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Vineyards in Northern U.S. States: Farm Size and Productivity Relationship

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Abstract

Purpose – The production efficiency of agricultural crops has been the subject of numerous studies in the field of agricultural economics. This study examines the production efficiency of emerging vineyards in the 14 northern U.S. states and aims to understand raw input and managerial factors affecting the grape production with focusing on the effect of farm size.
Research design, data, and methodology – Using a unique survey dataset that was collected from 176 vineyards in 2012, we employed data envelopment analysis (DEA) for estimation of production efficiency in individual vineyards. Production efficiency is regressed on various input and managerial covariates to understand factors influencing the productivity.
Results – Although there exists positive correlation between the farm size and productivity of vineyards in Northern U.S. states, we find negative relationship when the farm size is instrumented by the additional farm size expansion indicator. The negative effect is more pronounced for the recently established vineyards.
Conclusions – This study suggests that there needs to be adequate managerial improvements for emerging vineyards in northern states for the achievement of increased productivity.

Keywords: Productivity, Farm size, DEA, Cold-Hardy Grape Cultivar.

JEL Classifications: M11, L66, Q13.

1. Introduction

The introgression of wild grape species native to North America (*Vitisriparia*) into grape cultivars that are suitable for wine production (*V.vinifera*) in the 1990s contributed to the recent development of 3,300 acres of vineyards in the northern states ranging from South Dakota to New Hampshire. Although the growth of the emerging industry seems promising, one of the major challenges to the sustainable development of the industry crucially depends on its ability to optimize the production practices. The mature vines that are older than 4 years commonly yield 3 to 5 tons per acre in warmer climate states. (Julian et al., 2008; Poling, 2007). However, as can be seen in Figure 1, production yields of majority of the vineyards located in the cold-climate northern states that are at least 4 years old of their establishment falls short of the optimal production range of 3-5 tons per acre[1].

This suggests that there is a room for significant productivity improvement for vineyards currently operating in northern states. Given that the production yields per unit of land is closely interconnected to the profitability of the vineyards, understanding of production mechanism and knowledge of what production management practices is unarguably important for the economic sustainability of the emerging industry.

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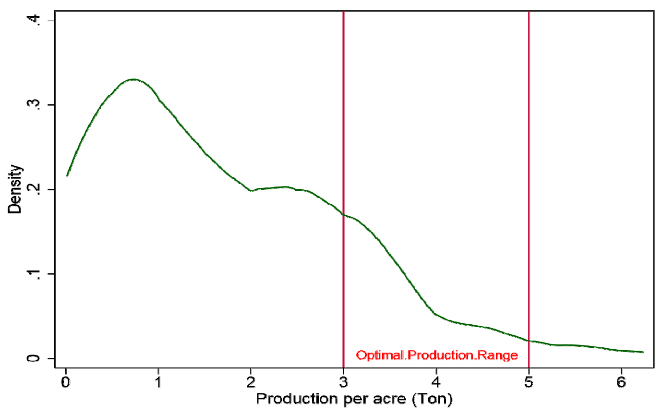
1) This range is a conservative measure. According to National Agricultural Statistics Service (NASS), national average grape yield per acre in 2011 was 7.76 tons/acre.



Source: Northern Grape Project (2012). Survey Data

<Figure 1> Northern States Vine Production per Acre Density Function

This study attempts to analyze production efficiency of the emerging vineyards in cold climate northern states using the unique survey dataset that was collected from 176 vineyards in 2012. Production efficiency is measured using data envelopment analysis (DEA) to empirically assess the relative efficiency of the individual vineyards within the emerging vineyards industry. In 2005, the average vineyard size was 121 hectares in North America (Nagayets, 2005), whereas the size is 1.99 hectares in northern U.S. states, knowing that vineyards in the northern U.S. states are of relatively small-size at a stage of rapid expansion, our analysis focuses on the effect of farm size on the productivity. In addition, productivity is influenced by the labor force, the labor force will be included in this study (Bahrami et al., 2013).

A good environment for the wine production is dry and hot sunny area. The U.S. Northern states are not less than the dry and sunny than Western region. While the California wine industry was already starting from year 1850, the history of the wine industry in the Northern states is short. The seeds, the cold-hardy grapes in Northern states are different from those of Western, Chardonnay and Sauvignon Blanc. In addition, the size of the vineyard in the Northern states are 300 wineries and 23 km2, but in California the number of farmhouses and vineyards are 5,900 wine growers and 660 wineries accounts for 98.9km2. There have been numerous studies on productivity of Californian vineyards, however, no studies have been conducted to examine productivity of vineyards in northern states.

The rest of this paper organized as follows. Section 2 introduces DEA and provides description of the model employed for the efficiency analysis of the vineyards. Section 3 discusses survey data. Estimation results are discussed in Section 4 and 5. Section 6 concludes.

2. Methodology

2.1. DEA

DEA is an application of non-parametric linear programming that is widely used in many disciplines to measure the production efficiency of a decision making unit (DMU). In order to briefly explain how DEA is conducted, one begin with a production set defined:

$$\Omega = \{(\mathrm{x}, \mathrm{y}) \in \mathbb{R}_{+}^{l+m} | \mathrm{x} \text{ can produce } \mathrm{y}\} \quad (1)$$

implies a vector of l inputs (x) can produce a vector of m output (y). Next, input requirement set x(y) which relates to the set of inputs required to produce given level of output conditional on the current state of technology is defined:

$$\mathrm{X}(\mathrm{y}) = \{\mathrm{x} \in \mathbb{R}_{+}^{l} | (\mathrm{x}, \mathrm{y}) \in \Omega\} \quad (2)$$

As is commonly assumed in production theory, input requirement set is assumed to be convex (i.e. $\forall x$, $x' \in$X(y) and all $\alpha \in$ [0,1], αx + (1 − α)$x' \in$X(y)) and satisfy weak free disposable of input (i.e. X(y) ⊆ X(λy) for λ <1). The production frontier is defined as a subset of X(y):

$$\mathrm{X}_e(\mathrm{y}) = \{\mathrm{x} | \mathrm{x} \in \mathrm{X}(\mathrm{y}), \theta\mathrm{x} \notin \mathrm{X}(\mathrm{y}), \forall(0,1)\} \quad (3)$$

then, input-oriented efficiency measure can be written as:

$$\theta k = \min\{\theta | \theta xk \in \quad x(yk) \quad (4)$$

where subscript k represents a particular decision making unit (DMU). The efficiency measure denoted as θ represents technical efficiency of the k-th unit as the Euclidean distance to the efficiency frontier. When θk=1, the k-th DMU is on efficiency frontier, whereas θk<1 indicates inefficiency. Finally, DEA model solves:

$$\theta_k^{VRS} = \min\{\theta | -y_k + \sum_{i=1}^{n} \lambda_i y_i \geq$$

$$0; \theta_{x_k} - \sum_{i=1}^{n} \lambda_i x_i \geq 0; \theta > 0; \sum_{i=1}^{n} \lambda_i = 1\} \quad (5)$$

The restriction $\sum_{i=1}^{n} \lambda_i = 1$ imposes convexity constraint and allows the model to explain variable returns to scale (VRS). Without the restriction, constant returns to scale (CRS) is assumed in the model. In other words, the efficiency measure of each DMUs (i.e. vineyards) is calculated only being benchmarked against DMUs of similar size. The fact that the size of vineyards is an especially crucial factor that might directly affect the efficiency level justifies our assumption of VRS. Scale efficiency, θˆkSE is the ratio of efficiency estimates under the assumption of VRS to efficiency estimates under assumption of CRS:

$$\hat{\theta}kSE = \hat{\theta}kVRS \, / \, \hat{\theta}kCRS \quad (6)$$

A DMU is scale efficient when $\hat{\theta}_k^{SE} = 1$.

2.2. Conventional Application of Second-stage Method

With efficiency measures of individual vineyards (DMU) calculated from DEA model, OLS, to bit regression was used in the second stage in order to understand channels through which productivity is affected by differing management practices. The two-stage model employing DEA to estimate efficiency scores in the first stage and parametric methods to estimate impact of managerial variables that has impact on the production efficiency in second-stage is commonly used in the organizational efficiency studies (Ng & Wei, 2012; Banker & Natarajan, 2008) and have been shown to be consistent even in the presence of low levels of correlation between input variables used in first-stage and explanatory variables used in the second stage and to outperform models solely based on parametric models (Banker & Natarajan, 2008).

2.3. Instrumental Variable (IV) Methods in the Second-stage

The parametric conditional analysis is also conducted using three different productivity measures:

$$Productivity_i = \beta_1' Productivity_i + \tau_1' Soil\ Test_i + \tau_2' Sales\ Channel_i + \eta_1' Age\ of\ Farm_i + \epsilon_i\} \quad (7)$$

where the dependent variable, Productivity for vineyard i, indicates three different productivity measures i) Total Factor Productivity (total quantity of grape output/total input measured by amount of expenditure on production) ii) land productivity (total quantity of grape output per acre) iii) labor productivity (total quantity of grape output per labor), β1 is the parameter of interest that shows the relationship between farmsize and production efficiency. The Soil Test is the categorical variable indicating frequency of soil test in the operation. The Sales Channel variable is included to examine whether difference in established sales channel affect the TE. Age of Farm controls for the experience of the farm. We also control for the Ph level of soil as well as hardiness zone location that controls for the weather variations across the northern states.

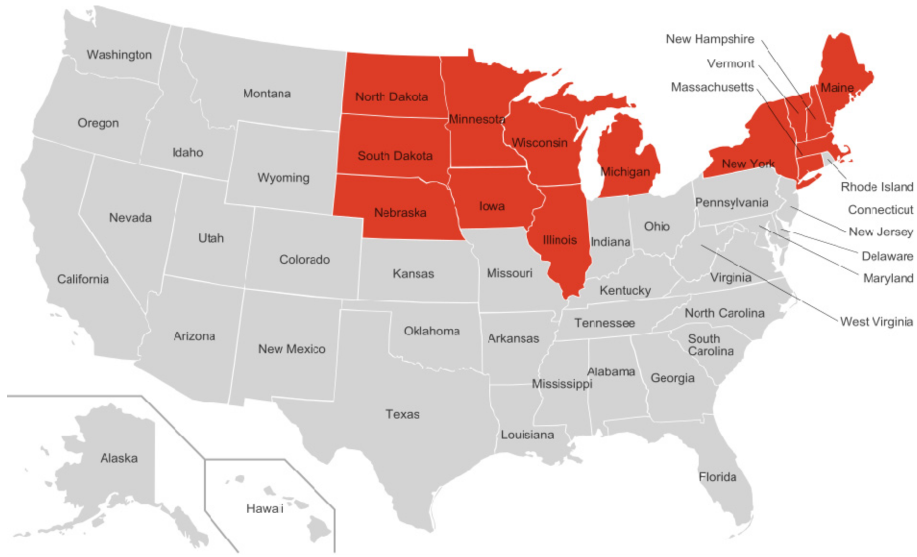
The estimation of the parameters in equation (7) using conventional OLS regression suffer from classical omitted variable bias if factors in the error term and covariates on the right hand side of an equation (Xi) are correlated $(\mathrm{E}(\epsilon_i|\boldsymbol{X}_i) \neq 0)$.

As non-labor inputs will accompany with increase in the farm size, we assume that those uncontrolled factors in ihas positive effect on TE. In this case, if $Corr(FarmSize_i|\epsilon_i) > 0$, which seem highly likely, then β1isupwardbiased.Similarly, $Corr(FarmSize_i|\epsilon_i) < 0$ leads to the downward biased coefficient. So as to overcome this problem and to identify effect of farm size on the productivity, we use IV methods using a dummy variable indicating expansion of farm land since the establishment of the vineyards.

3. Data

Data were obtained in 2012 from a primary survey carried out to winery and vineyard owners in 14 northern states. Data was carried out in the same manner asked directly to farmers (Mago, 2014; Madzimure et al., 2014). The survey was designed to obtain information related to the sales, production and management of wineries and vineyards using cold-hardy grapes in their production. Industry associations provided grower and winery lists in the northern states. In 2011, the survey was sent to 2,746 members of these lists and response rate was 18 percent (501 responses). An online survey that consisted of 72 questions pertaining to production and sales was sent to vineyards that were registered with the industry associations in each state, which were provided by industry associations in each 14 states. Among 2,746 members that online survey went out, a total of 501 responses (18 percent) were collected from wineries and vineyards combined. This study only uses a sub-sample of the survey that pertains to vineyards owners whose intention of growing grapes is to commercial sale or use. After excluding vineyards that were established after 2008 and dropping observations that are missing important variables for the analysis, the dataset used in this study contains 176 observations. <Table 1> shows summary statistics of the variables[2]. Various summary reports have been published as a result of this survey. This paper also employs the survey and scrutinizes winery policies related to winery operations.

2) USDA SCRI (United States Department of Agriculture Specialty Crops Research Initiative) program funded the Northern Grapes project.



<Figure 2> 14 Northern States

<Table 1> Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
DEA Output: Production(in lbs)	18,561.735	44,615.269	47	400,000	176
DEA Inputs: Annual Total Expense	238,762.993	3,014,368.206	50	40,000,000	176
Number of Vines	2,615.875	4,617.190	26	48,000	176
Vineyards Size(in acre)	4.958	7.394	0.1	64	176
Productivity(in ton)	1.552	1.412	0.016	6.594	176
Year of Establishment	2002.898	5.99	1973	2008	176
Age of Farm	5.102	5.99	0	35	176
Number. Vine. Per. Acre	521.017	219.962	120	2,232.857	176
Number. Labor.Hours.Per.Acre	327.676	567.408	0	5,333.333	176
Expanded. Acreage	0.602	0.491	0	1	176
Sales Channel: (Base. Other) 1.Own farm	0.250	0.434	0	1	176
2.Contract	0.438	0.497	0	1	176
3.Network	0.085	0.280	0	1	176
Soil Test: (Base. Never) 1.Once	0.267	0.443	0	1	176
2.Every 5-10 years	0.051	0.220	0	1	176
3.Every 3-5 years	0.289	0.454	0	1	176
4.Every 1-2 years	0.261	0.440	0	1	176

4. Results

4.1.Overall Efficiency

The technical efficiency (TE) scores for vineyards in the northern states are shown in <Table 2>. The mean value of TE indicates the surprisingly low level of production efficiency. The substantial inefficiency of vineyard production is prevalent, regardless of the model assumption of scales of economy. The scale efficiency of 0.935 implies that inefficiency due to economies of scale is relatively low, given that average vineyards are running at only a 35% level of production efficiency of the vineyards on the frontier.

<Table 2> Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
VRS TE	0.352	0.278	0.002	1	176
CRS TE	0.322	0.254	0.002	1	176
SCALE	0.935	0.096	0.474	1	176

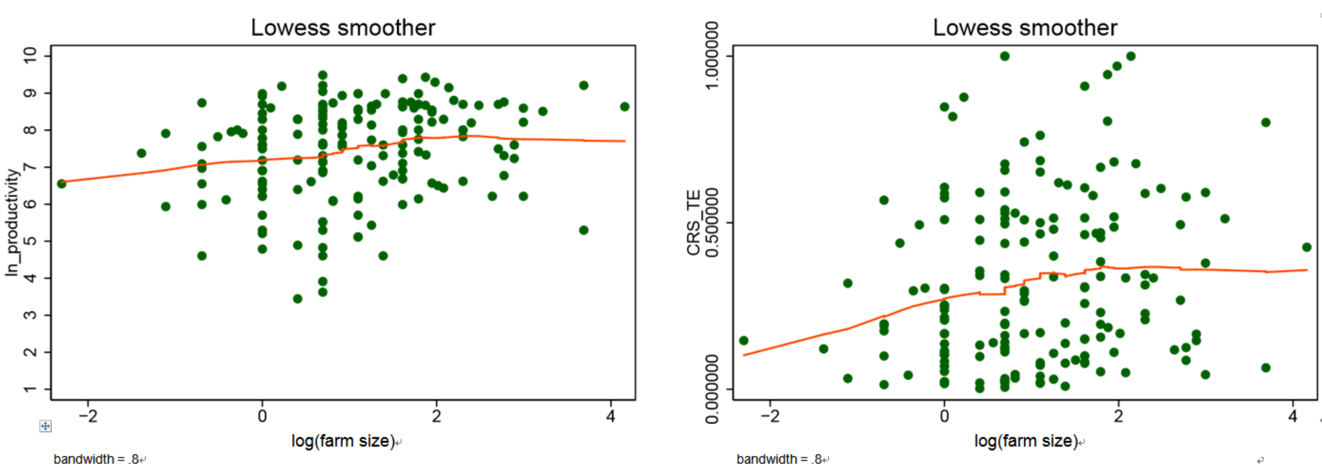
The result of scale efficiency shows that 18.03% of the vineyards exhibit CRS, 15.85% exhibit DRS and the majority of them (66.12%) exhibit IRS.

4.2. Farm Size and Productivity

Consistent with findings of previous literature concerning the farm size and productivity relationship in the U.S. (Alvarez & Arias, 2004; Sumner, 2014; Sharma et al., 1999), the nonparametric conditional means estimates by local linear regression show that a positive relationship between farm size and production efficiency is observed in both partial productivity (yield/acre) and technical efficiency (TE) <Figure 3>.

The estimates from conditional analysis is presented in <Table 3>. The bivariate regression result in specification (1) shows positive and statistically significant relationship between farm size and TE, as in the case in the non-parametric regression. The effect of land size deteriorates as other covariates are controlled for, the frequency in the soil test is positively correlated with the TE and appears to exhibit monotone effect. The vineyards that sells its grape to its own winery exhibit higher TE than the vineyards that has sales channel other than sales to its own farm, contract and network. In specification (4), age of farm is added to the model; the result indicates that the vineyards with longer histories are positively correlated with increased production efficiency. This result is intuitive since the vineyards with longer histories must have accumulated experience that benefits their production efficiency. One thing that should be given particular attention is that the coefficient on farm size is no longer statistically significant. This finding is surprising, as it indicates that it is not the farm size that defines the production efficiency but, rather, other unobservable variables such as farmers' motivation, capability and experience that are partially captured in the controlled variables. One can infer from the fading positive effect of land size on TE that factors in the error term is indeed positively correlated with land size and that the factors exhibit positive effect on TE.

In order to identify the effect of land size on TE, we instrument for farm size using a dummy variable that indicates whether the vineyard have expanded its size since its establishment. To be a valid instrument, the instrument needs to be correlated with the farm size, but exert no direct impact on the production efficiency. Although the

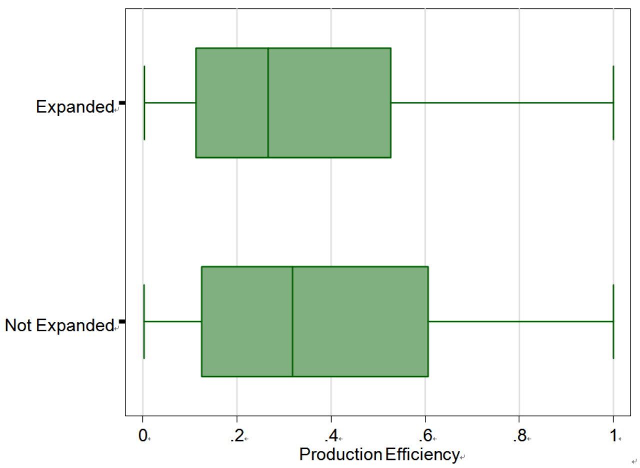


(a) Land Productivity vs. Land Size

(b) Technical efficiency vs. Land Size

<Figure 3> Nonparametric Regression of Technical Efficiency

exogeneity of the IV is not empirically testable, there is good reason to believe that the dummy variable indicating expansion of farm land is a valid IV. One important thing to note is that 59% of the vineyards in the sample have expanded planted acreage since establishment. The fact that a majority of vineyards have expanded in size might be due to the emerging nature of the industry that is particular to northern states rather than the virtuous cycle of efficient vineyards' expansion. This speculation is supported by the efficiency comparison between those who expanded and those who did not, as shown in <Figure 4>.



Question: Have you added planted acreage since your vineyard was established?

<Figure 4> Production Efficiency Boxplot Comparison by Land Expansion Dummy

One can infer from the comparison that production efficiency does not systematically vary depending on the IV. Also, results from a t-test and ANOVA fail to reject the mean and variance difference between the two groups. Furthermore, the exogeneity test of the farm size and relevance test of the IV is conducted. As can be seen in the bottom panel of

<Table 3>, the exogeneity tests reject the null hypothesis of no endogeneity at a statistically significant level, also, the F-statistic of 2.7 - 7.3 suggests that the instrument is sufficiently strong. The monotonicity requirement is automatically satisfied as land size increase with its expansion. These evidences validate the use of the IV model in this study. The results from both 2 stage least square IV and the tobit IV methods show, interestingly, a negative relationship between farm size and productivity with a statistical significance at the 15% level. The change in the sign of the coefficient seems to indicate that an increase in farm size decreases productivity. Moreover, as discussed in the earlier section, large-scale farms may benefit from their ability to procure non-labor inputs that might affect the production efficiency. The IV-tobit model is estimated by using sub-samples that are established after the year 2000. The results in the specification (8) and (9) show the considerably larger and highly statistically significant negative effect of farm size on the production efficiency for those vineyards that were recently established. The estimated point estimates also show that the effect is economically significant. The negative effect of one percent increase in the farm size on production efficiency ranges from 0.201 to 0.204 units in the TE, which seem economically important.

5. Robustness Check

Although the production efficiency measure derived from DEA method is immune from the omitted variable bias in the first stage, the small sample size used in our analysis may bias the estimates as DEA requires large sample for the consistency of the estimator (Johnson & Kuosmanen, 2012). As a robustness check, IR relationship is examined solely based on the parametric estimation using yield productivity as dependent variable. The production theory based econometric approach is common in the literature (Barrett et al., 2010). The production function based model estimated in this section has the form:

$$Yield\ Productivity_i = \beta_1' Farm\ Size_i + \boldsymbol{X}_i \gamma_i + \tau_1' Soil\ Test_i + \tau_2' Sales\ Channel_i + \eta_1' Age\ of\ Farm_i + \epsilon_i\} \tag{8}$$

Where *Yield Productivity* is the partial productivity measure calculated by quantity produced/Land size in acre. Other covariates in the right hand side of equation remain same as before except that the input variables (X) are added in the model which contains number of vines per acre and number of labor hours per acre. The results are presented in <Table 4>. The overall relationship derived from the parametric approach is similar to the one observed in two-stage DEA approach, the relationship is economically important in that 1% increase in the farm size reduce yield productivity by 0.528%.

<Table 3> Second Stage Estimation Results

	Dep.V: Total Factor Productivity								
	Whole Sample							Estab after 2000 only	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) Tobit	(6) IV-2sls	(7) IV-Tobit	(8) IV-2sls	(9) IV-Tobit
ln(farm size in acreage)	0.043*** (0.016)	0.027* (0.017)	0.011 (0.019)	-0.005 (0.018)	-0.005 (0.021)	-0.105* (0.067)	-0.107* (0.068)	-0.201*** (0.092)	-0.204*** (0.094)
Soil Test: (Base.Never)									
1.Once		0.031 (0.051)	0.017 (0.051)	0.041 (0.051)	0.041 (0.062)	0.050 (0.065)	0.051 (0.066)	0.024 (0.076)	0.024 (0.078)
2.Every 5-10 years		0.126 (0.114)	0.114 (0.118)	0.063 (0.122)	0.071 (0.096)	0.091 (0.102)	0.100 (0.105)	0.049 (0.130)	0.060 (0.134)
3.Every 3-5 years		0.119*** (0.051)	0.109*** (0.052)	0.114*** (0.050)	0.115** (0.061)	0.153*** (0.068)	0.155*** (0.070)	0.089 (0.079)	0.089 (0.081)
4.Every 1-2 years		0.141*** (0.058)	0.124** (0.064)	0.139*** (0.061)	0.140*** (0.065)	0.201*** (0.079)	0.204*** (0.080)	0.108 (0.087)	0.111 (0.090)
Sales Channel: (Base.Other)									
1.Own farm			0.102* (0.062)	0.090* (0.059)	0.090* (0.058)	0.200*** (0.093)	0.202*** (0.094)	0.264*** (0.121)	0.264*** (0.124)
2.Contract			0.055 (0.050)	0.039 (0.048)	0.038 (0.048)	0.062 (0.052)	0.061 (0.053)	0.122** (0.067)	0.121** (0.069)
3.Network			0.019 (0.054)	0.021 (0.052)	0.018 (0.073)	0.023 (0.076)	0.020 (0.078)	-0.025 (0.089)	-0.028 (0.091)
Farm Age				0.011*** (0.003)	0.011*** (0.003)	0.015*** (0.004)	0.015*** (0.004)	0.042*** (0.011)	0.042*** (0.011)
_cons	0.276*** (0.023)	0.206*** (0.039)	0.182*** (0.044)	23.022*** (6.723)	22.971*** (6.462)	30.211*** (8.158)	30.282*** (8.326)	84.422*** (21.827)	84.659*** (22.445)
Relavance test for IV(F-statistic)						19.649	-	12.618	-
Exogeneity test-Hausman (F-statistic)						2.717	2.900	6.707	7.300
N	176	176	176	176	176	176	176	146	146
R2	0.032	0.074	0.090	0.152					

Robust standard errors in parentheses
* p<0.15, **p<0.1,***p<0.05

6. Conclusion

This study examines production efficiency of emerging vineyards in the 14 northern U.S. states and aims to understand factors affecting the grape production efficiency using primary survey dataset collected from emerging vineyard. The study of production efficiency is especially relevant for the vineyards in northern U.S. states as the benchmarking examples for the productivity improvement is rare in the region and grape production practices from more established region such as in California can be contextually different. We find that there is room for significant productivity improvements in the northern U.S. states, especially when compared to grape production in vineyards located in states that has longer history of production such as vineyards in California. Although there exists positive correlation between the farm size and productivity of vineyards in Northern U.S. states, we find negative relationship when the farm size is instrumented by the additional farm size expansion indicator. The negative effect is more pronounced for the recently established vineyards, which suggests that there needs to be adequate managerial improvements for emerging vineyards in northern states for the achievement of increased productivity with expansion of its size.

This paper does not provide explanation of the mechanism at work contributing to the farm size and productivity relationship. However, as relative advantage of larger farms in procuring financial inputs and other non-labor inputs has been considered as a major factor that positively influences the production efficiency as the farm size

<Table 4> Parametric Test Results

	Dep.V: ln(Yield/acre)						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) IV-2sls	(7) IV-2sls
ln(farm size in acreage)	0.257*** (0.080)	0.220*** (0.070)	0.143*** (0.072)	0.027 (0.090)	-0.057 (0.085)	-0.250 (0.286)	-0.528* (0.367)
ln(Number.Vine.Per.Acre)		1.183*** (0.221)	1.127*** (0.239)	1.085*** (0.249)	1.004*** (0.254)	1.022*** (0.219)	0.999*** (0.253)
ln(Number.Labor.Hours.Per.Acre)		0.029 (0.058)	0.007 (0.057)	-0.001 (0.052)	-0.011 (0.046)	-0.020 (0.054)	-0.040 (0.066)
Soil Test: (Base.Never)							
1.Once			0.019 (0.292)	-0.074 (0.302)	0.053 (0.294)	0.072 (0.280)	0.008 (0.312)
2.Every 5-10 years			0.075 (0.649)	-0.004 (0.672)	-0.262 (0.665)	-0.204 (0.441)	-0.282 (0.535)
3.Every 3-5 years			0.551*** (0.266)	0.493** (0.272)	0.534*** (0.266)	0.615*** (0.301)	0.422 (0.331)
4.Every 1-2 years			0.600*** (0.266)	0.492** (0.292)	0.576*** (0.280)	0.699*** (0.340)	0.390 (0.360)
Sales Channel: (Base.Other)							
1.Own farm				0.788*** (0.291)	0.738*** (0.278)	0.950*** (0.396)	1.153*** (0.500)
2.Contract				0.404* (0.270)	0.342 (0.258)	0.381** (0,227)	0.541** (0.284)
3.Network				0.215 (0.365)	0.252 (0.363)	0.246 (0.338)	0.134 (0.373)
Farm Age					0.058*** (0.015)	0.065*** (0.018)	0.198*** (0.044)
_cons	7.206*** (0.130)	-0.213 (1.381)	-0.008 (1.499)	0.094 (1.513)	0.412 (1.541)	0.379 (1.327)	0.532 (1.593)
Relavance test for IV(F-statistic)						19.734	13.193
Exogeneity test-Hausman(F-statistic)						0.524	1.885
N	176	176	176	176	176	176	146
R2	0.045	0.177	0.219	0.255	0.317	0.300	0.226

Robust standard errors in parentheses
* p<0.15, **p<0.1,***p<0.05

increases (Wiggins et al., 2010), presence of nonlinear effects of farm size on productivity may explain the findings of this study.

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