the same year, Washington exported more than $15.1 billion in food and agricultural products, ranking third among U.S. states.[2] We use export data from 2012–2014 for the 24 Washington agricultural industry groups to estimate the parameters needed for in-sample predictions of Washington agricultural exports by industry group. We also use export data from California's agricultural industry groups and export data from Washington's non-agricultural industry groups from 2012–2014 to estimate gravity equation parameters for out-of-sample predictions.

Within each of the in-sample and out-of-sample exercises, we estimate the coefficients for the gravity equation using two specifications and two estimators, giving us four sets of parameters. We take one set of parameters and apply them to the data on economic size and distance variables, giving us a prediction of exports from each Washington agricultural industry group to every market. We calculate the difference between that prediction and the actual data and then create a list of markets ordered by that difference. Next, we create an ordered list of market deviations using each of the other three sets of parameters. We call a market “underserved” if that market appears in the top 5% of at least three of the four rankings of differences between actual exports and predicted exports. Similarly, markets are “overserved” when that market appears in the bottom 5% of at least three of the four rankings.

We find that despite controlling for distance, market size, and industry group, many European markets are underserved by a wide range of Washington agricultural industry groups. In particular, Washington exports to Germany, Italy, Norway, and Turkey are much less than predicted for many industry groups. Brazil and Venezuela, for example, receive far fewer exports from many of Washington's agriculture industry groups than predicted by the gravity equation. In general, Washington exports to East Asia match or exceed gravity equation predictions. The Philippines, Canada, and Hong Kong are also overserved by many of Washington's agricultural industrial groups.

Under- and Overserved Markets

The gravity equation relates the economic size of the exporting and the importing country as measured by gross domestic product (GDP) and the distance between the two to export value:

$$X_{sj} = Y_s^{\beta_1} \cdot Y_j^{\beta_2} \cdot D_{sj}^{\beta_3} \cdot exp\left(\beta_0 + \varepsilon_{sj}\right). \quad (1)$$

[1] An industry group is a production classification made by the U.S Bureau of the Census that is more aggregated than an industry but more detailed than a sector. It corresponds to a four-digit North American Industry Classification Scheme (NAICS) code.
[2] Washington State Department of Agriculture: http://agr.wa.gov/aginwa (accessed July 19, 2016).

Equation (1) is the traditional form of the gravity equation and indicates that exports, X_{sj}, from state s to country j are proportional to state GDP, Y_s; GDP of trade partner country j, Y_j; and the geographic distance between state s and country j, D_{sj}. The parameter β_0 is a constant and ε_{sj} is the error term. Parameters β_1, β_2, and β_3 indicate the importance of each variable in determining exports. If the parameter values are known, the gravity equation (1) can generate a prediction of exports from state s to country j given data on the right-side variables of country sizes and distance.

Anderson and van Wincoop (2003) argue that unobserved characteristics of exporting states and importing countries may be important for estimating the parameters without bias. They call these unobserved unilateral characteristics "multilateral resistance terms." To account for them, we use fixed effects on the importing countries, d_j. Additionally, we are interested in predicting exports at the level of individual four-digit NAICS industry groups. Therefore, we control for observed and unobserved features of industry group n with fixed effects, g_n. The g_n controls allow the gravity effect to differ across products at the level of industry group. We transform the dependent variable into exports as the share of state income and log-linearize equation (1) to get

$$(2) \qquad \log\left(\frac{X_{sjn}}{Y_s}\right) = \beta_2 \log Y_j + \beta_3 \log D_{sj} + \sum_{j=1} \delta_j d_j + \sum_{n=1} \gamma_n g_n + \beta_0 + \varepsilon_{sjn},$$

where δ_j and γ_n are the coefficients on the country and industry-group binary variables. There is no variation across Washington industry groups from exchange rates; common official language; country-level historical factors; country-specific demand factors such as income, preferences, or tastes; or other variables often used in gravity equation analysis. Those variables are accounted for by the importing country effect, d_j. The industry group effect, g_n, accounts for industry group specific trade policies, industry group-level economies of scale, and other effects on groups of products. However, Y_j is co-linear with d_j in equation (2). Thus, we use one specification with the economic size of importing countries and another specification with a fixed effect for the importing country:

$$(3) \qquad \log\left(\frac{X_{sjn}}{Y_s}\right) = \beta_2 \log Y_j + \beta_3 \log D_{sj} + \sum_{n=1} \gamma_n g_n + \beta_0 + \varepsilon_{sjn}$$

$$(4) \qquad \log\left(\frac{X_{sjn}}{Y_s}\right) = \beta_3 \log D_{sj} + \sum_{j=1} \delta_j d_j + \sum_{n=1} \gamma_n g_n + \beta_0 + \varepsilon_{sjn}.$$

The distance parameter, β_3, comes from the variation in distance from all of the foreign markets in the sample.[3]

Observations with zero exports are common in trade data and in our data as well. As a consequence, log transformation generates missing values when exports are zero. To address this issue, Santos Silva and Tenreyro (2006) propose a nonlinear Poisson pseudo-maximum

[3] The presence of the country fixed effect creates a degree of multicollinearity with distance in specification (4). The presence of multicollinearity in specification (4) does not affect the robustness of our results, however. This is because (1) we still obtain statistically significant estimates despite the presence of multicollinearity, (2) multicollinearity does not prevent precise predictions, and (3) we base our results on the *rank ordering* of markets, which is not affected by changes to the point estimates from the regression used to make quantitative trade flow predictions as all markets are predicted using the same parameter estimates.

likelihood (PPML) estimator for which the log transformation is not needed. No specific distribution is required for the data. Arvis and Shephard (2013) show that the PPML is the only estimator that equalizes the totals of actual and modeled values. Though the PPML estimator has many benefits, it suffers from a lack of statistical power compared to OLS. Because OLS and PPML are both common in the literature of trade flow estimation, we use both approaches to estimate the parameters. Applying each of the two estimators to gravity specifications (3) and (4) yields four sets of estimated parameters. We then plug those estimated parameters back into the gravity equations along with data on the independent variables to calculate four predictions of Washington exports for each agricultural industry group to each country.

Regardless of the parameters, the gravity equation always predicts some amount of positive exports. Thus, all industry-markets with zero Washington exports in the data must be underserved. The question is the degree to which the zero exports in the data contrast with the amount of positive exports predicted by the gravity equations. For analysis, we partition the results into those industrial group markets in which there is a positive amount of Washington exports in the data and those in which the exports are zero in the data.

For each industrial group market observation with zero actual exports, we calculate the absolute difference from each of the four predicted values and actual exports. Then, for each industry group, we order the differences across all markets that also have zero exports using one set of parameter estimates at a time. This creates four lists of markets for each industry-group, ordered by the size of the difference between the predicted value and the actual value of exports. Each of the predictions is given equal weight. Next, we find the top 5% of market observations with the largest actual difference in each of the four lists. We define markets that exceed the 5% threshold in at least three of the four lists as *underserved* markets. The reason we require markets to be above the threshold on at least three of the lists is so that the market is thought to be underserved by each specification and each estimator at least once. We define markets that appear in at least three of the four bottom percent tails as *overserved* markets. For the non-zero export markets, we use a similar procedure except we use percentage difference instead of the actual difference to identify the under- and overserved industrial group markets. Using percentage difference controls for the size of the market.

To see how our procedure works, consider an out-of-sample exercise for the oilseeds and grains farming industry group (NAICS 1111). We split the observations into those markets receiving zero exports and those markets receiving positive exports.

The results for those markets receiving at least some exports are shown in Figure 1. Each panel in the figure is the list of markets ordered by the percentage difference from the model's prediction to the data using one of the sets of parameters obtained from running the data through specifications (3) and (4) with OLS and PPML. The y-axis of each panel is the ordered list of countries normalized into a percentile. The x-axis is the percentage difference between the model's prediction and actual exports, so that positive values indicate how much more that specification of the gravity equation predicts compared to the data.

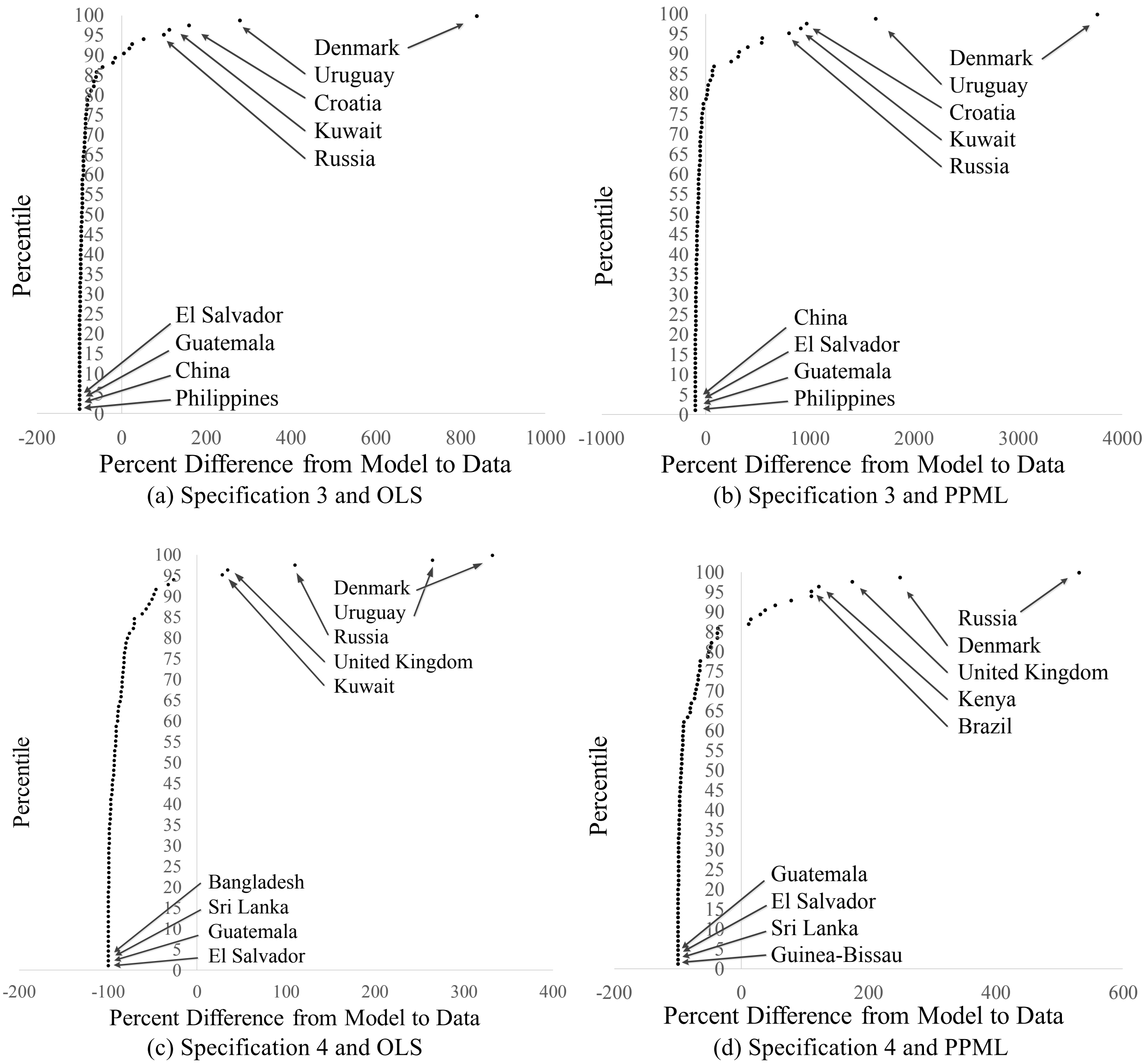


Figure 1. Out-of-Sample Exercise: Four Lists of Markets Ordered by Percent Difference from Data to Model Prediction for Oilseeds and Grains Farming (NAICS 1111) Exports.
Notes: Larger values indicate the model predicts more exports than the data show.

As can be seen from the top right of all four panels, the model predicts that Denmark should receive more exports than the data show it actually does. Denmark is the top market for three of the four panels, and the second top-most market in the fourth panel. Thus, Denmark fits our criteria of an ``underserved" market. Kuwait, Russia, and Uruguay are other underserved markets. Although the United Kingdom appears near the top of all four panels, it is not in the top 5% of markets on at least three of the panels and so does not fit our criteria of an underserved market. We find that El Salvador, Guatemala, and the Philippines are overservered markets, as they appear in the bottom 5% of at least three of the four panels in Figure 1.

Figure 1 also predicts how much each market is under- or overserved. In panel (a), we find that Denmark is predicted by that particular model to receive eight times more exports than it actually receives, while in panel (c) it is predicted to receive about 350% more. This uncertainty about the *true* model is why we define under- and overserved markets using a relative threshold (the top and bottom 5% of ordered markets) and why we require a market to appear in at least three of the four gravity equation specifications. It is interesting that we find asymmetry in the results in that the percentage difference for the underserved markets is many times larger than for the overserved markets.

As is clear from Figure 1, the markets are distributed according to the difference between the models' predictions and the data, and sometimes there is no clear gap in that distribution for a clean demarcation of underserved or overserved markets. We choose the top and bottom 5% of markets as our threshold, though we could just have easily chosen any other. The reason we choose 5% is to identify the three or four *most* under- and overserved markets. We do not want a threshold that is so relaxed that the number of markets would be too long to be informative. Though we define under- and overserved markets with a 5% threshold for ease of reporting and understanding our results, the underlying results are continuous in nature.

Data

We perform two exercises using different sets of data. In the first exercise, we use data on Washington agricultural exports from 2012–2014 to estimate the parameters in specifications (3) and (4). The parameter estimates will be the values for the mean Washington agricultural export pattern. Since we also want to predict the data on Washington agricultural exports, this is an in-sample prediction exercise. There are two advantages of this method. First, the industry-group fixed effect controls for the amount of production so that we do not confuse low exports of industry group n generally with low production of industry group n in Washington specifically. Second, since we are using data from Washington agriculture, we know the high applicability of the results. The disadvantage is that because the results are in the context of the mean pattern of Washington agricultural exports, we cannot determine whether *all* of Washington's agricultural industrial groups are underserving a particular market. To do that, we combine data on California's agricultural exports with data on Washington's exports of non-agricultural industry groups only from 2012–2014. This out-of-sample prediction exercise allows us to determine whether any of Washington's agricultural industrial sectors deviate from the mean pattern of trade overall rather than from the mean pattern of Washington's agricultural trade.

The export data are the nominal value of Washington and California exports to 163 foreign destinations from 2012 to 2014 in 109 industry groups coded by the North American Industry Classification System (NAICS) and are obtained from WiserTrade.[4] Of the 109 four-digit NAICS industry groups, 24 are agricultural industrial groups. According to Cassey (2009), who discuss the sources and collection of these data, export data from Washington and California are of relatively good quality in the sense that they measure exports produced in those states rather than shipments from interior states. Also, zero observations are true values and not bottom codes. We deflate the nominal export data to 2009 values using the U.S. CPI index.[5] We then average

[4] http://www.wisertrade.org/home/portal/index.jsp (accessed July 19, 2016).
[5] https://research.stlouisfed.org/fred2/series/CPIAUCSL (accessed July 19, 2016).

the three years of data so that our results are not being driven by an idiosyncratic year. Even with this averaging, 8,976 observations (50.5% of the total) show zero exports. Because of the constant term in specifications (3) and (4), one industry group is dropped in each regression to avoid collinearity.

To measure economic size, GDP data from 2012 to 2014 for the 163 foreign markets are collected from the World Bank.[6] Washington and California GDP data are from the U.S. Bureau of Economic Analysis.[7] We deflate all GDP data by the U.S. CPI and then average as with the export data. The geographic distances between the two states and the foreign destinations are calculated using coordinates of country capitals and U.S. state population centroids. Though there are 163 foreign markets in our data, each of our distributions may have less than 163 points because we have partitioned the results into those with zero actual exports and those with positive actual exports. In specification (4), one foreign market is dropped in each regression to avoid collinearity with the country controls.

Under- and Overserved Markets

Table 1. Parameter Estimates

Data	**In-Sample Estimates**				**Out-of-Sample Estimates**			
Equation	**3**	**3**	**4**	**4**	**3**	**3**	**4**	**4**
Estimator	**OLS**	**PPML**	**OLS**	**PPML**	**OLS**	**PPML**	**OLS**	**PPML**
Y_j	0.741***	1.297	-		0.839***	0.871***		
	(0.034)	(4.210)	-		(0.012)	(0.058)		
D_{sj}	-0.971***	-0.707	-7.544***	-7.622	-1.201***	-0.756**	-2.587**	-1.657*
	(0.205)	(16.475)	(0.985)	(3,301.793)	(0.065)	(0.388)	(0.390)	(1.037)
Cons.	-23.392***	-37.723	50.888***	52.333	-27.274***	-30.465***	9.868***	1.728
	(1.969)	(185.205)	(7.709)	(25,352.300)	(0.639)	(3.463)	(3.008)	(8.130)
N	1,265	3,912	1,265	3,912	8,791	17,767	8,791	17,767
$\widehat{R^2}$	0.388	0.286	0.615	0.342	0.503	0.329	0.649	0.367

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 90%, 95%, and 99% level. Values in parentheses are standard errors clustered at the industry group-country level.

Table 1 lists the parameter values we estimate using the data and that we use in the various models to make export predictions. Despite some quantitative differences in the estimates obtained from OLS and PPML within specifications (3) and (4), the estimates for the coefficient on the foreign market GDP are largely in line with the literature, as are the parameter estimates for bilateral distance under specification (3) for both in-sample and out-of-sample exercises. The estimates for the coefficient on bilateral distance for specification (4) in the out-of-sample exercise are slightly larger in absolute value but also within the range of findings in the literature. The point estimates for the in-sample exercise for specification (4) are, however, several times larger than those estimated by either OLS or PPML in the literature. This result reflects the unique data we use in that the industry group fixed effects for the in-sample exercise account for the amount of production of the industry group. Though the point estimates are in line with the literature for in-sample PPML results for specification (3), they are not statistically significant.

[6] http://data.worldbank.org/indicator/NY.GDP.MKTP.CD (accessed July 19, 2016).
[7] https://research.stlouisfed.org/fred2/release?rid=140 (accessed July 19, 2016).

This is due to the poor power of the PPML estimator and is one empirical drawback of that method. Because there is some disagreement in the rank ordering of the predictions from each model, we require an underserved market to appear in the top 5% of three out of four lists. Spearman correlations between the predictions range from 0.99 to 0.67 for markets with positive trade.

In-Sample Results

We begin by looking at the results for the in-sample exercise. For each of the 24 agricultural industry groups, Table 2 indicates underserved markets with zero exports, underserved markets with positive exports, and overserved markets as defined by our criteria. Recall that we use absolute difference for those markets that receive zero exports in the data, whereas we use percentage difference for those markets that receive positive exports in the data.

Consider the first row of Table 2: oilseeds and grains (NAICS 1111). Although 78 markets do not receive any oilseed and grain exports from Washington, none of the markets that receive zero exports fall into our definition of an underserved market because there is no market in the top 5% in at least three of the four ordered lists of markets. According to our criteria, we find three markets receiving positive exports that are underserved by oilseeds and grains. These are Denmark, Kuwait, and Uruguay. We also find that Washington exports more oilseeds and grains to El Salvador and Guatemala than predicted by the gravity equation. Keep in mind that the in-sample results show markets that deviate from the mean trade pattern of Washington agricultural industry groups. We find that all 24 industry groups underserve at least one market, though forestry products only underserve Mexico.

Whereas Table 2 lists the under- and overserved markets by industry group, Table 3 lists markets by the number of industry groups that underserve or overserve it. The top portion of the table lists the markets that receive zero exports from the greatest number of industry groups, as well as the names of those industry groups. Six Washington industry groups do not export to Venezuela, five for India, and four for Spain. Although Italy, Denmark, and Taiwan receive some exports from the listed industry groups, they receive fewer exports than expected in those industry groups. Note that although industry groups such as mushrooms and nurseries appear for multiple countries, no industry group appears in every row. This suggests that the absence of mushroom and nursery product exports has more to do with those specific markets than with the industry group in Washington overall. Hong Kong and the Philippines are overserved by the greatest number of Washington agricultural industry groups.

Figure 2 shows the geographic distribution of under- and overserved markets according to the in-sample predictions. The figure shows the number of industry groups we find underserving each market receiving zero exports for panel (a), positive exports for panel (b), and overserving each market in panel (c). The figure is a graphical representation of Table 3. Though it is useful to see the geographic distribution of markets, it can also mislead because of the small geographic size of many European countries.

Table 2. Under- and Overserved Markets by Industry Group: In-Sample Predictions

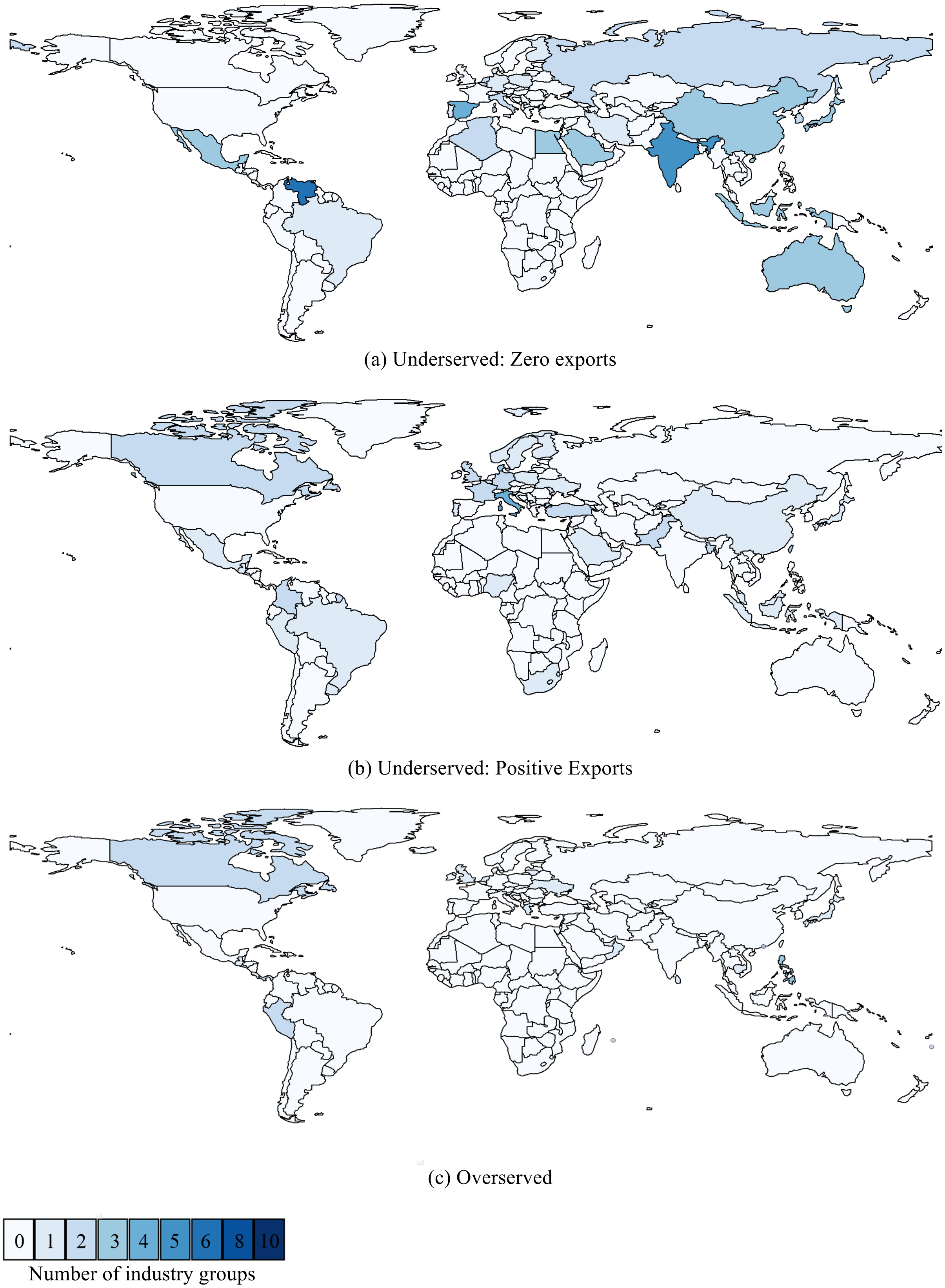
NAICS	Industry Group	Underserved: Zero Exports	Underserved: Positive Exports	Overserved
1111	Oilseeds & grains		Denmark, Kuwait, Uruguay	El Salvador, Guatemala
1112	Vegetables & melons	Finland	Bangladesh, China, Switzerland	
1113	Fruit & tree nuts	Poland, Portugal	Germany, Italy, Ukraine	
1114	Mushrooms & nursery	Australia, India, Indonesia, Saudi Arabia, Venezuela	Taiwan	Belgium, Netherlands
1119	Other agriculture	Venezuela	Bangladesh, Pakistan, South Africa	Oman, United Arab Emirates
1121	Cattle	China, Japan, South Korea	United Kingdom	Canada
1122	Swine	China, Japan, Mexico	Canada	Peru
1123	Poultry & eggs	South Korea	Japan	Hong Kong
1124	Sheep & goats	Mexico, Japan, Saudi Arabia	Canada	Philippines
1125	Farmed fish	Australia, India, Indonesia, Netherlands	Taiwan	Peru
1129	Other animals	Australia, India, Indonesia, Spain	Belgium, Taiwan	Greece
1132	Forestry products	Mexico		
1133	Timber & logs	Brazil, Venezuela	Indonesia	Japan
1141	Fish		El Salvador, Pakistan, Saudi Arabia	Lithuania, Mauritius Ukraine
3111	Animal foods	Italy, Netherlands, Russia	Mexico	Philippines
3112	Grain & oilseed milling	Belgium, Denmark	Germany, Norway	Philippines
3113	Sugar & confectionery	Italy, Spain, Venezuela	Colombia France	Hong Kong, Singapore
3114	Fruit &vegetable preserves	Egypt	Denmark, Italy, Nigeria	Panama
3115	Dairy products	Germany, Spain	Denmark, Guatemala, United Kingdom	Sri Lanka
3116	Meat products	Belgium, India, Saudi Arabia	Brazil, France	Hong Kong
3117	Sea food (canned)	Saudi Arabia, Venezuela	Colombia, Malaysia	United Kingdom
3118	Bakery & tortilla	India, Russia, Spain	Italy, Peru	Canada
3119	Foods (NESOI)	Egypt, Iran	Finland, Poland, Sweden, Turkey,	
3121	Beverages	Egypt, Venezuela	Turkey, Portugal	Cambodia, Tonga

Notes: Countries are ordered alphabetically.

Table 3. Number of Industry Groups by Market: In-Sample Predictions

Market	No.	Industry Groups
		Underserved: Zero exports
Venezuela	6	Mushrooms & nursery, Other agriculture, Timber & logs, Sugar & confectionary, Sea food (canned), Beverages
India	5	Mushrooms & nursery, Farmed fish, Other animals, Meat, Bakery & tortilla
Spain	4	Other animals, Sugar & confectionary, Dairy, Bakery & tortilla
Australia	3	Mushrooms & nursery, Farmed fish, Other animals
China	3	Cattle, Swine, Sheep & goats
Egypt	3	Fruit & vegetable preserves, Foods (Nesoi), Beverages
Indonesia	3	Mushrooms & nursery, Farmed fish, Other animnals
Japan	3	Cattle, Swine, Sheep & goats
Mexico	3	Swine, Sheep & goats, Forestry products
Saudi Arabia	3	Mushrooms & nursery, Meat, Sea food (canned)
Belgium	2	Grain & oilseed milling, Meat
Italy	2	Animal foods, Sugar & confectionary
Netherlands	2	Farmed fish, Animal foods
Russia	2	Animal foods, Bakery & tortilla
South Korea	2	Cattle, Poultry & eggs
		Underserved: Positive exports
Italy	4	Fruit & tree nuts, Fruit & vegetable preserves, Dairy, Bakery & tortilla
Denmark	3	Oilseeds & grains, Fruit & vegetable preserves, Dairy
Taiwan	3	Mushrooms & nursery, Farmed fish, Other animals
Bangladesh	2	Vegetables & melons, Other agriculture
Canada	2	Swine, Sheep & goats
Colombia	2	Sugar & confectionery
France	2	Sugar & confectionery, Meat
Germany	2	Fruit & tree nuts, Grain & oilseed milling
Pakistan	2	Other agriculture, Fish
Turkey	2	Foods (Nesoi), Beverages
United Kingdom	2	Cattle, Dairy
		Overserved
Hong Kong	3	Poultry & eggs, Sugar & confectionery, Meat
Philippines	3	Sheep & goats, Animal foods, Grain & oilseed milling
Canada	2	Cattle, Bakery & tortilla
Peru	2	Swine, Farmed fish

Notes: Includes all countries with more than one underserved or overserved industry group. For each country, industry groups are ordered by NAICS code.



(a) Underserved: Zero exports

(b) Underserved: Positive Exports

(c) Overserved

Figure 2. Geographic pattern from in-sample predictions

Because the in-sample predictions are obtained by using data on Washington agricultural industry groups, we know the results have high applicability. But since the results are deviations from the mean trade pattern of Washington agriculture, we cannot know whether any of the industry groups deviate from the mean of the overall pattern of trade.

We turn to out-of-sample predictions to answer that question.

Out-of-Sample Results

Table 4 is the same as Table 2 except that it contains the results from the out-of-sample exercise. Compared to Table 2, the number of countries listed for each industry group may increase. For example, we did not find any country receiving zero exports in oilseeds and grains that fit our criteria of being underserved according to the in-sample exercise. But in the out-of-sample exercise we find that Norway and Switzerland receive zero exports from Washington and do fit our criteria for being underserved. When there are at least some exports, we find Denmark, Uruguay, and Kuwait are underserved, as with the in-sample results. But our out-of-sample exercise also finds that Russia is an underserved market for oilseeds and grains, as seen in Figure 1. We add the Philippines to the list of overserved markets, in addition to El Salvador and Guatemala. Identifying new underserved markets with the out-of-sample exercise occurs in many other industry groups.

Like Table 3, Table 5 lists the number of industry groups for each under- or overserved market. Of the 24 agricultural industry groups, Norway does not receive exports from and is underserved by ten of them. Norway is followed by Germany, India, and Saudi Arabia at five industry groups each. In the category of countries that receive some exports, Italy is underserved by six industry groups, followed by Turkey with four. The Philippines is overserved by eight industry groups.

Figure 3 shows the geographic distribution of under- and overserved markets according to the out-of-sample predictions. Similar to Figure 2, we find a concentration of underserved markets in Europe, with a few others in South America and Central Asia.

Table 4. Underserved and Overserved Markets by Industry Group: Out-of-Sample Predictions

NAICS	Industry Group	Underserved: Zero exports	Underserved: Positive exports	Overserved
1111	Oilseeds & grains	Norway, Switzerland	Denmark, Kuwait, Russia, Uruguay	El Salvador, Guatemala, Philippines
1112	Vegetables & melons	Austria, Finland, Poland, Norway	Bangladesh, Italy, Switzerland	Dominican Republic, Nicaragua
1113	Fruit & tree nuts	Austria, Ireland, Poland	Argentina, Italy, Turkey, Ukraine	Vietnam
1114	Mushrooms & nursery	Arabia, Australia, Indonesia, Saudi India	Brazil, Taiwan	Belgium, Netherlands
1119	Other agriculture	Austria, Norway, Venezuela	Bangladesh, Pakistan, South Africa, Switzerland	Oman, United Arab Emirates
1121	Cattle	China, Germany, Japan, South Korea	United Kingdom	Canada
1122	Swine	China, Germany, Japan, Mexico, United Kingdom	Canada	
1123	Poultry & eggs	Germany, Russia, South Korea, United Kingdom	Mexico	Hong Kong
1124	Sheep & goats	Mexico, United Kingdom, Germany, China, Japan	Canada	Philippines
1125	Farmed fish	Australia, India, Netherlands	Taiwan	
1129	Other animals	Australia, Brazil, India, Indonesia, Saudi Arabia	Belgium, Taiwan	Greece
1132	Forestry products	Mexico, Russia, Saudi Arabia		Dominican Republic
1133	Timber & logs	Brazil, Norway, Sweden, Turkey	Indonesia, Italy	Japan
1141	Fish	Austria, Czech Republic, Qatar	Argentina, Bahamas, El Salvador, Kazakhstan, Pakistan	Georgia, Lithuania, Ukraine
3111	Animal foods	France, Italy, Netherlands, Norway, Russia, Turkey	Mexico	Philippines
3112	Grain & oilseed milling	Belgium, Denmark, Poland, Turkey	Ireland, Norway	Philippines, Vietnam
3113	Sugar & confectionery	Italy, Spain, Turkey	Brazil, Colombia France	Hong Kong, Japan
3114	Fruit &vegetable preserves	Finland, Norway	Denmark, Italy, Poland, Nigeria	Philippines
3115	Dairy products	Germany, Norway, Spain, Switzerland	Italy, United Kingdom	Indonesia, Philippines, SriLanka
3116	Meat products	Belgium, India, Norway, Saudi Arabia, Sweden	Brazil, France, Switzerland	Hong Kong, Philippines, Vietnam
3117	Sea food (canned)	Norway, Saudi Arabia	Turkey, Malaysia	United Kingdom
3118	Bakery & tortilla	France, India, Norway, Russia, Spain	Italy, Netherlands, Peru	Canada, Philippines, Japan
3119	Foods (NESOI)	Egypt	Finland, Kazakhstan, Poland, Sweden, Turkey	Belgium
3121	Beverages	Ireland	Azerbaijan, Portugal, Turkey	Cambodia, Solomon Islands

Notes: Countries are ordered alphabetically.

Table 5. Number of Industry Groups by Market: Out-of-Sample Predictions

Market	No.	Industry Groups
		Underserved: Zero Exports
Norway	10	Oilseeds & grains, Vegetables & melons, Other agriculture, Timber & logs, Animal foods, Fruit & vegetable preserves , Dairy, Meat Sea food (canned), Bakery & tortilla
Germany	5	Cattle, Swine, Poultry & eggs, Sheep & goats, Dairy products
India	5	Mushrooms & nursery, Farmed fish, Other animals, Meat, Bakery & tortilla
Saudi Arabia	5	Mushrooms & nursery , Other animals, Forestry products, Meat , Sea food (canned)
Austria	4	Vegetables & melons, Fruit & tree nuts, Other agriculture, Fish
Russia	4	Poultry & eggs, Forestry products, Animal foods, Bakery & tortilla
Turkey	4	Timber & logs, Animal foods, Grain & oilseed milling, Sugar & confectionery
Australia	3	Mushrooms & nursery, Farmed fish, Other animals
China	3	Cattle, Swine, Sheep & goats
Japan	3	Cattle, Swine, Sheep & goats
Mexico	3	Swine, Sheep & goats, Forestry products
Poland	3	Vegetables & melons, Fruit & tree nuts, Grain & oilseed milling
Spain	3	Sugar & confectionery, Dairy, Bakery & tortilla
United Kingdom	3	Swine, Poultry & eggs, Sheep & goats
Belgium	2	Grain & oilseed milling, Meat
Brazil	2	Other animals, Timber & logs
Finland	2	Vegetables & melons, Fruit & vegetable preserves
France	2	Animal foods, Bakery & tortilla
Ireland	2	Fruit & tree nuts, Beverages
Indonesia	2	Mushrooms & nursery, Other animals
Italy	2	Animal foods, Sugar & confectionery
Netherlands	2	Farmed fish, Animal foods
Sweden	2	Timber and logs, Meat products
Switzerland	2	Oilseeds & grains, Dairy
South Korea	2	Cattle, Poultry & eggs
		Underserved: Positive Exports
Italy	6	Vegetables & melons, Fruit & tree nuts, Timber & logs, Fruit & vegetable preserves, Dairy, Sea food (canned)
Turkey	4	Fruit & tree nuts, Sea food (canned), Foods (Nesoi), Beverages
Brazil	3	Mushrooms & nursery, Sugar & confectionery, Meat
Switzerland	3	Vegetables & melons, Other agriculture, Meat
Taiwan	3	Mushrooms & nursery, Farmed fish, Other animals
Argentina	2	Fruit & tree nuts, Fish
Bangladesh	2	Vegetables & melons, Other agriculture
Canada	2	Swine, Sheep & goats
France	2	Sugar & confectionery, Meat
Kazakhstan	2	Fish, Foods (Nesoi)
Mexico	2	Poultry and eggs, Animal foods
Pakistan	2	Other agriculture, Fish
Poland	2	Fruit & vegetable preserves, Foods (Nesoi)
United Kingdom	2	Cattle
		Overserved
Philippines	8	Oilseeds & grains, Sheep & goats, Animal foods, Grain & oilseed milling, Fruit & vegetable preserves, Dairy, Meat, Bakery & tortilla
Hong Kong	3	Poultry & eggs, Sugar & confectionery, Meat
Japan	3	Timber & logs, Sugar & confectionery, Bakery& tortilla
Vietnam	3	Fruit & tree nuts, Grain & oilseed milling, Meat
Belgium	2	Mushrooms & nursery, Foods (Nesoi)
Canada	2	Cattle, Bakery & tortilla
Dominican Rep.	2	Vegetables & melons, Forestry products

Notes: Includes all countries with more than one underserved or overserved industry group. For each country, industry groups are ordered by NAICS code.

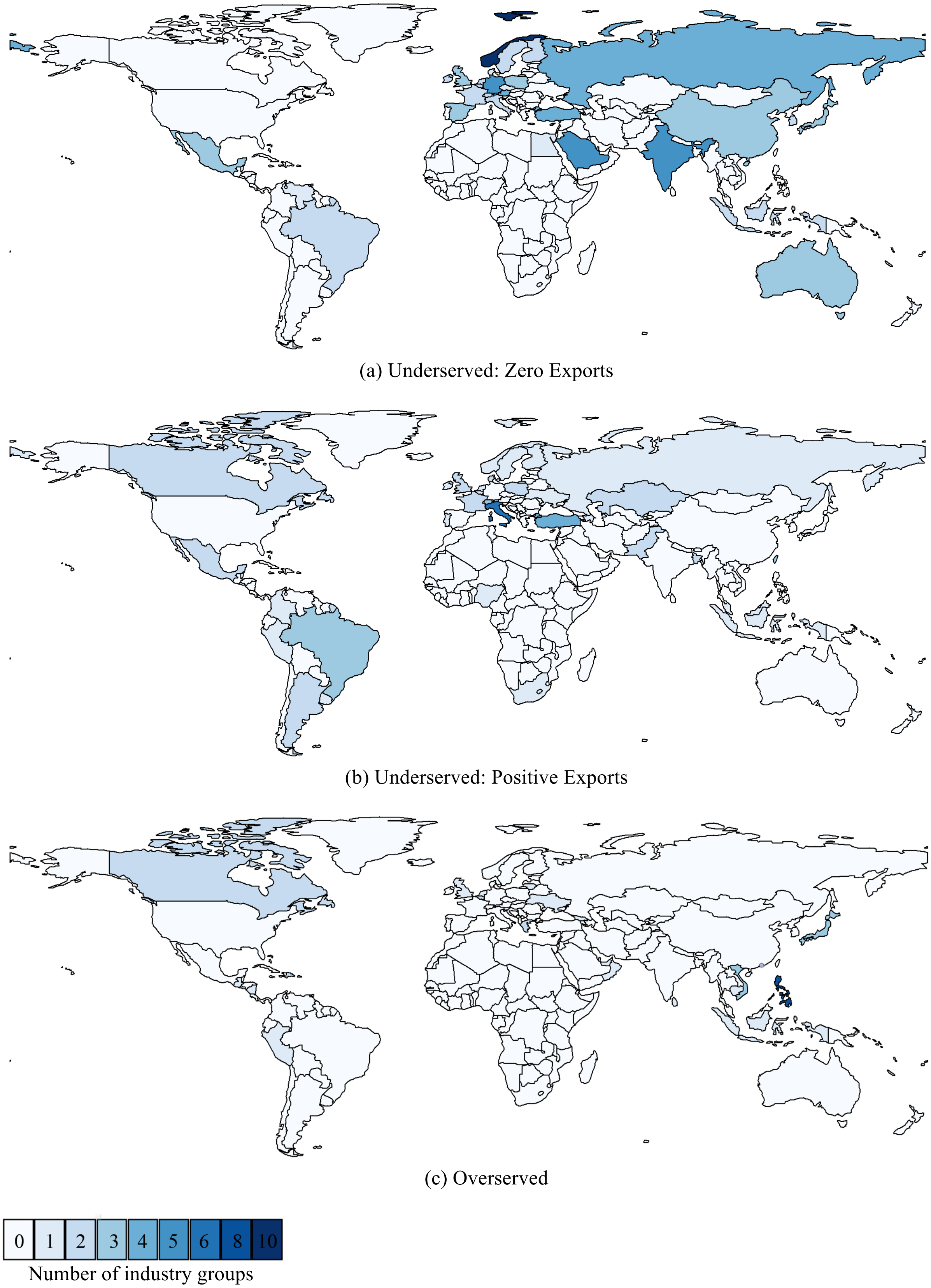


Figure 3. Geographic Pattern from Out-of-Sample Predictions

Many of Washington's underserved markets are in the European Union, but not all countries in the European Union are underserved. For example, Eastern European countries such as Romania, Estonia, Bulgaria, and Slovakia are not underserved by any industry group. If markets were underserved due to European Union rules or trade restrictions, then all countries in the European Union should be underserved, which we find not to be the case. Outside of the European Union, many Washington agricultural industry groups underserve Norway. We examine Norway in more detail below.

On the other hand, Washington exports match or exceed predicted exports to to East Asia, even controlling for the fact that Washington is among the closest states to East Asian markets. Taiwan, however, is an exception. No industry group overserves Taiwan. Rather, Washington State industry groups—including mushrooms, nursery, and related products; farmed fish and related products; and other animals—underserve Taiwan according to our criteria in both the in-sample and out-sample exercises. We study Taiwan further below.

Japan is an interesting market in that it is underserved by three industry groups (cattle; swine; and sheep, goats, and fine animal hair) but also overserved by three different industry groups (timber and logs; sugar and confectionery products; and bakery and tortilla products). This result coincides with the previous legal barrier greatly restricting Washington from exporting more cattle, swine, and sheep to Japan. Something similar may be happening in Canada, which is overserved by cattle and bakery and tortilla products but underserved by swine and sheep, goats, and fine animal hair.[8] Mexico, though it is a NAFTA member, is underserved by poultry and eggs as well as animal foods. Mexico is also the only market we find to be underserved by forestry products.

These results identify markets and industry groups with exports that deviate from a gravity model prediction of exports. Since the gravity model accounts for trade patterns with bilateral distance and market size, the fact that some markets and industry groups deviate from the gravity model prediction means the actual trade pattern is driven by other, non-gravity factors. The examples of Japan, Canada, and Mexico illustrate the benefits of our method in that we learned that some of Washington's industry groups need further analysis to understand the trade pattern. That deeper analysis may make it possible to identify opportunities for increased exports.

Two Case Studies

Our method has identified a few foreign markets that are underserved by Washington's agricultural industry groups. We undertake a slightly more detailed analysis of Norway and Taiwan to understand what variables outside those in the gravity equation may explain the trade pattern and assess whether there are opportunities to expand sales.

Norway is perhaps the leading market in terms of being underserved by many of Washington's agricultural industry groups. Norway, even though not a European Union country, follows most EU policies and import regulations. As can be seen from Table 4, Norway receives zero canned seafood from Washington. One reason for this that is outside of the model is that Norway is itself

[8] http://consumersunion.org/news/whats-all-the-fuss-about-the-canadian-border-and-beef-imports/ (accessed May 29, 2017).

a global leader in exports of canned fish. However, Norway imports canned fish products from Denmark, Iceland, Peru, Russia, and the United Kingdom, so the fact that Norway has a comparative advantage in canned seafood products does not fully explain why Washington exports zero canned seafood products there. The United Kingdom, another market with a comparative advantage in canned seafood products, is by comparison overserved by Washington. We might think that Norway represents huge export potential given that it does not impose a tariff on canned seafood products,[9] but Norway does ban imports of genetically modified foods, including the farm-raised salmon commonly canned and exported from Washington. Norway's potential as a market for these products is therefore limited.

There is potential for Washington to increase exports to Norway of fish oils, canned groundfish, and non-farmed canned salmon without the need to alter Norway's trade restriction. Thus we think there is a possibility of limited trade expansion from Washington to Norway in canned seafood. Many of Washington's other industry groups have limited export potential to Norway for the same reason: restrictions on imports of genetically modified foods. Without federal assistance to modify Norway's ban on the import of genetically modified foods, other markets may be better candidates for immediate export expansion.

Taiwan is one of the largest markets for the United States and Washington.[10] Washington is Taiwan's third-largest trading partner, yet we find it is underserved by three industry groups in both the in-sample and out-of-sample exercises, despite the fact that Washington does not underserve many other East Asian markets. The industry groups are mushrooms and nursery products, farmed fish, and other animals. We find that Taiwan has a comparative advantage in the production of and is a net exporter to the United States of mushrooms and farmed fish.[11] The reason we identify Taiwan as being underserved in these markets is that the gravity model does not distinguish between countries that have comparative advantage and disadvantage at the industry-group level. Similar to Norway, though Taiwan is a net exporter of farmed fish, it does import other types of farmed fish from China, Vietnam, Norway, and Chile. There are no explicit import restrictions on U.S exports. It may indeed be possible for Washington's farmed fish industry group to target Taiwan for expanded exports, in particular if the industry group can identify a type of farmed fish that is not obtainable from Taiwan's other trading partners.

Conclusion

We identify markets that are under- and overserved by Washington's 24 agricultural industry groups using four sets of parameters for the gravity equation. We document deviations in the trade pattern from the mean pattern of Washington's agricultural trade and the mean pattern of overall trade using in-sample and out-of-sample predictions. Our purpose is to describe a method of identifying underserved markets that could be applied to any state or industrial sector in order to take the first, but by no means final, step in drawing attention to markets that are candidates for targeted export expansion.

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[9] http://www.fao.org/docrep/005/Y4325E/y4325e0a.htm (accessed May 29, 2017)
[10] https://ustr.gov/countries-regions/china/taiwan (accessed May 29, 2017)
[11] https://www.usitc.gov/publications/332/pub1746.pdf (accessed May 29, 2017)

For the case of Washington agricultural industry groups, we find that many European countries are underserved by more than a few of Washington's agricultural industry groups. Norway, Italy, and Germany receive far fewer exports from Washington than our models predict in many different agricultural industry groups. India and Brazil are other examples. These may be good markets to study to understand whether there is a systemic cause or unrealized potential for expansion. Another market that seems worthy of a closer look for expansion is Taiwan. Given Washington's success in exporting to the Philippines, Vietnam, Hong Kong, and Japan, lessons from those countries might be applied to increase exports to Taiwan.

We have identified markets that are most under- and overserved, though others could be considered as well, depending on the thresholds used and criteria applied. While we have identified under- and overserved markets with respect to what the gravity equation predicts, we have not attempted to understand *why* certain markets are under- or overserved. For some markets, it could be that tariffs or phytosanitary restrictions prevent Washington from exporting the number of goods the state otherwise would. In other cases, the issue could be logistical, a lack of consumer demand from preferences, or historical accident. In other cases, it could be because the market is itself a global export leader in a particular industry group.

While we do not attempt to identify the causes for the trade patterns we document, we believe that a list of under- and overserved markets will assist industry groups in focusing attention on markets that could potentially lead to the largest increase in exports and give direction for further study to determine whether trade expansion is possible. Because our method is based on comparing actual trade patterns to those predicted by the simple gravity equation (and that model predicts trade patterns from bilateral distance and market sizes only), there are certainly many other factors affecting trade patterns. The next step is for policy analysts or industry experts to determine the extent to which other factors matter and whether there are chances for export expansion through steps such as better logistics and marketing.

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