IMPACTS OF REGIONAL DESIGNATIONS ON RETURNS FROM COLLECTIVE REPUTATIONS

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Abstract:

This paper examines the economic returns to dynamic regional designations present in agricultural markets. Geographical indications (GIs) define region-based collections of producers sharing terroir. Exploiting this geography-quality nexus, firms employ regional collective reputations to signal product quality to consumers. We develop an empirical framework to study the simultaneous employment of firm and collective reputations and to disentangle the dynamic effects of increasing regional designations (i.e., narrowing the GI space). The model incorporates a familiarity term, which decreases in the number of regions and directly affects consumers' abilities to use information about firm- and region-specific product quality. As the number of GIs increases, the returns to each region's collective reputation increase to a point and then begin to fall. The results indicate a crowding-out of the benefits of regional specificity with significant impacts on aggregate returns. These findings suggest policies restricting the proliferation of GIs may increase firm-level revenues.

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1. Introduction

Branding and labelling reduce consumers' search costs; consumers who would otherwise incur significant costs independently obtaining information about all products' qualities can rely on brands and labels as a proxy for true quality. This brand-quality association has been addressed extensively in the psychology and marketing literature (Dillon et al., 2001; van Osselaer and Janiszewski, 2001; Punj and Hillyer, 2004). Recognizing consumers' reliance on brand, firms invest in their brand and include as much information on their labels as they deem useful. Joint inclusion of firm and collective (e.g., regional) labels has become a common marketing strategy among manufacturers of consumer products, and both label types are associated with consumer-perceived reputations (for example, see Menival and Charters, 2014). Firm reputation provides information about the past quality of all goods produced by a particular firm. Collective reputations impart information about the quality of some broader group of member firms sharing a unique, identifying characteristic (e.g., firms that are all members of a club would share the collective reputation associated with that club). A collective reputation can be shared by firms holding specific quality or production standards, those working together in some sort of niche market, or simply those sharing a production region.

The purpose of this article is to examine the dynamic effects of increasing the number of named or branded sub-regions within a given greater region. To develop a tractable and intuitive model, we use geographical indication (GI) –a name used to identify a product's region of origin – and the GI space to illustrate our design. We are interested in firms' use of a collective reputation in the absence of any explicit quality or production standards. Our empirical analysis supports the hypothesis that, in the absence of minimum quality or production standards, increasing the number of named regions beyond a critical level will have deleterious effects on firms' welfare.

In the most basic sense, GI labels impart information to consumers about a good's production location (i.e., terroir). This acts as an indicator of shared quality via a perceived quality-geography nexus (Menapace and Moschini, 2012). For example, Washington apples are commonly associated with high-quality fruit, while Japan has a reputation as a high-quality producer of electronics. A collective reputation is an asset to firms selling high-priced experience goods – those goods for which quality cannot be directly observed prior to consumption. It provides consumers a notion of what attributes and quality levels to expect from their purchases across a broader section of the market than strictly the firm level. However, excessive reliance on collective reputation in labeling schemes has drawbacks. One such example can be seen in the French wine industry, where there are more than 300 distinct wine regions[1]. Wine critic Michel Bettane writes that the GI system has been abused there, arguing that France has drastically exceeded the number of GIs that accurately indicates regional differences in wine (Bettane, 2011).

In this paper, we examine the dynamic restrictions of narrowing the collective reputation space. Specifically, we address the dynamic component whereby the number of regions sharing a collective reputation is not fixed. We investigate the marginal effects of narrowing the GI space used for product branding and test whether the relationship between revenue and collective reputation is insulated from increases in the number of named regions. Our empirical analysis

[1] Different industries in different countries have different names for this regional-designation concept. As in our empirical examination below, the wine industry in the U.S. uses American Viticulture Areas (AVAs) to define distinct regions, while in France, a GI is denoted as an Appellation d'Origine Contrôlée (AOC). The specifications are slightly different, but the similarities are such that this paper considers them to be identical. We will herein use the terms "GI" and "regional designation" synonymously to describe an officially recognized region (in the case of wine, this is a region of origin for grapes used in wine production).

demonstrates that as the number of named regions increases, the relationship between revenue and collective reputation follows an inverted-U shape, with collective reputation having a strong positive effect to a point and decreasing thereafter. The implications of this research tend to support policies of increased scrutiny over the designation of new GIs.

The economic literature on product differentiation is extensive. Salop (1979) shows that under certain circumstances, the market may overprovide variety compared to socially optimal levels. Conceptually, this result applies to regional branding whereby an unrestricted market may overprovide regional designations. Though in our model we assume the number of regional designations is exogenously determined, the results are consistent with Salop's predicted overabundance of variety.

Product heterogeneity, as represented to consumers through branding and product-label specificity, can potentially play a key role in consumers' decision-making calculus. However, as labels become too encumbered with information, it becomes harder to tease out the marginal effects of each inclusion (Lusk, 2003), potentially owing to a diminishing marginal utility of attributes. Since the true quality of experience goods is unobservable *ex ante*, consumers must rely on their prior knowledge to inform their expectations. Those priors are constructed from consumers' beliefs about firm and regional quality (i.e., reputations). Recognizing this, firms invest in reputation. Shapiro (1983) formalizes this process in a dynamic competitive equilibrium model, treating reputation as a stock that grows based on firm investment in quality.

Research on collective reputations shared across firms remains in its early stages, but the literature is growing. We define *reputation* as a dynamic function of quality, with better reputations reflecting consistently higher quality. We define *collective reputation* as the reputation of a GI or region-specific aggregate of firms. Firm and collective reputations are similar conceptually, but the latter involves a weighted aggregation of members' production quality within a given region.

A firm producing experience goods has several options. It can build its reputation independently through investment in quality, treating its reputation as an asset (Shapiro, 1983). Alternatively, a firm can rely partly on the reputation of some group of which it is a member (Tirole, 1996), in our case a GI. The first approach requires large-scale production for consumers' search costs to be met with the opportunity of repeat purchase, and the second allows firms the ability to free ride on the existing GI's reputation. In practice, many firms, especially in food and agricultural markets, follow a combination of these two approaches.

Winfree and McCluskey (2005) explain that collective reputation is a non-excludable, non-rival public good. As such, firms have an incentive to freeride on collective reputation, which creates a disincentive to invest in quality. In some cases, firms agree to allow a regulatory or enforcement entity to oversee members utilizing the specific collective reputation and employ exclusionary quality standards to deter free ridership. In other cases, firms may rely on a central regulatory body for enforcement of standards or membership across multiple collective reputations. Financial (e.g., entry cost) and geographical constraints are among the main reasons firms may be excluded from a GI in the U.S., whereas firms in other countries often face additional regulatory restrictions. If GIs are large enough to support firm entry, new entrants can benefit from the free advertising and built-in reputation of a successful GI (van Zanten, Bruwer, and Ronning, 2003). This could effectively flood the market with new competitors and usher in demand for further regional separations (Agarwal and Barone, 2005). Recent work by Castriota and Delmastro (2015) demonstrates that collective reputation and group size exhibit an inverted-U relationship – as the number of producers in a given coalition (similar to our GI, but with quality standards and rules for membership) increases, the collective reputation increases to a maximum value and decreases thereafter. In their model, Castriota and Delmastro treat collective reputation as the dependent variable conditional on membership, among other regressors. In contrast, we treat collective reputation as a regressor to determine a reputation's effect on revenue.

Several papers have adapted Shapiro's standard firm-specific model to account for the collective reputation of GIs (for example, see Costanigro, McCluskey, and Goemans, 2010; Menapace and Moschini, 2012). Costanigro, McCluskey, and Goemans (2010) examine a data set similar to our own from a different perspective. They find that consumers' use of firm and collective reputations – as evidenced by their effects on an implicitly determined price – varies across price quantiles, with collective reputation being a stronger determinant of price in the lower-priced segments and individual firm reputation being more influential in the higher-priced segments. Intuitively, a consumer's cost of being wrong increases with higher prices. Therefore, consumers are more willing to face the search costs of acquiring information on individual firms when the cost of being wrong is higher. Our analysis corroborates Costanigro, McCluskey, and Goemans' (2010) results, but our emphasis is on how firm and collective reputations' effects on prices vary as the number of regional designations increases. We include a brief investigation of how firm and collective reputations influence prices across price quantiles, but we further consider how these relationships change with increased regional specificity.

Unlike individual firm reputation, collective reputations allow single firms to reach a broader section of the market. Individual firms can benefit from collective reputation spillovers (Gergaud, Livat, and Warzynski, 2012), but those gains are bounded. Schamel (2009) shows that as regional reputations gain credence, the value of individual firm reputations decrease and prices rely more on collective reputation. Though Schamel (2009) uses international data with more broadly specified regions, we find dissimilar results in an empirical investigation of Washington.

As noted above, the inclusion of GIs on product labels has been shown to influence prices. The hedonic regression approach decomposes the marginal price effects of specific product attributes (Lancaster, 1966; Rosen, 1974). Several papers have used this approach to show that individual firms' product prices reflect their GI's collective reputation. Schamel and Anderson (2003) consider the influence of individual factors on the market prices of different bottles of wine. Though their results for the influence of GIs on prices are mixed, they uncover an upward trend in premia for specific GIs from 1992 to 1999 vintages in Australia, estimating hedonic regression equations for each vintage separately. Frick and Simmons (2013) consider price effects of collective reputations as measured by membership in specific professional organizations that enforce quality standards. They argue that the presence of free riders nullifies incentives to invest in regional reputations. Endogenous price fluctuations by GI indicate consumers' willingness to pay for specific product attributes. For firms to benefit from including GIs on their labels, consumers must use this information in purchasing decisions. Ample evidence indicates that consumers do in fact use this information, though to varying degrees (Atkin and Johnson, 2010; Jin et al., 2011; Menival and Charters, 2014).

Relevant to the policy implications of research on collective reputations, Menapace and Moschini (2012) focus on the effects of GI certification (e.g., firms within a GI being legally compelled to meet minimum quality standards), positing that firm and collective reputations can beneficially coexist. Though our study does not specifically examine GI certification, our research taken in conjunction with Menapace and Moschini's (2012) results has implications for more restrictive policies on the adoption of new regional designations and the governance of existing ones. We further discuss policy toward the end of our results section.

2. Theoretical Framework

We first examine the nature of the GI space and how more narrowly defined regional designations affect the information available to consumers. We begin with a finite two-dimensional plane (or main region) containing N firms. If no subregions are defined within the main region (GI_1), the number of regional designations is one, as illustrated in Figure 1(a). Consumers' perception of product quality in GI_1, defined as an aggregate measure of the quality of all member firms' products, is uninformative in making choices between products within the region. It is costly for consumers to independently obtain information about each firm in GI_1, but this is the only approach available when one GI is designated.

The original space may be divided (equally or unequally), which provides weakly additional information about product quality within the smaller area, also increases information search/processing costs. A single division yields two regional designations. In Figure 1(b), the two regions are the broadest region, GI_1, and a more narrowly defined subset of the original GI space, GI_2. Consumers retain their existing knowledge of individual firms' reputations for quality, but now there is additional information about these two sets of products, each sharing a common regional designation. For simplicity, we assume that each firm utilizes only one designation based on the most narrowly defined subset of which the firm is a member (i.e., we ignore nesting effects). In Figure 1(b), any firms located within GI_2 utilize the GI_2 regional designation and any firms located outside of GI_2 utilize the GI_1 designation. In the context of apples, GI_1 could be the U.S. and GI_2 could be Washington. This increased specificity allows consumers to make more informed purchase decisions.

As the number of regional designations increases, hence increasing specificity by narrowing the GI space, consumers get more information about groups of products. A central authority can make as many divisions as she wishes pursuant to any regulations in place, but the number of regional designations is bounded by the number of firms, N. Once the number of regional designations, J, reaches the number of firms (such that $N = J$), GIs impart no information to consumers that is unique from information about the individual firms contained therein. Thus, the technical constraint on the number of regional designations is N. In the context of apples, this is equivalent to reducing the size of regional designations each to comprise only a single grower. If grower information is also known to consumers, then GIs do not offer additional information. Figure 1(c)-(f) demonstrated this complete narrowing of the GI space to $J = N$. A looser but still pertinent constraint on the number of regional designations concerns the number of firms in each designation. Any regional designation containing only one firm does not impart additional information to consumers. Hence, we have a more restrictive informational constraint dictating that the number of regional designations not exceed half the number of firms ($J \leq N/2$).

We can examine these relationships more formally with a model, keeping these restrictions in mind. For simplicity, we assume that each firm produces a fixed quantity of output per period, normalized to one. By abstracting away from a joint decision over quantity and quality, we consider an individual firm's choice of quality $x_{i,j,t}$, where i indexes the firm, j indexes the region, and t indicates the given period. With experience goods, consumers cannot perceive quality prior to purchase (Nelson, 1970), so they must rely on reputations as a proxy for quality. Each firm has a time-specific individual reputation, $r_{i,t}$, independent of its regional delineation. Similarly each region has a time-specific collective reputation, $R_{j,t}$, which is an aggregation of individual members' product quality within the region. Both reputation variables are recursively constructed to account for consumers' priors. In the general case, firm reputation can be formulated as

$$r_{i,t} = \alpha_1^r r_{i,t-1} + \alpha_2^r \sum_j x_{i,j,t}, \tag{1}$$

where $\alpha_1^r \in [0,1]$ and $\alpha_2^r \in [0,1]$ are weights assigned to priors and current quality across all the firm's products, respectively. And similarly, regional reputation can be constructed as

$$R_{j,t} = \alpha_1^R R_{j,t-1} + \alpha_2^R \sum_i x_{i,j,t}, \tag{2}$$

where $\alpha_1^R \in [0,1]$ and $\alpha_2^R \in [0,1]$ are weights assigned to priors and current quality across all firms in the region, respectively. We assume the reputation variables are bounded between zero and 1, which is guaranteed by $\alpha_1^r + \alpha_2^r = 1$, $\alpha_1^R + \alpha_2^R = 1$, and $x_{i,j,0} \in [0,1]$. As Shapiro (1983) notes, reputation is an asset that should be treated as a dynamic state variable, and qualitative results should be similar regardless of the reputation variable's construction.

Our conceptual framework is similar to that of Costanigro, Bond, and McCluskey (2012), where firm and collective reputations are derived recursively and firms maximize profit in each period subject to those dynamic reputation constraints. However, since costs are not directly observable, we focus exclusively on the revenue side. Price is an implicit function of our reputation variables such that

$$p_{i,j,t} = p\big(r_{i,t}, \phi(J) R_{j,t}, x_{i,j,t}\big), \tag{3}$$

where $\phi(J)$ is a familiarity parameter that is decreasing in the total number of regional designations, J (i.e., $\phi'(J) < 0$). The familiarity parameter encapsulates the decreasing ease with which consumers are able to disentangle information about collective reputations as the number of regions becomes unwieldy. Our goal is to test our conjecture that as the number of regional designations in the market increases, firms' marginal returns to collective reputations begin to decline.

More specifically, our intention in the ensuing empirical analysis is to show that the marginal effect of collective reputation on price is increasing along with number of regional designations to a point, and after that threshold number of regional designations is exceeded the marginal effect of collective reputation on price begins to decrease. Formally, we examine whether there is some critical number of regional designations, $\bar{J}$, such that $\left.\frac{\partial p}{\partial R}\right|_{J<\bar{J}} > 0$ and $\left.\frac{\partial p}{\partial R}\right|_{J>\bar{J}} < 0$. We find that, at least in the case of the Washington wine industry, such a critical $\bar{J}$ exists.

3. Data

To examine the model and test our intuitive hypotheses in a real-world context, the wine industry provides a practical case study where expert reviews act as a proxy for product quality. We collected our unbalanced panel data on ratings and reviews, regions, prices, production, vintages, and firms from *Wine Spectator* magazine for the period 1985-2013. Worldwide data are available, but differences in GI definitions and rules, as well as country-specific petitioning processes for GI creation, may limit meaningful analysis on such a broad scale. To minimize these issues and isolate a specific GI space in which to work, the analysis herein will focus on Washington state. This framework could be extended to examine other regions individually or a broader aggregate, such as the Pacific Northwest. Washington is presently of particular interest because it is a newer, emerging region within the industry, and regional designations were formed during the period of study.

Though we have data on the actual locations where wines are sourced, we are primarily interested in those wines for which the firm has explicitly lists a GI on its label. A specific GI label may be used if and only if certain thresholds are met.[2] Incorporating only stated GIs in our analysis is appropriate since general consumers will not have access to information on a wine's geographic source beyond what is available on the label or in published reviews.[3]

Prices are those quoted directly from the firms rather than the secondary retail market. For uniformity, we exclude all bottles of unusual volume from our analysis. We begin with 9,601 rating observations, but of those only 9,243 contain the requisite information to warrant inclusion in the estimation procedure. We also exclude 120 non-vintage bottles that cannot be used to construct age and recursive reputation variables. A summary of the data grouped by vintage is available in Table 1.

Individual firm-level data were collected manually from firm websites. Measurement is annual, and we use end-of-year GI totals to account for issues of implementation and product-release dates. Wine prices are adjusted to 1982-1984 values by a consumer price index for alcohol.

In the past, firm age has often acted as an instrument for reputation since consumers presumably consider longevity to be a good proxy for quality (Ju Choi and Kim, 1996). The idea

[2] The current U.S. threshold necessitates that 85% of wine contained in a given bottle must be sourced from within the named GI, or 75% if the GI is a state or county rather than an AVA. The current standard in Washington state for use of the state name or an in-state AVA is stricter, requiring that 95% of the wine contained must be from the region specified.

[3] In this way, we also sidestep one of the issues inherent in nested regions: firms in the narrowly defined nested regions may choose a broader GI for their product label. We investigate consumers' perceptions of quality and reputation, which are calculated based on what consumers observe. Firms' choices over GI label specificity are exogenous to consumers' direct perceptions of firm and collective reputation.

is that wineries that survive must meet some standard of quality. When numerous firms are of a similar age, however, this survivor-quality link does not provide much distinct information to consumers. Without losing sight of the important dynamic nature of consumer perception in reputation construction, we provide a more robust analysis. We include age as a control in the empirical model, but we build explicit recursive variables for firm and collective reputations below using expert-ratings data that are available to consumers (often even at the point of purchase).

4. Empirical Model

Wine prices are implicitly determined through product attributes. Quantity is determined by the harvest and/or the amount of grapes purchased, both occurring prior to final product quality assessment. Quality is assessed after production and cannot be changed *ex post*. Production costs are unknown to consumers. We have proxy observations of quality, so we use price as our dependent variable, which is implicitly determined by perceived quality attributes. Under the hedonic price approach of Rosen (1974), price can be decomposed into its primary elements; in this case the most basic elements are firm reputation, GI reputation, quality, and number of GIs. We begin with a general price equation for each bottle of wine:

$$p = p(r, R, x, J), \tag{4}$$

where p is price, x represents a bottle's quality, r is firm reputation, R is GI reputation, and J is the total number of GIs. This model is convenient as it allows for the calculation of marginal willingness to pay for specific product attributes; for example, $\partial p/\partial R$ indicates the effect on price of a unit increase in collective reputation.

For a baseline regression, we consider a linear model such that

$$p_{i,j,t} = \beta_0 + \beta_1 r_{i,t} + \beta_2 R_{j,t} + \beta_3 x_{i,j,t} + \beta_5 J_t + \epsilon_{i,j,t}, \tag{5}$$

where i indexes the firm, j indexes the regional designation, and t indexes the vintage. We examine the robustness of our initial model specification by including additional potential determinants of price: $Z_{i,j,t}$ are other exogenous time-dependent explanatory variables, $Z_{i,j}$ are other exogenous static regressors, and Z_t are vintage fixed effects.

We tested multiple specifications – including some with nonlinear components – but the qualitative results remained similar across models. We ignore any GI nesting and all variables for each observation employ the narrowest GI used in labeling. Before performing any regression analysis using this model, the variables proxies must be explicitly defined and constructed. The goal here is to indicate some heterogeneous, ordinal values associated with reputations that are not imparted simply with region dummies and age variables.[4] To estimate the value of a collective reputation, one must disentangle its effects from the individual firm reputation effects on potential revenue.

Since quality is not directly observable, we use wine ratings as a proxy for quality. Reputations are dynamic, so we calculate firm and GI reputations recursively, as modified from equation (1) for simplicity of programming. Firm i's reputation is

$$\tilde{r}_{i,t} = \frac{1}{1+\rho^r}\left[\rho^r \tilde{r}_{i,t-1} + \left(J_{i,t}^{-1}\sum_{j=1}^{J_{i,t}} x_{i,j,t}\right)\right], \tag{6}$$

where $\{i, j, t\}$ references a combination of firm i, GI j, and vintage t (i.e., $\{i, j, t\}$ represents a bottle index), $J_{i,t}$ denotes the number of GIs in which firm i produces a bottle in vintage t, and

[4] We test region dummies and age variables as robustness checks.

ρ^r is a weighting parameter to account for the relative emphasis of consumer priors and current quality aggregates.

We calculate GI reputations similarly as

$$\tilde{R}_{i,t} = \frac{1}{1+\rho^R}\left[\rho^R \tilde{R}_{i,t-1} + \left(I_{j,t}^{-1} \sum_{i=1}^{I_{j,t}} x_{i,j,t}\right)\right], \tag{7}$$

where ρ^R is a weighting parameter similar to that used in the firm reputation calculation and $I_{j,t}$ is the number of firms in GI j for vintage t. For both reputation variables, the initial value is mean quality in the first period of inclusion – for initial firm reputation it is a mean across firm production in a firm's initial vintage, and for initial GI reputation it is a mean across all production for that GI's initial vintage. Though we considered including a measure of exposure for the reputation calculations (e.g., controlling for retail locations), we ultimately determined this would require data from points of purchase, which is beyond the scope of this paper. We begin our analysis with $\rho^r = 1$ and $\rho^R = 1$, in other words assuming that priors and current quality are equally weighted in reputation construction. We later relax that assumption to see whether the estimation results change significantly.

Note that the baseline includes an intercept and excludes our exogenous controls in which we are not immediately interested. To this baseline, we add other controls ($Z_{i,j,t}$, $Z_{i,j}$, and Z_t) and modifications (e.g., $\rho^\ell = [0,10]$ for $\ell = \{r, R\}$) to test the robustness of our results. Some important specifications are outlined in more detail below. After testing many model specifications, we find the most variation in the dependent variable is explained by the model

$$p_{i,j,t} = \beta_0 + \beta_1 \tilde{r}_{i,t} + \beta_2 \tilde{r}_{i,t}^2 + \beta_3 \tilde{R}_{j,t} + \beta_4 \tilde{R}_{j,t}^2 + \beta_5 x_{i,j,t} + \beta_6 x_{i,j,t}^2 + \beta_7 J_t + \sum_{h=1}^{H} \beta_{h+7} Z_{h,i,j,t} + \sum_{t=1}^{T-1} \beta_{t+H+7} Z_t + \epsilon_{i,j,t}, \tag{8}$$

where $Z_{h,i,j,t}$ is a set of H controls for red wine, interactions between red wine and other variables, scarcity (defined as the inverse of production), age and age-squared, variety dummies, estate and reserve dummies, and a dummy indicating whether Washington is listed explicitly on the bottle, and Z_t is a control for $T - 1$ vintage fixed effects. In our more detailed analysis below, it is necessary to drop some of the terms (e.g., quadratic baseline regressors and vintage and variety dummies) for uniformity across certain smaller data subsets.

5. Results

5.1 Basic Model

First, we regress price on firm and collective reputation, ratings, and the total number of GIs, using all 9,123 observations (see Table 2). All the variable coefficients in the baseline model are statistically significant to at least the 95% level. At this aggregate level of analysis, both firm reputation and rating have larger marginal effects on price than GI reputation. We disaggregate the data below in a quantile regression to further examine the magnitude of marginal reputation effects.[5] Analysis of the baseline model regression reveals a significant inverse relationship between price and the number of GIs. Our conceptual framework outlines the existence of a familiarity parameter through which an increase in the number of GIs would have a negative effect on consumers' abilities to incorporate GI information. The negative marginal effect of the dynamic GI total in each model specification supports our conjecture.

[5] GI reputation's marginal effect on price is not of a large magnitude for individual prices, but extrapolating to calculate returns on production for the region, these small marginal effects can be substantial.

Model 2 examines the marginal effects on price of interactions between firm and collective reputations as a precursor to our quantile regression below. This interaction effect is positive and significant, though the magnitude is only a fraction of the independent reputations' effects. The magnitude of firm reputation's marginal effect on price decreases between Models 1 and 2, while that of the collective reputation increases (a larger negative effect), and both remain highly statistically significant. This indicates price is affected by reputations both independently and jointly, though the variation in price is observed more strongly through the independent reputations directly.

Model 3 includes the inverse of production (in cases) as a measure of product scarcity. As expected, price and scarcity move in the same direction. In Model 4, we include a dummy for red wine and red wine interaction terms for the other variables. There exist significant differences between red and white wine and the way their attributes influence price, so including these interaction terms should reduce error in the model specification. However, it is notable that several GIs have reputations built primarily around only red or only white wine; hence, removing one color subset from the aggregate data could potentially introduce bias in the estimates. For this reason, we opt to include a red dummy and interaction terms instead of restricting the analysis to only a red or a wine subset. That said, Table 3 presents estimation results for Model 1 and a separate specification similar to Model 3 above with quadratic reputation and age variables for red and white wine subsets. Examining the estimation results in Table 2 for Model 4 (again using the full data set) one may observe that controlling for red wine increases the explanatory power of the model – the adjusted R^2 increases from 40.0% in Model 3 to 47.4% in Model 4. For the mean bottle attributes, there exists a substantial premium on red wine, as expected.

Model 5 includes controls for other qualitative label features – the inclusion of "Washington," "Estate," and "Reserve" – and an age variable measuring time to market (i.e., the time between vintage and review). Incorporating these controls, the reputation coefficient estimates are qualitatively similar and they remain statistically significant. The addition of "Reserve" to the label accompanies a significant price premium, which is intuitive as this label is meant to indicate quality and exclusivity. Less expected is the lack of statistical significance on the premium for estate wines, but that changes in subsequent specifications.

Models 6 and 7 add the potential for curvature in the reputation variables' effects, and these models also control for (1) variety and (2) variety and vintage, respectively. Though the sign changes for the GI reputation coefficient in the final two specifications, the aggregate effect (calculating the combined effect of GI and squared-GI reputation estimates) changes minimally for the mean bottle. The quadratic specification in the baseline variables alone does not significantly impact the explanatory power of the model. Few of the individual vintage effects are statistically significant, and controlling for them reduces the explanatory power of the total number of GIs as the two are highly correlated. Given this collinearity and other data constraints on varieties in smaller subsets, the specification used in subsequent sections is similar to that in Model 5, wherever possible. Further, our analysis indicates the presence of heteroscedasticity in the model, so White standard errors are reported.

To test the robustness of the preceding results to the specific construction of reputation calculations, we examine several reputation weights and a GI dummy replacing GI reputation, taking a value of one whenever any GI narrower than the state level is employed and zero otherwise. The results are presented in Table 4. Shapiro (1983) finds that qualitative results and intuition should tend to hold regardless of the mechanism used for reputation formation.

Following that line of logic, we initially used a baseline weight of $\rho = 1$ to construct both of the reputation variables. To see whether the estimation results obtained employing our initial GI and firm reputation calculations – from equation (6) and (7) – are robust to changes in the weights used in their construction, we tested a range of such weights: $\rho \in [0,10]$.

As the results in Table 4 indicate, reputation weights do not shift the coefficients to any large degree. Going from perfect ignorance of the past ($\rho = 0$) to an intense reliance on the past in reputation construction ($\rho = 10$), the coefficient on GI reputation increases by approximately 26.2%, and it remains statistically significant. Similarly, firm reputation and total GIs remain statistically significant, and they decrease by 15.7% and 6.4%, respectively, across the same range of reputation weights. The changes in coefficient magnitudes are less important than any qualitative differences. This analysis suggests that if consumers have a longer recall in their mental construction of reputations, this will tend to increase the amplitude of GI reputation's marginal effect on price and retard the marginal effect of firm reputation. None of the changes in reputation construction affects the direction in which the other variables affect price, as Shapiro (1983) predicts. The change is statistically significant but not large enough to warrant testing separate reputation constructions for all specifications below.

Similarly, we do not observe much qualitative difference when we drop specific GI reputations in favor of a GI-inclusion dummy variable, as shown in the first column of Table 4. The magnitude of the GI dummy differs from that of GI reputation since the values are of differing magnitudes. Aside from that, the other coefficient estimates change minimally from the specification with GI reputations, and the directions of the other coefficient estimates do not change.

Though the results are not reported here, we tested model specifications using GI-specific dummy variables and firm fixed effects instead of GI and firm reputation variables. The goal of this paper, however, is to interpret the broader effects of GI reputations on price, so disaggregating the data to account for region-specific variables does not provide lucrative estimates to satisfy this end. Including firm fixed effects did not significantly alter the estimates of our coefficients of interest, but it significantly reduced the degrees of freedom in the model. For the smaller subsets below, using the firm reputation variable is preferable to firm fixed effects in terms of tractability and interpretation.

The target of this analysis is to examine individual divisions of the GI space to determine how the marginal effects of the explanatory variables on price are changing over time. Employing the aggregate data to this end leads to difficulties of interpretation. To conduct a robust analysis of individual divisions of the GI space, we subset the data by date range based on the introduction of new GIs. If coefficient estimates change significantly across these subset ranges, then the price effects of those variables are time inconsistent (i.e., the price effects are dynamic). Using the preferred specification from Model 5, we present the results of this analysis in Table 5.

In Figure 3, we observe a few important features of the coefficients estimated in regressions on these date-range subsets. Firm reputation and product scarcity maintain statistical significance across all date ranges; the former trends upward and the latter trends down. Firm reputation is becoming a more decisive component in price determination as the number of GIs is increasing. The coefficient estimate for GI reputation, on the other hand, trends upward to a point and then falls. Depending on the specification, the apex of GI reputation's effect on price is between six and nine GIs. For the impact analysis below in Section 5.4, we use a slightly modified specification, which pinpoints the highest GI reputation coefficient estimate in price determination at six GIs.

To further investigate this dynamic relationship between GI reputation and price, we stratify our data to specific vintages in an approach similar to Schamel and Anderson's (2003) analysis. Under this approach, we cannot control for total number of GIs since that variable is fixed for a given year. Figure 4 illustrates the changes in each of the coefficients from 1990-2012.[6] The trends are qualitatively similar to those from the GI date ranges above, but patterns are more distinct and discernible with this partitioning of the data.

As in the GI-date-range subset, annual firm reputation coefficients trend upward. Rating coefficients and age do not have a strong trend over time. The finding most important to our argument follows from our intuition that GI reputation has a fleeting effect on price. Figures 3(c) and 4(c) show that positive price effects stemming from GI reputation in Washington trend upward to a point and then decrease, following a shallow inverted-U path. The price effects attributable to GI reputation hover near zero after 2008 and occasionally are negative. If this trend continues, then the profit-maximizing strategies of affected firms would not include demanding additional GIs. This supports our inclusion of a familiarity term incorporating the notion that as more GIs are introduced, consumers eventually reach a saturation point beyond which further delineations yield lower returns. In other words, the empirical result is similar to our conjecture that for some $\bar{J}$ (in this case it is six GIs), we should find that $\left.\frac{\partial p}{\partial R}\right|_{J<\bar{J}} > 0$ and $\left.\frac{\partial p}{\partial R}\right|_{J>\bar{J}} < 0$. Though this is the result we expected to find, additional tests are necessary to ensure that the results are robust.

[6] We dropped years in which we had fewer than 50 observations to ensure the robustness of our results.

5.2 Price segmentation and quantile regression

We next examine whether there exist structural breaks in GI reputation's effect on price by price segment. Following Costanigro, McCluskey, and Mittelhammer (2007), we locate an optimal set of three break points (segmenting the market into four distinct price classes) using a joint minimum sum of squared errors (SSE) across prices in the four segments. Optimal breaks were determined using a grid search over combined SSE for 113,564 distinct subset combinations. This goodness-of-fit analysis identified the following optimal ranges. To maintain consistency across the literature, we adopt the names used by Costanigro, McCluskey, and Mittelhammer (2007): the *commercial* segment (below \$10), the *semi-premium* segment (between \$10 and \$18), the *premium* segment (between \$18 and \$30), and the *ultra-premium* segment (\$30 and above).

The results shown in Table 6 are consistent with the findings of Costanigro, McCluskey, and Mittelhammer (2007), but in quantifying regional reputations, we provide a slightly more nuanced result. Our estimation results indicate that GI reputation factors positively into only the lowest-priced commercial segment. For premium segments, GI reputation and price exhibit an inverse relationship. This result is intuitive – consumers purchasing commercial wine may reduce search costs by relying on GI reputation as a proxy for quality across large swaths of low-price alternatives. Choosing among products in the premium segments, the costs associated with choosing poorly increase and consumers are more likely to spend additional effort. The effects of firm reputation on price are positive and increase with price segments. The reputation effects by price segments are illustrated in Figure 5.

We also investigate the relationship between price and our two reputation variables using the more rigorous approach of quantile regression (Koenker and Bassett, 1978). The results are similar to those under our price segmentation framework, but the relationship is clearer with the more robust and uniform quantile regression using 20 quantiles. As shown in Figure 6, collective reputation has a stronger effect on price for the lower price quantiles and the effect diminishes for higher price quantiles. The opposite holds for the effects of firm reputation on price, which is lower for lower price quantiles and increases in higher price quantiles. Again, this suggests that consumers are more willing to incur the higher search costs of investigating individual firms/products in the higher price quantiles while the broader information imparted by a collective reputation is sufficient for products in the lower price quantiles.

Further separating the data into date ranges by the number of GIs in use, we conduct the same quantile regressions and compare the price quantile results across GI-date ranges. Though we conducted this analysis for all variables in Model 5, the results presented here are for only the variables of interest (i.e., firm and GI reputation variables in Figures 7 and 8, respectively). Firm reputation exhibits an increasing influence on price corresponding to higher price quantiles until the number of GIs reaches 13. By contrast, collective reputation has a less defined effect across quantiles when fewer GIs existed. As the number of GIs increased, the effect more clearly mirrors the aggregate effects described above. The influence of collective reputation on price across quantiles is similarly less pronounced with 13 GIs. This further supports our argument that as the number of GIs increases and consumers are less familiar with each, collective reputation becomes a less viable source of information, regardless of price.

5.3 Individualized approach

A noteworthy caveat in generalizing the approach in Section 5.1 to characterize the effects of adding regional designations is that the estimates obtained examine the mean price effects of variables in a highly aggregated data set. For example, marginal effects may differ across subregions, and those differences are not captured in the models above. Prior to this point, we have not considered the treatment effect of adding a single, specific regional designation. Even if, on average, the price effects of adding an additional regional designation are negative, there may exist incentives for specific regional designations to be created if the returns to that particular region are expected to be positive. To consider this potentiality, we utilize the difference-in-difference approach. A difference-in-difference model estimates the effect of a treatment (e.g., GI creation) on the treated group. It requires a properly specified control group that remains unaffected by the treatment. To maintain the necessary distance between control and treatment groups, we restrict our data to a subset including Yakima Valley and bottles without a specified GI. We examine the effects of segregating Yakima Valley on (1) firms remaining in Yakima Valley (indirect treatment group), (2) those changing to a new GI (direct treatment group), and (3) those that remain unaffected (control group). The group staying within the initial GI is affected by the reduction in number of firms sharing the GI as well as a change in reputation. Based on the nature of our data, we ultimately use something akin to a difference-in-difference-in-difference model as follows:

$$\begin{aligned} p_{i,j,t} = \beta_0^d + \beta_1^d D_{it}^{Yakima} + \beta_2^d \tilde{r}_{it} + \beta_3^d x_{ijt} + \\ \delta_s D_{ist} + \gamma_s I_{t\geq\tau}(s) + \xi_s D_{ist} I_{t\geq\tau}(s) + \xi_{Yakima} D_{it}^{Yakima} I_{t\geq\tau}(s) + \epsilon_{ijt}^d \end{aligned} \tag{9}$$

where D_{it}^{Yakima} is a dummy for Yakima Valley, s denotes the treatment GI, δ_s is the coefficient of the treatment group dummy D_{ist},[7] γ_s is the coefficient on the treatment-in-effect indicator variable $I_{t\geq\tau}(s)$ (where τ indicates the start of the treatment period, so if $t \geq \tau$ then the treatment is in effect and $I_{t\geq\tau}(s) = 1$), ξ_s is the coefficient of the treatment effect on the treated group, and ξ_{Yakima} is the treatment effect on Yakima non-inclusive of the direct treatment group.

Before examining the model in equation (9), we restrict the sample to include only within-group changes – a difference-in-difference model excluding any terms utilizing D_{it}^{Yakima} (i.e., the second and eighth terms in equation (9)) – using exclusively Yakima Valley data rather than including the non-GI control group. Using this approach allows us to consider changes specific to the Yakima region before comparing those to an external control. Table 7 provides estimation results for the models under both data subsets (Yakima only and the one containing a non-GI control group) for each of three sequential regional segmentations of Yakima Valley.

For the initial treatment in which Red Mountain split away from Yakima Valley in 2001, we use data from 1995-2003. We observe that the treatment effects are positive regardless of whether we use the external control group. For the properly specified difference-in-difference-in-difference model, the treatment effects on Red Mountain and Yakima Valley are positive, but only the former is statistically significant. There is a price premium associated with both Yakima Valley and Red Mountain compared with non-GI bottles.

The further partitioning of Rattlesnake Hills from Yakima Valley in 2006 illustrates a trend similar to that described in our initial models in Section 5.1. Using data from 2001-2009, we find the treatment effects of adding Rattlesnake Hills are all smaller in magnitude than those

[7] This dummy incorporates bottles that provide GI information both before and after a GI is certified, and it required some subjective analysis to determine which bottles in the post-treatment treatment group tied back to similar bottles in the pre-treatment treatment group.

of adding Red Mountain. Prior to including the external control group, the coefficient estimate for the treatment-in-effect dummy variable is negative and significant, indicating post-treatment prices are lower on average for the full Yakima Valley subset. Estimates including the non-GI control group provide similar results – prices are lower on average, the treatment effect on Rattlesnake Hills is small but positive and not significant, and the treatment effect on Yakima Valley is negative but not significant. The treatment effects for the Snipes Mountain partition in 2009, estimated using data from 2001-2013, are negative, of a higher magnitude, and statistically significant.[8] The results of this analysis of treatment effects closely follow those obtained using the aggregate data in Section 5.1.

Rattlesnake Hills faced significant opposition when its petition for creation was submitted. To ensure that our results hold beyond Yakima Valley, we perform a similar analysis for partitioning within the much larger Columbia Valley. The results obtained are qualitatively similar; however, the overlapping breaks in that region make it more difficult to disentangle the individual effects. Again, the empirical analyses support our argument that price returns to the proliferation GIs in Washington follows an inverted-U shape, and at this point Washington has passed the peak.

5.4 Estimated impact and implications

To demonstrate the financial significance to the Washington wine industry of increasing the number of regional designations beyond the $\bar{J}$ threshold, we provide a brief and simplified counterfactual example. Holding all else constant, we compare observed outcomes with an

[8] The longer date range of this subset was necessary to capture a sufficient number of treated bottles in this unbalanced panel. The results are robust to controls for previous partitions; however, the results presented in Table 7 exclude these controls for prior partitions.

alternative trajectory where the number of regional designations is held fixed at six – the number of regions at which GI reputation has the largest effect on price, according to estimates from several of our initial model specifications. From this, we construct predicted prices from which we subtract the true, observed prices. If we wanted to construct impacts in terms of revenue, we could multiply those price differences by the quantity produced and sum over all observations. However, this approach would not provide a high level of accuracy given that prices are not fully determined by the variables in the model and our data do not include all Washington wines. Regardless, this price analysis will give some indication of the potential financial impact of overproviding information in the form of regional designations. This model requires a re-coding of any regions beyond the initial six back to their original GI and then a recalculation of regional reputations based on only six GIs.

More pedantically, we estimate the coefficients conditional on the number of GIs being at its empirical maximum in terms of the GI reputation's effect on price:

$$p_{i,j,t|J=6} = \beta_0 + \beta_1 r_{i,t|J=6} + \beta_2 R_{j,t|J=6} + \alpha X_{i,j,t|J=6} + \epsilon_{i,j,t|J=6}, \tag{10}$$

where α is a vector of coefficients and X includes rating, a red dummy and interaction terms, and other controls from Model 5. Running a regression of equation (10), we obtain an estimate for $\hat{\beta}_2$. We then estimate coefficients conditional on subsequent ranges of GI totals, $J = \{7, \ldots, 13\}$,

$$\begin{aligned} p_{i,j,t|J=\{7,\ldots,13\}} = \beta_{0*} + \beta_{1*} r_{i,t|J=\{7,\ldots,13\}} + \beta_{2*} R_{j,t|J=\{7,\ldots,13\}} \\ + \alpha_* X_{i,j,t|J=\{7,\ldots,13\}} + \epsilon_{i,j,t|J=\{7,\ldots,13\}}, \end{aligned} \tag{11}$$

individually estimated for each GI-date range so that $\hat{\beta}_{0*}$, $\hat{\beta}_{1*}$, and $\hat{\beta}_{2*}$ are each vectors (and $\hat{\alpha}_*$ is a matrix) with estimates for each GI-date range. Using those estimates, we then replace $\hat{\beta}_{2*}$ with our fixed $\hat{\beta}_2$ and the GI-date-range-specific coefficients to predict what prices would be if GIs had been fixed at our defined optimum. We can then compare the means of the true and estimated prices to get an estimate of the impact of increasing the number GIs beyond the optimum. Figure 9 provides an illustration of GI proliferation's estimated impact on prices. We observe that the mean of estimated prices are higher in the restricted model, between 17.50% and 42.94%. The variance is relatively high, with the standard deviation exceeding the difference between true and estimated prices in all except the final date range. By fixing only one of the coefficients, this should provide more conservative price estimates in terms of magnitude than simply fixing all coefficients; however, this approach is only as accurate as the assumption that only GI reputation is affected by the changing number of GIs.

Given the strong negative effects of increasing the number of regional designations beyond their threshold of positive returns, it is necessary to consider why new regional designations continue to proliferate. There are several explanations. The first is along the lines of Morton and Podolny (2002), who find that some firms in the California wine industry are maximizing owner utility instead of pure profit functions. In this scenario, the owners' marginal utility gains from increased specificity and more rigid identification outweigh their lost revenue. Another possibility is that those firms or individuals petitioning for new designations are unaware of the broader impacts of their actions. While both cases may be true, this latter explanation leads us to question the efficacy of existing policy in mitigating financial loss.

In the U.S. wine industry, anyone can petition to introduce a new regional designation[9] – sometimes identifying an entirely new area with no existing GI and other times overlapping or breaking up an existing one. A petition must demonstrate a degree of heterogeneity in the proposed GI compared with existing regions sufficient to warrant a new GI. These petitions often

[9] See the U.S. Department of the Treasury, Alcohol and Tobacco Tax and Trade Bureau website for a more thorough explanation of the petitioning process: https://www.ttb.gov/wine/ava.shtml.

cite geological or climatic differences between new and existing GIs as support. Once a petition is submitted, a comment period ensues, presumably followed by a tally of the comments for and against to determine passage. Membership in a GI is nonrivalrous, and in the U.S. it only depends on the geographic source of inputs rather than specifying or enforcing minimum quality standards. In other words, the limitations to region creation are minimal and reputation maintenance is not a priority among existing regions in the U.S.

As we have shown, the value of adding new regional designations can have deleterious effects on aggregate firm revenues. In order to ensure the long-run welfare of firms, two paths can be considered, each with its own merits. The *ex ante* approach would be to introduce strict analytical methods when creating a new regional designation. In this case, the regulating body would place restrictions on (or more intensely scrutinize the addition of) new regional designations. Decisions under this approach would incorporate statistical analysis rather than pure reliance on the terroir aesthetic to guarantee that the industry does not suffer from information fatigue. The more arduous the process and the more difficult the path to acceptance, the fewer regions would be created. Of course, the major disadvantage of this approach is that it would necessarily hinder the creation of regions that could be added with positive returns.

Menapace and Moschini (2012) describe an *ex post* approach whereby minimum quality standards maintain a quality threshold that may not be reachable through free market action. This places no constraints on the entry of new regional designations, but GI certification allows collective reputations to act as a proper quality assurance mechanism for consumers. While this does not directly address the information proliferation of increasing regions with decreasing consumer familiarity, it should reduce the free-rider problem associated with a collective reputation. Without the incentive to shirk in a new GI, low-quality firms' incentive to petition for new designations may be reduced, hence indirectly reducing the pace of GI creation.

6. Conclusion

The marginal effects of GI reputation on price are dynamic and vary across regions. As the number of GIs increases, consumer familiarity with each individual GI decreases. We find that the influence of a GI's reputation on price increases to a point and then decreases as the number of regions crosses a certain threshold, regardless of whether reputations are increasing or decreasing. Our findings have policy implications for the number of GIs introduced and minimum quality standards for inclusion in a region. As long as GI reputations have a positive effect on price, any policy leading to an increase in quality could still provide benefits to firms. As the magnitude of GIs' effects on prices decreases, so do the benefits of regional quality standards.

The Washington wine industry has experienced a significant boom in recent years. Mean prices and production have increased. This uptick may be partially responsible for the increasing number of regional designations as firms seeking more product heterogeneity (in the form of specificity) petition for more regions. Without much formal analysis available to firms, they may be unable to disentangle the causes behind price changes for themselves. Until the large economic upturn ebbs and markups become sufficiently small, it is unlikely that firms will intensely investigate how prices fluctuate with GI use and the number of GIs available.

There could exist an optimal number of GIs given all the parameters. But as our empirical analysis seems to indicate, an optimal point could be very difficult to identify and is likely a moving target. Finding the correct balance of information when short-run outcomes are not easily observed would be difficult. Indeed, it may require the informed decisions of a social planner (in the U.S. wine industry case, the Alcohol and Tobacco Tax and Trade Bureau) where the existing process of adding new regional designations is deemed to yield suboptimal results.

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Appendix: Tables and Figures

Table 1. Summary of unbalanced panel data with observations arranged by year.

Vintage	Bottles	Total Firms	Total GIs in WA
1985	2	2	3
1986	6	5	3
1987	15	9	3
1988	28	16	3
1989	46	28	3
1990	57	31	3
1991	69	37	3
1992	194	59	3
1993	254	61	3
1994	279	68	3
1995	295	69	4
1996	209	60	4
1997	309	75	4
1998	312	81	4
1999	325	89	4
2000	349	99	4
2001	380	112	5
2002	448	131	5
2003	426	122	5
2004	416	135	6
2005	517	163	7
2006	608	181	9
2007	643	185	9
2008	663	195	9
2009	755	227	11
2010	775	225	11
2011	466	157	11
2012	240	111	13
2013	37	28	13

Table 2. OLS with multiple model specifications controlling for exogenous variables.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	-161.5099***	-87.5568***	-152.8412***	-84.9074***	-88.7370***	998.8426***	1078.0603***
	(4.392)	(8.358)	(4.212)	(3.748)	(3.561)	(84.042)	(96.225)
Bottle rating	0.4706***	0.4615***	0.4474***	0.2153***	0.1514***	-6.6176***	-6.6226***
	(0.032)	(0.032)	(0.030)	(0.026)	(0.025)	(0.795)	(0.795)
Bottle rating, squared						0.0402***	0.0402***
						(0.005)	(0.005)
Firm reputation	1.5576***	0.7101***	1.4656***	0.8797***	0.9269***	-17.5984***	-19.4960***
	(0.059)	(0.101)	(0.056)	(0.049)	(0.046)	(2.101)	(2.372)
Firm reputation, squared						0.1072***	0.1183***
						(0.012)	(0.014)
GI reputation	0.0063**	-1.0046***	0.0066***	-0.0024	0.0224**	-0.2138***	-0.4761***
	(0.003)	(0.105)	(0.002)	(0.002)	(0.011)	(0.067)	(0.078)
GI reputation, squared						0.0025***	0.0054***
						(0.001)	(0.001)
Total GIs	-0.5350***	-0.5632***	-0.5560***	-0.4336***	-0.4358***	-0.5139***	-0.0967
	(0.026)	(0.026)	(0.025)	(0.023)	(0.023)	(0.027)	(0.254)
Scarcity (inverse production)			621.7470***	498.7179***	435.0263***	287.6192***	242.1353***
			(39.469)	(61.325)	(54.175)	(61.449)	(56.364)
Washington					2.0209**	-0.0351	-0.5112
					(0.911)	(0.903)	(0.834)
Estate					0.4835	0.6438*	0.5706*
					(0.362)	(0.337)	(0.332)
Reserve					2.5966***	2.8002***	2.7552***
					(0.300)	(0.285)	(0.278)
Age					2.0448***	1.0960***	1.7183***
					(0.243)	(0.235)	(0.233)
Age, squared					-0.1410***	-0.0378	-0.0831**
					(0.043)	(0.040)	(0.040)
Reputation Interaction		0.0117***					
		(0.001)					
Red†	No	No	No	Yes	Yes	Yes	Yes
Variety, fixed effects	No	No	No	No	No	Yes	Yes
Vintage, fixed effects	No	No	No	No	No	No	Yes
Observations	9,123	9,123	9,123	9,123	9,123	9,123	9,123
Adj. R^2	0.336	0.349	0.400	0.474	0.496	0.562	0.575
F statistic	1157.365	977.860	1218.283	821.707	599.550	300.817	190.678

Statistical significance is reported at the 90% (*), the 95% (**), and the 99% (***) levels.
Standard error reported in parentheses below coefficient estimates are White's heteroscedasticity-consistent robust standard errors.
† Also controlling for red interactions with other variables; for space, those additional controls' coefficient estimates are not reported.

Table 3. Coefficient estimates for separate red and white subsets.

	Model 1		Model 2	
Variable	Red	White†	Red	White†
Constant	-159.4294***	-78.0308***	505.6876***	182.7431***
	(5.446)	(3.976)	(37.507)	(42.224)
Rating	0.3526***	0.2193***	-14.8916***	-5.8464***
	(0.040)	(0.028)	(0.878)	(0.983)
Rating Squared			0.0882***	0.0361***
			(0.005)	(0.006)
Firm reputation	1.6179***	0.7923***	1.4847***	0.7062***
	(0.072)	(0.052)	(0.057)	(0.050)
GI reputation	0.0052	-0.0061**	0.0061*	-0.0037*
	(0.004)	(0.002)	(0.003)	(0.002)
Total GIs	-0.5394***	-0.2276***	-0.5863***	-0.2469***
	(0.035)	(0.024)	(0.031)	(0.021)
Age	1.4868***		3.4764***	
	(0.115)		(0.470)	
Age Squared			-0.3203***	
			(0.075)	
Scarcity			500.3075***	462.9031***
			(40.593)	(66.821)
Observations	6,508	2,536	6,508	2,536
Adj. R^2	0.314	0.259	0.419	0.422
F statistic	595.407	222.466	586.855	308.860

Statistical significance is reported at the 90% (*), the 95% (**), and the 99% (***) levels.

Standard error reported in parentheses below coefficient estimates are White's heteroscedasticity-consistent robust standard errors.

† White is not aged, so that variable is omitted.

Table 4. GI dummies and a range of reputation weights used to test robustness of results to reputation construction.

Variable	$\rho = 1$	$\rho = 0$	$\rho = 1/2$	$\rho = 2$	$\rho = 10$
Constant	-87.9423***	-65.9551***	-82.6407***	-90.1654***	-69.6747***
	(3.607)	(3.444)	(3.558)	(3.562)	(3.151)
Rating	0.1516***	0.2023***	0.1467***	0.1880***	0.3320***
	(0.025)	(0.026)	(0.025)	(0.024)	(0.023)
Firm reputation	0.9327***	0.5963***	0.8573***	0.9072***	0.5025***
	(0.046)	(0.045)	(0.047)	(0.045)	(0.031)
GI dummy	0.5633				
	(0.838)				
GI reputation		0.0271**	0.0230**	0.0227**	0.0342***
		(0.012)	(0.011)	(0.011)	(0.013)
Total GIs	-0.4286***	-0.3015***	-0.3972***	-0.4491***	-0.3209***
	(0.023)	(0.022)	(0.023)	(0.023)	(0.022)
Scarcity	436.7678***	450.267***	440.1326***	433.9341***	451.3615***
	(54.465)	(61.791)	(56.071)	(54.252)	(62.503)
Washington	0.7303	2.2498**	2.0145**	2.0617**	2.8541**
	(0.819)	(1.029)	(0.938)	(0.928)	(1.129)
Estate	0.4872	0.5237	0.5066	0.4287	0.2626
	(0.362)	(0.376)	(0.368)	(0.355)	(0.364)
Reserve	2.5954***	2.2935***	2.5399***	2.5755***	2.0923***
	(0.300)	(0.305)	(0.301)	(0.300)	(0.306)
Age	2.0510***	2.1843***	2.0519***	2.1089***	2.4186***
	(0.243)	(0.239)	(0.241)	(0.246)	(0.245)
Age, squared	-0.1417***	-0.1579***	-0.1398***	-0.1536***	-0.2026***
	(0.043)	(0.042)	(0.042)	(0.043)	(0.043)
Red†	Yes	Yes	Yes	Yes	Yes
Observations	9123	9123	9123	9123	9123
Adj. R^2	0.496	0.466	0.488	0.499	0.468
F statistic	599.262	530.884	579.519	606.912	535.015

Statistical significance is reported at the 90% (*), the 95% (**), and the 99% (***) levels.
Standard error reported in parentheses below coefficient estimates are White's heteroscedasticity-consistent robust standard errors.
† Also controlling for red interactions with other variables; for space, those additional controls' coefficient estimates are not reported.

Table 5. Regression using date-range subsets by total GIs currently in existence in Washington.

Variable	1984-1994 (3 GIs)	1995-2000 (4 GIs)	2001-2003 (5 GIs)	2004 (6 GIs)	2005 (7 GIs)	2006-2008 (9 GIs)	2009-2011 (11 GIs)	2012-2013 (13 GIs)
Constant	-27.7791*	-73.91112***	-70.7471***	-150.7192***	-96.4594***	-144.2112***	-97.6452***	-97.8455***
	(15.627)	(7.101)	(11.453)	(56.242)	(14.286)	(20.751)	(11.669)	(15.735)
Rating	0.1621***	0.2033***	0.1829**	0.1626	0.2152*	0.2028***	0.1024	-0.0907
	(0.034)	(0.042)	(0.074)	(0.105)	(0.130)	(0.065)	(0.091)	(0.108)
Firm reputation	0.2984***	0.7137***	0.6679***	1.1382**	0.9758***	0.9740***	1.0373***	1.2563***
	(0.072)	(0.093)	(0.122)	(0.486)	(0.229)	(0.103)	(0.129)	(0.231)
GI reputation	-0.0899	-0.0088	0.0324*	0.5038	-0.0093	0.5309**	0.0204	0.0037
	(0.176)	(0.038)	(0.018)	(0.454)	(0.025)	(0.214)	(0.025)	(0.011)
Scarcity	118.6284***	706.7608***	646.4754***	491.9140*	464.7132**	425.6159***	464.2260***	489.1020***
	(22.158)	(81.300)	(119.813)	(253.669)	(181.775)	(72.868)	(115.453)	(78.510)
Washington	-7.0361	-0.6238	2.6790*	43.0334	-1.0135	46.9649**	2.5207	0.3600
	(14.918)	(3.311)	(1.523)	(39.808)	(1.677)	(18.942)	(2.125)	(0.755)
Estate	5.0854***	0.5012	1.3221	1.0084	1.5620	-0.3193	0.4443	-0.3122
	(0.928)	(0.839)	(1.181)	(1.606)	(1.673)	(0.575)	(0.721)	(0.619)
Reserve	2.1601***	2.3841***	4.0975***	3.8936***	3.3351*	3.5137***	2.5496***	1.3504
	(0.448)	(0.439)	(0.871)	(1.408)	(1.868)	(0.876)	(0.835)	(1.725)
Age	1.3199***	1.2834***	0.6894***	0.6987**	0.2490	0.4783**	1.3086***	1.3202***
	(0.211)	(0.132)	(0.194)	(0.323)	(0.292)	(0.202)	(0.274)	(0.407)
Red†	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950	1799	1254	416	517	1914	1996	277
Adj. R-squared	0.503	0.585	0.433	0.500	0.472	0.512	0.501	0.595
F statistic	69.670	181.879	69.310	30.586	33.920	144.085	144.218	30.017

Statistical significance is reported at the 90% (*), the 95% (**), and the 99% (***) levels.
Standard error reported in parentheses below coefficient estimates are White's heteroscedasticity-consistent robust standard errors.
† Also controlling for red interactions with other variables; for space, those additional controls' coefficient estimates are not reported.

Table 6. Ordinary least squares estimates for pooled and segmented hedonic model.

		Price Segments			
	Pooled	Commercial	Semi-premium	Premium	Ultra-premium
Constant	-80.7146***	-17.3076***	-14.1858***	5.6190	1272.2859***
	(2.969)	(1.354)	(3.065)	(6.870)	(98.327)
Rating	-0.0591**	0.1213***	0.1235***	-0.1994**	-14.5226***
	(0.028)	(0.014)	(0.034)	(0.079)	(1.165)
Firm reputation	1.0794***	0.1242***	0.1912***	0.3919***	1.3610**
	(0.045)	(0.016)	(0.026)	(0.057)	(0.546)
GI reputation	-0.0370***	0.0133***	-0.0175***	-0.0394***	-0.9091**
	(0.009)	(0.003)	(0.005)	(0.011)	(0.409)
Scarcity	485.1411***	238.6555***	71.0204***	61.9425***	316.0391
	(35.308)	(32.808)	(12.101)	(19.527)	(203.060)
Washington	-3.0488***	0.8205***	-1.5537***	-3.7923***	-80.4326**
	(0.766)	(0.283)	(0.404)	(1.006)	(36.331)
Estate	0.4677	-0.1437	0.1832	1.6186***	-3.5209**
	(0.373)	(0.176)	(0.215)	(0.565)	(1.422)
Reserve	2.7953***	1.1939***	0.6281***	-0.5827**	6.0951***
	(0.306)	(0.158)	(0.129)	(0.255)	(1.863)
Age	1.1415***	0.4556***	0.0610	0.4002***	3.8347***
	(0.085)	(0.037)	(0.041)	(0.102)	(0.772)
Red†	Yes	Yes	Yes	Yes	Yes
Observations	9123	3661	3508	1609	345
Adj. R-squared	0.472	0.325	0.115	0.083	0.190
F statistic	815.699	177.363	46.496	15.498	9.083

Statistical significance is reported at the 90% (*), the 95% (**), and the 99% (***) levels.
Standard error reported in parentheses below coefficient estimates are White's heteroscedasticity-consistent robust standard errors.
† Also controlling for red interactions with other variables; for space, those additional controls' coefficient estimates are not reported.

Table 7. Estimation results from difference-in-difference and difference-in-difference-in-difference models used to test for treatment effects of separating Red Mountain (2001), Rattlesnake Hills (2006), and Snipes Mountain (2009) from Yakima Valley.

	Red Mountain (1995-2003)		Rattlesnake Hills (2001-2009)‡		Snipes Mountain (2001-2013)‡	
Variable	*Diff-in-Diff*	*Diff-in-Diff-in-Diff*	*Diff-in-Diff*	*Diff-in-Diff-in-Diff*	*Diff-in-Diff*	*Diff-in-Diff-in-Diff*
Constant	-67.5535***	-86.0147***	-82.9339***	-115.0123***	-70.1872***	-78.4342***
	(14.278)	(11.559)	(27.543)	(20.913)	(19.140)	(14.267)
Yakima Valley		1.0144**		0.5703		1.7160***
		(0.414)		(1.002)		(0.636)
Red Mountain	1.4110*	0.3499				
	(0.725)	(0.778)				
Rattlesnake Hills			8.0813*	-0.2666		
			(4.668)	(3.837)		
Snipes Mountain					5.1338**	2.0521
					(2.485)	(1.619)
Treatment in Effect	1.2704*	0.2991	-2.0926*	-2.7872***	-0.9308	-0.2270
	(0.703)	(0.534)	(1.120)	(1.010)	(0.648)	(0.623)
Treatment Effect on Treated	0.7280	3.4602**	-2.2861	0.9874	-6.9326**	-5.0828**
	(1.857)	(1.715)	(4.839)	(4.163)	(3.148)	(2.585)
Treatment Effect on Yakima Valley		0.2482		-0.1128		-2.2134**
		(0.907)		(1.352)		(0.866)
Rating	0.0634	0.0562	0.4535***	0.4116***	0.2863**	0.2898***
	(0.078)	(0.073)	(0.145)	(0.141)	(0.126)	(0.110)
Firm reputation	0.8002***	1.0042***	0.5624*	0.9837***	0.5789***	0.6791***
	(0.180)	(0.167)	(0.302)	(0.240)	(0.209)	(0.141)
Scarcity	452.8896	490.2545***	389.860***	433.1799***	553.8665***	651.8946***
	(280.083)	(146.437)	(146.376)	(129.533)	(122.316)	(107.367)
Estate	3.8118***	4.6686***	1.8438	0.3758	1.3770	0.2914
	(1.256)	(1.035)	(1.178)	(1.588)	(1.168)	(1.246)
Reserve	2.0404**	2.5139***	-3.0321**	0.2426	-2.2143*	0.1.2269
	(0.915)	(0.769)	(1.351)	(2.114)	(1.148)	(1.618)
Age	0.6081	0.9349***	2.0910***	0.9720**	1.5908***	0.3519
	(0.438)	(0.191)	(0.727)	(0.451)	(0.518)	(0.342)
Red†	Yes	Yes	Yes	Yes	Yes	Yes
Observations	400	860	412	446	550	901
Adj. R-squared	0.497	0.569	0.461	0.512	0.522	0.512
F statistic	27.324	67.790	24.452	28.433	37.655	56.584

Statistical significance is reported at the 90% (*), the 95% (**), and the 99% (***) levels.
Standard error reported in parentheses below coefficient estimates are White's heteroscedasticity-consistent robust standard errors.
† Also controlling for red interactions with other variables; for space, those additional controls' coefficient estimates are not reported.
‡ Longer date range used to increase observations for treatment group prior to treatment. Tests for cross-treatment effects between models did not prove significant.

Figure 1. Firms (dots) in dynamic GI space with increasing regional specificity (i.e., more narrowly defined regions).

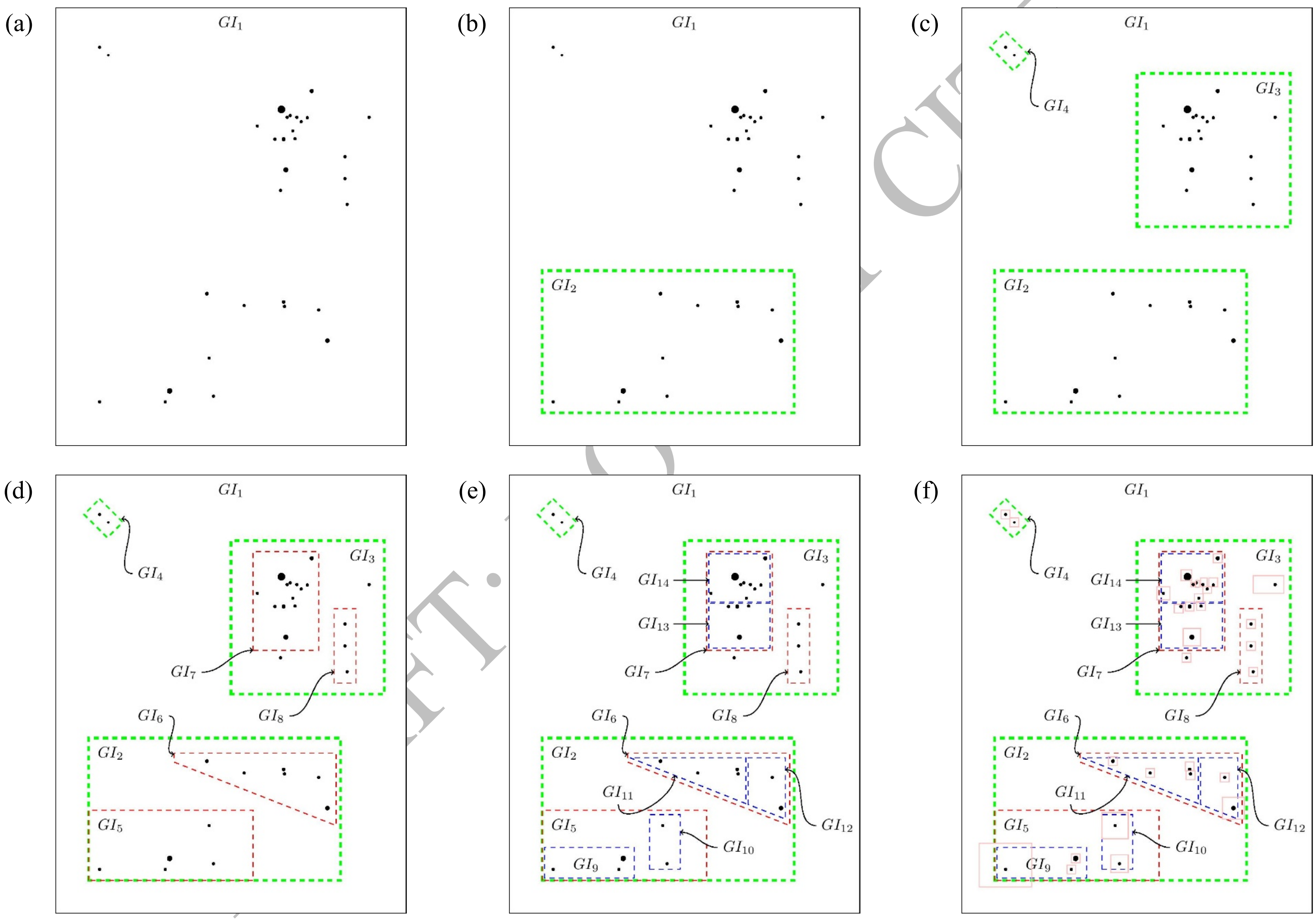
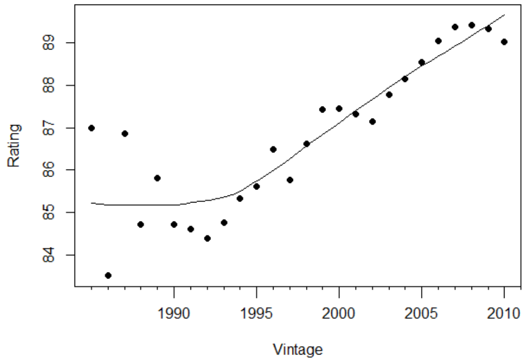
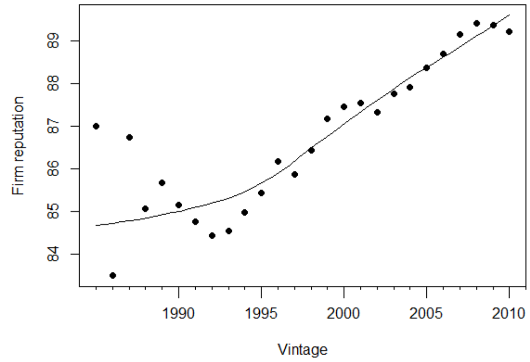


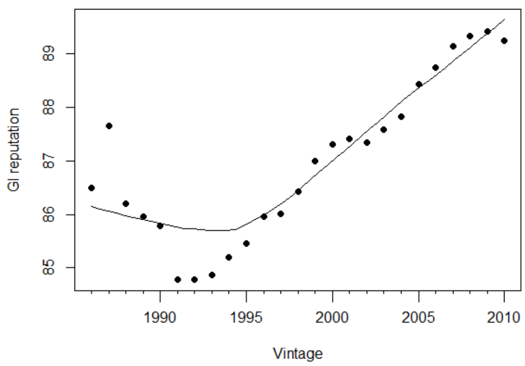
Figure 2. Annual plots of mean in-sample variable values illustrating changes over time.



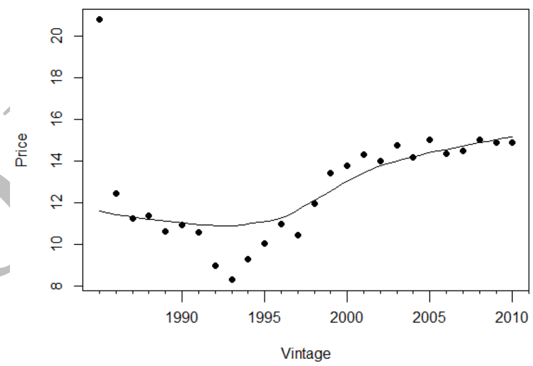
(a) Mean rating



(b) Mean firm reputation

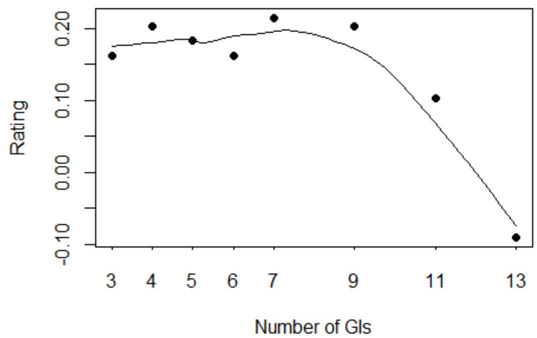


(c) Mean GI reputation

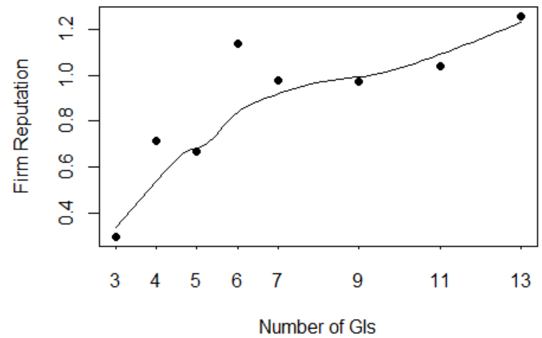


(d) Mean price

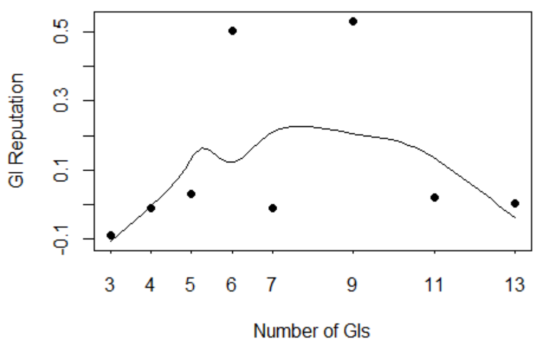
Figure 3. Plots of coefficient estimates by date ranges for GI totals indicating individual regressors' dynamic effects on price.



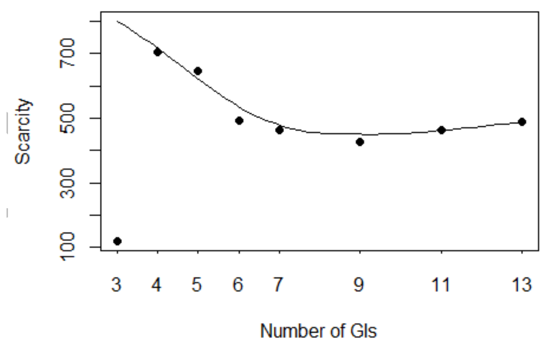
(a) Rating coefficients



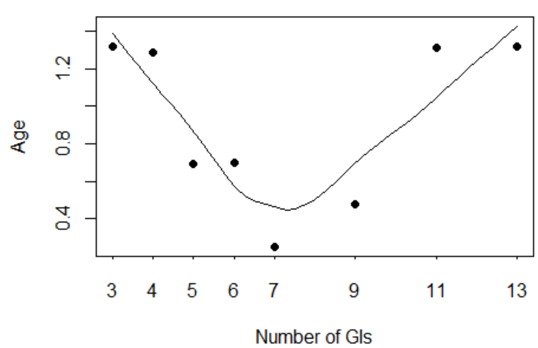
(b) Firm reputation coefficients



(c) GI reputation coefficients

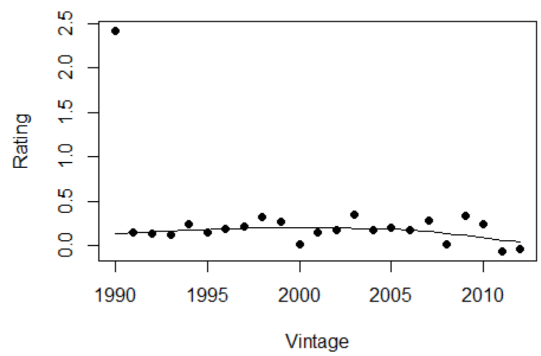


(d) Scarcity coefficients

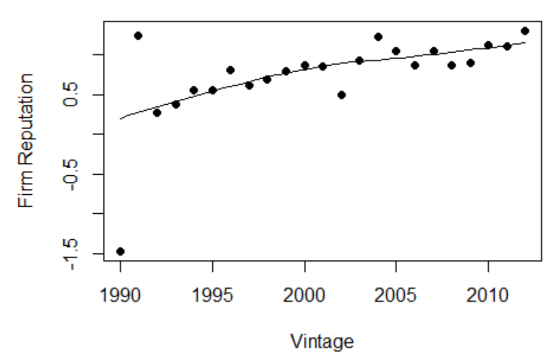


(e) Age coefficients

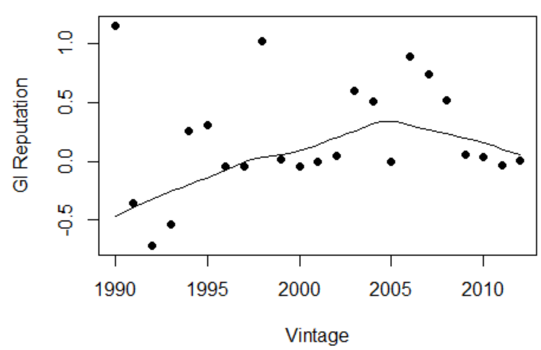
Figure 4. Plots of coefficient estimates by vintage indicating individual regressors' dynamic effects on price.



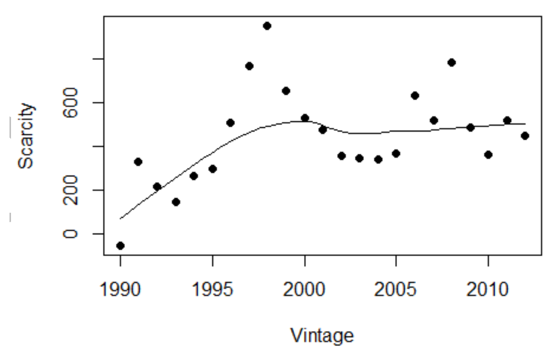
(a) Rating coefficients



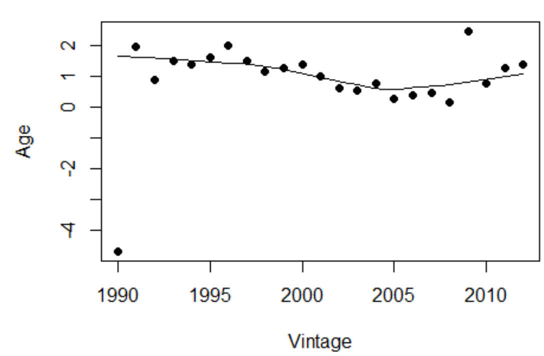
(b) Firm reputation coefficients



(c) GI reputation coefficients



(d) Scarcity coefficients



(e) Age coefficients

Figure 5. Price segmentation of aggregate data by minimized sum of squared errors.

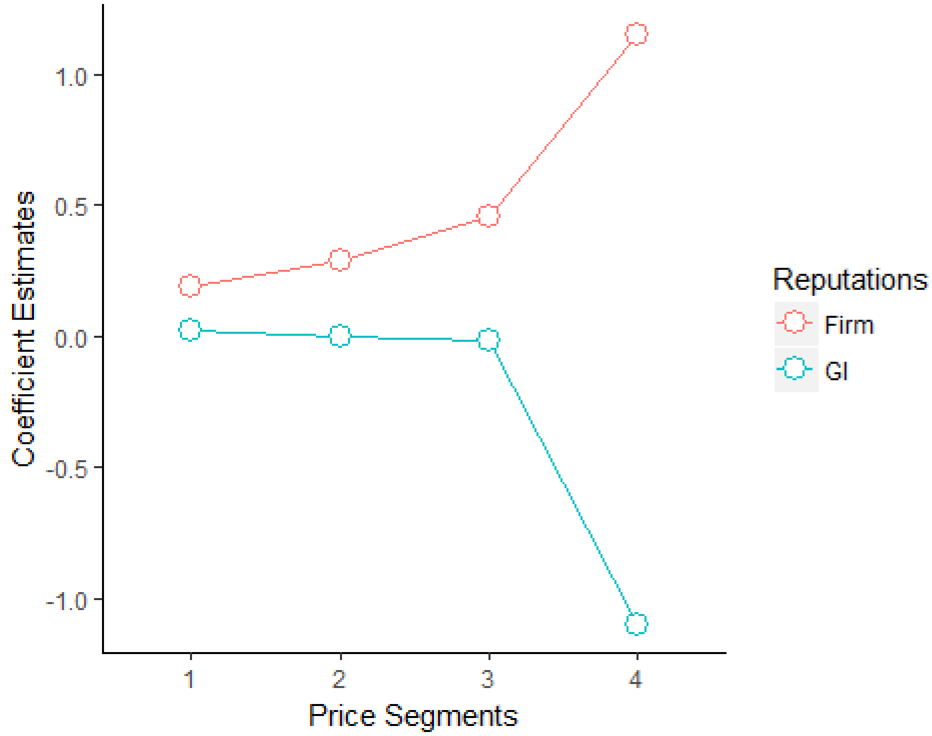


Figure 6: Quantile regression of price on explanatory variables with 20 segments.

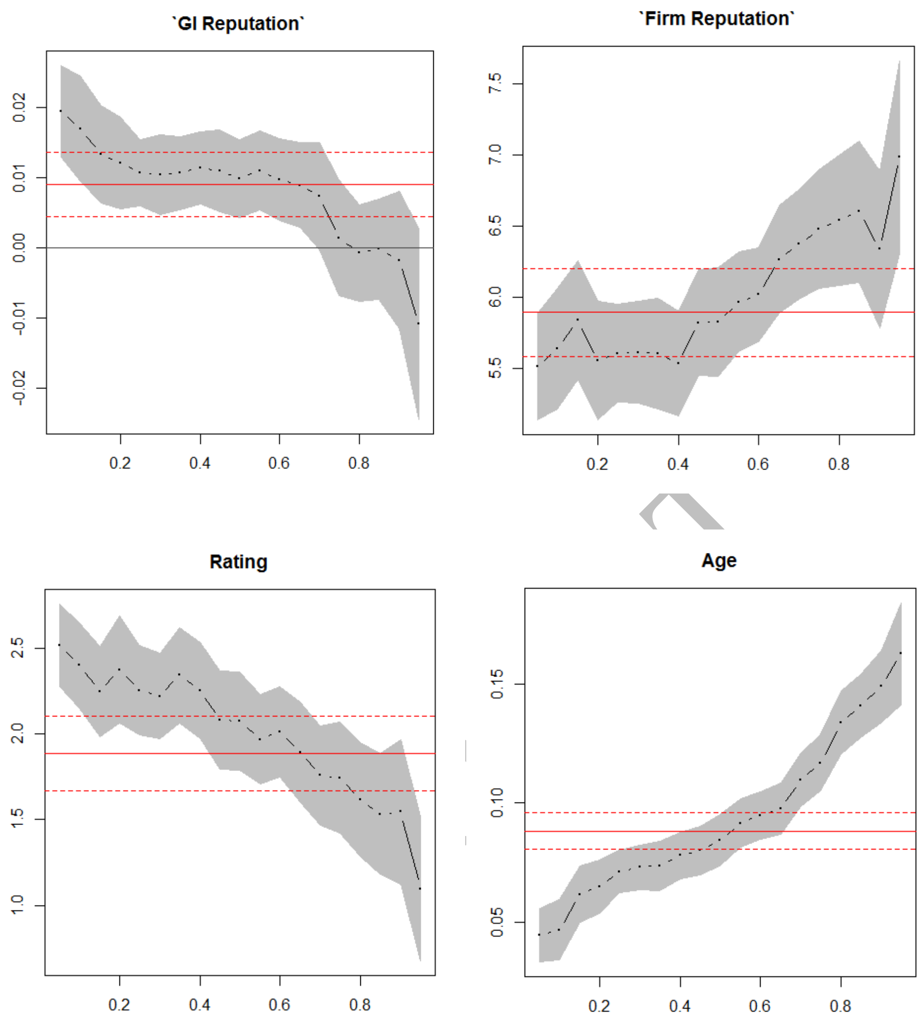


Figure 7. Firm reputation coefficient estimates by price quantile for specific GI ranges.

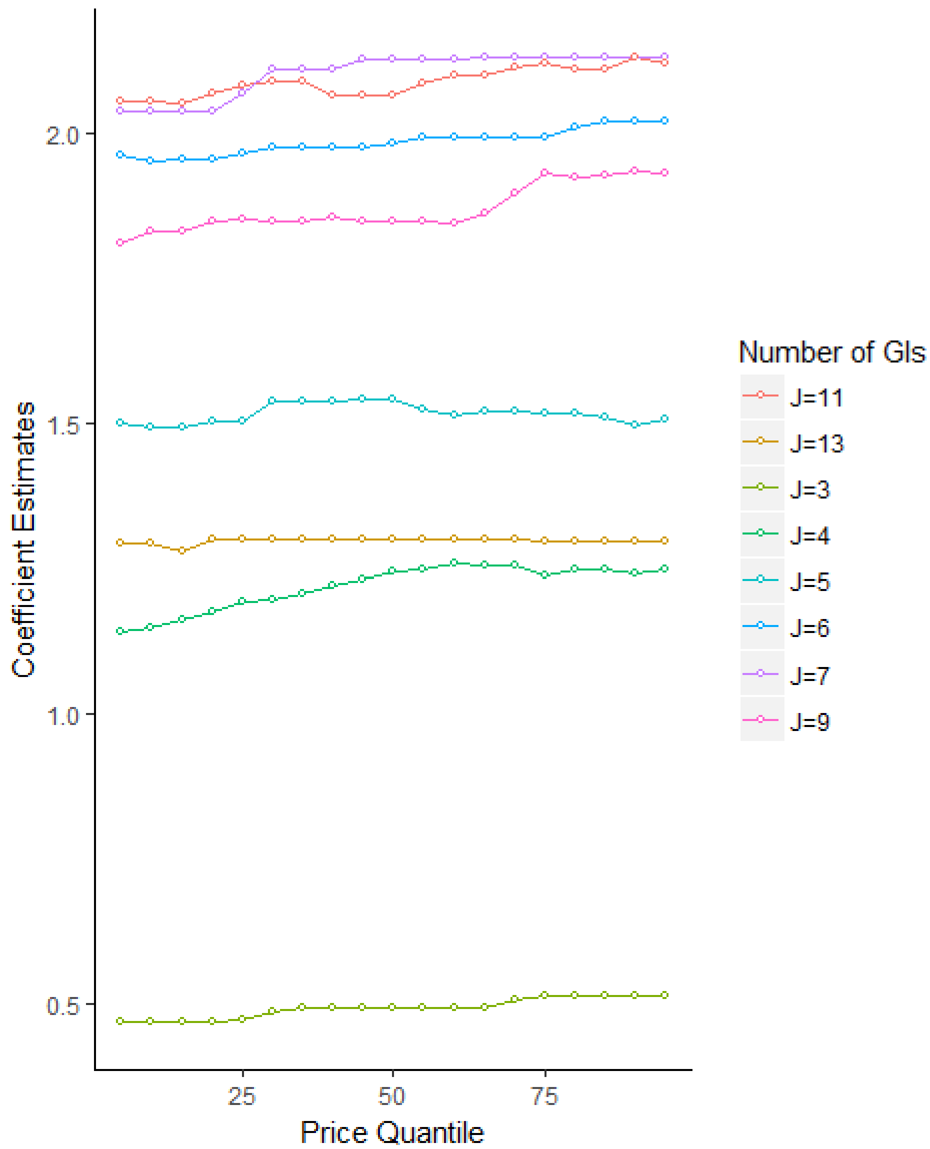


Figure 8. GI reputation coefficient estimates by price quantile for specific GI ranges.

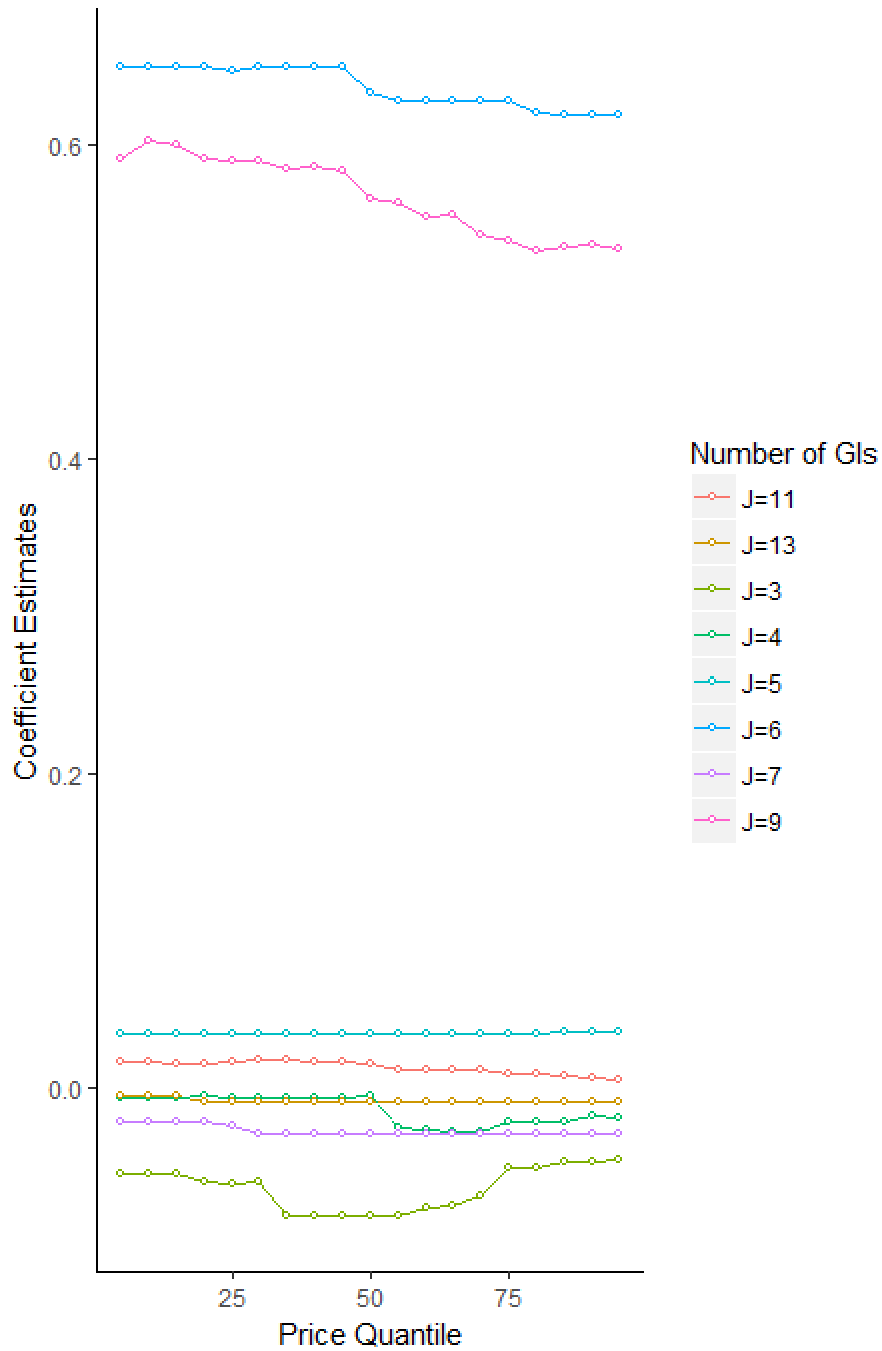
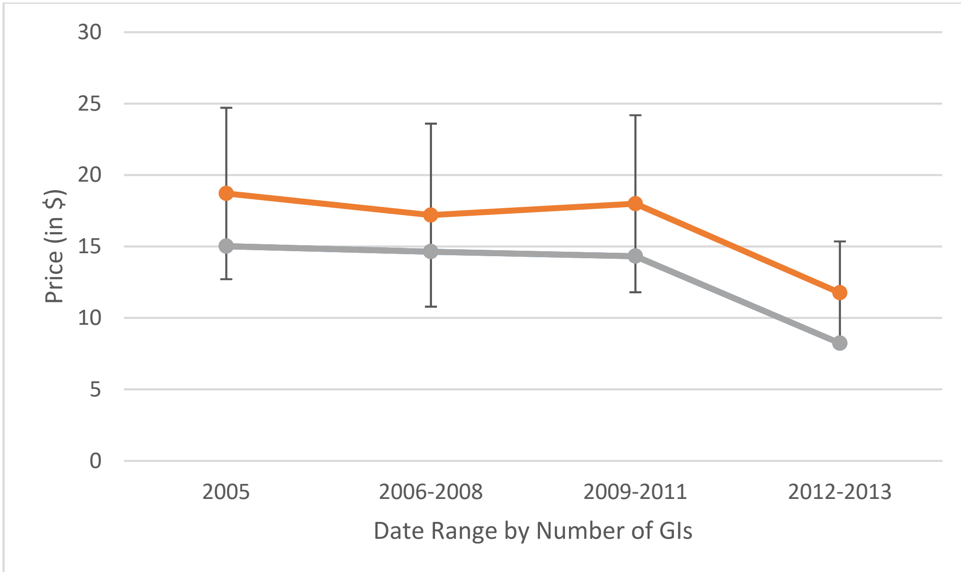


Figure 9. Impact on mean price of increasing the number of regions beyond the optimal empirical maximum.



***Standard deviation in price for estimates given as bar measure.**