Do Clusters Really Matter for Companies' Competitive Strategies?
Evidence at the Country Level

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Abstract

Building on a rich descriptive literature emphasizing the role of regional clusters in global competitiveness, this paper investigates whether cluster strength in a country induce companies in that country to prioritize quality-oriented rather than low-cost strategies. The empirical analysis takes into account both supply- and demand-side factors of the cluster environment, exploiting a detailed country-level panel dataset based on the 2000-2004 Executive Opinion Surveys of the World Economic Forum. The analysis addresses two econometric challenges. First, quality-oriented companies may be more likely to select into innovative clusters. A second problem arises if country-specific unobserved market shocks simultaneously change the cluster environment and induce companies to alter their strategies. These endogeneity problems are addressed by implementing a semiparametric, country-fixed effect model, building on the technique pioneered by Olley and Pakes (1996). The results suggest a positive and robust relationship between the strength of clusters in a country and national companies' adoption of quality-oriented strategies in global markets. Moreover, this relationship holds for groups of countries with different levels of economic development. Interestingly, the availability of local suppliers seems a more relevant cluster attribute in developing countries than in advanced countries.

Key words: industrial clusters; company strategy; country heterogeneity; semiparametric analysis.

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1. Introduction

Over the past several decades, the strength of industrial clusters has been increasingly emphasized as a determinant of the global competitive advantage of regions and nations. While traditional explanations of the role of location highlight access to natural resources or scale economies in production, more recent work in strategy and economics focuses on the complex interplay between cooperation and competition that occurs in leading regional clusters (Porter 1990, 1998, 2003, Saxenian 1994, Swann 1998). In the context of innovation-based global competition, industrial clusters may allow for the transfer of tacit knowledge across nearby firms, while facilitating product differentiation through local competitive pressure.[1]

Though many researchers studying strategy and international business emphasize the impact of clusters on firm strategy and performance, few studies undertake a systematic empirical investigation of the role of industrial clusters. Moreover, nearly all prior empirical research focuses on the relationship between clusters and economic performance, as measured by employment, patenting, firm survival, and the like. This paper focuses instead on the impact of industrial clusters on company strategy choice and specifically, whether the prevalence and depth of clusters ("strong clusters") in a country induce companies in that country to prioritize quality-oriented rather than low-cost strategies. The term quality-oriented strategy means that companies compete on the basis of unique processes and/or products, while low-cost strategy refers to companies primarily seeking easy, cheap access to natural resources and inputs.[2] In both high-tech and low-tech activities, companies might prioritize quality or low-cost strategies. For example, the eye-glasses cluster in Italy (Belluno) competes primarily on unique products (design and new materials), while the software cluster in India competes on the basis of abundant and cheap labor (Arora, Gambardella and Torrisi, 2004).[3]

[1] Examples of clusters include Silicon Valley's microelectronics, biotechnology and venture capital; the California wine cluster; and the Italian footwear clusters. See Van der Linde (2002) for numerous cluster examples.
[2] Throughout this paper, the terms quality-oriented, quality-differentiated and innovation-oriented strategy are used interchangeably.
[3] See Belluno: Valley of Glasses (www.italtrade.com/focus/glasses.htm) for detailed information on the Belluno eye-glasses.

Strategy choice is at the heart of company performance (Porter, 1996). Measuring the effect of clusters on company strategy sheds light on how clusters improve the competitiveness of companies, regions and nations. Industrial clusters may increase global competitive advantage by helping companies reduce costs and by promoting innovation. I hypothesize that stronger industrial clusters induce companies to compete primarily on the basis of quality-differentiation. If firms are located nearby and use a similar pool of specialized inputs, firms' capabilities may become similar and the risk of failing may increase (Sorenson and Audia 2000, Stuart and Sorenson 2003). Therefore, for companies in clusters to survive, they will need to find new ways to gain competitive advantages, such as through innovation and providing unique value (see, e.g., Porter 1990, 1998, 2000, Glaeser, et al., 1992, Saxenian 1994, and Swann 1998). Companies will choose the proper strategy drawing on the critical local resources, including input conditions, sophisticated local customers, reputation and collaboration with partners and suppliers.

This paper presents a systematic empirical analysis of the impact of industrial clusters on the strategy of the average company in a country, controlling for a country's institutional and macroeconomic environment. While most cluster literature focuses on supply-side cluster benefits, the proposed empirical model considers both supply and demand factors. The empirical analysis exploits a detailed country-level panel dataset based on the 2000-2004 Executive Opinion Surveys (EOS) developed by the World Economic Forum.

The country-level analysis of clusters has a four-fold motivation. First, the study of clusters at the country level has been poorly explored in the empirical literature. In contrast, an increasing number of national and European policy initiatives are focusing on clusters as a tool to implement effective economic policies, such as attracting new foreign and domestic firms in industries that support the activities of existing and nascent clusters and funding collaborative research in clusters (Yehoue 2005, Cortright 2006, Ketels, et al., 2006, Ketels and Memedovic 2008).[4] Second, the EOS Survey data are

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[4] See also the European Cluster Observatory for detailed information on policies and initiatives relevant to clusters in European countries (http://www.clusterobservatory.eu).

most accurate for country level analysis. This Survey is designed to measure the sophistication of the strategy of companies in a country and the quality of the national business environment. Using this reach Survey we measure the cluster environment of a country and the types of strategies of the companies in that country (referred as "national companies"). Third, industrial clusters are present across countries and sectors. Innovative clusters are found in high-tech sectors (e.g., computers, biotechnology and nanotechnology) as well as in more traditional sectors (e.g., textiles, wine and eye-glasses), and a cluster often integrates traditional and sophisticated industries. Finally, there are relevant inter-cluster linkages across nearby regions within a country that contribute to promote the global competitiveness of a country's companies. Successful regional clusters connect with other clusters in nearby regions (Porter 1998, 2003, Delgado, Porter and Stern, 2007). For example, the aerospace vehicles and defense cluster in Tucson (Arizona) benefits from neighboring regions in California and Arizona that are national leaders in the same and related clusters.[5]

While globalization has changed the cluster scene with regional clusters becoming more specialized and establishing a more global value chain, the role of location has increased (Porter, 1998, 2001; Ketels and Memedovic 2008). The growth of clusters and companies in a location is facilitated by the possibility to establish linkages with other locations, including outsourcing some value chain activities to other regions and countries (Rugman and Verbeke, 1993; Delgado, Porter and Stern, 2007; Huggins 2008; Asmussen, Pedersen and Dhanaraj, 2009). Firms based in the most advanced clusters often start or enhance clusters in other locations in order to reduce the risk of a single location, access lower cost inputs, or better serve particular regional markets (Arora, Gambardella and Torrisi 2004, Bresnahan, Gambardella and Saxenian 2001). Furthermore, in response to the increased globalization, countries and regions compete to offer the best business environment to attract firms in specific fields that support the activities of existing firms.

[5] Delgado, Porter and Stern (2007) separate the influence of convergence and cluster-driven agglomeration forces on the employment growth of regional industries, clusters, and regions in the US. They find that, after controlling for convergence forces, there are systematic evidences for cluster-driven agglomeration forces that occur across related industries within a cluster, across linked clusters and across neighboring regions.

This paper emphasizes that domestic location matters in a global market. I find that the cluster strength in a country encourages national companies to compete based on unique product and processes in international markets, reinforcing the idea that industrial clusters are a key component of national innovation systems (Porter 1990, Nelson 1993, Mowery and Nelson 1999, Den Hertog et al. 2001, Porter and Stern 2003).

The empirical analysis measures the effect of cluster attributes on company competitive strategy by correcting for two sources of endogeneity: (1) a selection effect and (2) contemporaneous correlation between clusters and unobserved factors driving company strategy.[6] First, a selection effect arises if measures of the strength of clusters simply reflect the likelihood that quality-oriented companies participate in strong clusters. Second, contemporaneous correlation between the cluster environment and the strategy of national companies may be driven by country-specific unobserved market shocks. Specifically, changes in customers' sophistication and in the intensity of competition in the local market might simultaneously change the cluster environment and induce companies to alter their strategies. Importantly, this market shock could also be interpreted as Survey respondents' expectations for economic growth. In other words, Survey companies in economies in boom may overestimate the cluster environment variables and the national companies' innovation strategies.

To address these sources of endogeneity, the empirical analysis uses a semiparametric, country-fixed effect model. The selection bias is addressed by introducing country-fixed effects, which help control for countries' initial conditions (including the (large or small) presence of innovative companies). The unobserved country shock is conditioned out by using the semiparametric method developed by Olley and Pakes (1996) and implemented by Levinsohn and Petrin (2003). This approach consists of finding an observable proxy variable (such as GDP per capita) that increases monotonically with the unobserved shock and using it to condition out the effect of the shock on the endogenous variables.

[6] While the analysis is this paper is at the country-level, the econometric challenges and method used in this paper might also apply for firm-level and industry-level studies.

As mentioned earlier, the results point to a positive and significant relationship between the strength of industrial clusters and the adoption of quality-oriented strategies. Although I expect clusters to benefit companies in all countries, companies located in developing versus developed countries, and in low- versus high-cluster-oriented countries might react to cluster attributes in different ways. In order to explore these issues, I apply the empirical method to different sub-samples of countries, as well. The analysis suggests that for the groups of low-GDP and low-cluster-oriented countries, the availability of qualified local suppliers is especially relevant to encourage national companies to implement quality strategies. These results seem to imply that the relationship between clusters and strategy depends on the stage of economic development.

The remainder of the paper is organized as follows. Section 2 explains the mechanisms by which clusters affect the competitive advantages and strategies of companies and develop the main hypothesis. Section 3 identifies the sources of endogeneity that affect the relationship between the cluster environment in a country and the competitive strategies of national companies. Section 4 explains the econometric model. Section 5 describes the data. Section 6 presents the empirical results. Finally, Section 7 concludes.

2. Industrial Clusters: Does Location Matter?

There is a broad and growing industrial cluster literature, which originates in Marshall's (1920) seminal work on agglomeration economies. A large portion of the literature focuses on explaining cluster formation and identifying at least three different types of economies of agglomeration: knowledge spillovers, input-output linkages, and labor market pooling (see e.g., Krugman 1991, Jaffe, Trajtenberg and Henderson 1993, Audretsch and Feldman 1996, and Ellison, Glaeser and Kerr 2007).[7] More recently, a few papers have looked at the dynamics of cluster formation (see e.g., Swann 1998, Dumais et al. 2002, Sorenson and Audia, 2000). These studies find that supply-side economies of agglomeration may

[7] See Hanson (2001) for a review of empirical evidence consistent with location-specific externalities.

deteriorate due to congestion costs, competition effects, and product cycles effects (mature versus old industries).

Another branch of the literature concentrates on the related question of how economies of agglomeration affect the competitive advantages and strategies of companies, regions and countries. These studies explore multiple output indicators, including the level and growth of employment, innovation, productivity, and firm creation (see e.g., Porter 1990, 1998, Glaeser et al. 1992, Saxenian 1994, Audretsch and Feldman, 1999, Furman 2003, Henderson 2003, Rosenthal and Strange, 2003, Bonte 2004, Delgado, Porter and Stern 2007, Glaeser and Kerr 2008, Feser et al. 2008).

Many prior cluster studies focus on the supply-side economies of agglomeration as the mechanism of cluster growth (including larger pools of skilled labor and specialized suppliers, as well as, knowledge spillovers). Over time, other studies have also incorporated additional agglomeration drivers, including local demand, competition and social networks. More specifically, studies of the effect of clusters on global competitiveness of countries and regions (Porter 1990, 1998; Saxenian 1994; Stoper 1997; Porter and Stern 2003; Bonte 2004) and studies of cluster dynamics and formation (Swann 1998, Arora, Gambardella and Torrisi 2004, Sorenson and Audia 2000) underline the demand-side cluster attributes, including local customer sophistication and the intensity of competition in the local market.[8]

This paper explores whether strong industrial clusters in a country affect the way national companies compete. Do clusters promote low-cost or quality strategies? *My hypothesis is that, while clusters could facilitate both lowering costs and raising quality, strong clusters (i.e., balanced cluster environment) will favor innovation strategies more than low-cost strategies*. In what follows, I will explain two cluster-growth mechanisms that support the idea that clusters may favor companies' quality-differentiated strategies. The first mechanism refers to the complex combination of cooperation and competition that takes place in clusters. The second mechanism is based on organizational or ecological theory.

[8] International trade papers also emphasize the role of demand (Fagerberg 1995, Aitken et al. 1997).

Clusters are geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions in particular fields that compete but also cooperate (Porter 1998, p. 197). Thus, firms within a geographically concentrated clusters share common technologies, skills, knowledge, inputs, consumers, and institutions, facilitating agglomeration across complementary and related industries and amplifying the pressure to innovate (Porter 1990, 1998, 2000; Saxenian 1994; Swann 1998; Feldman and Audretsch 1999; Delgado, Porter and Stern 2007). In other words, industrial clusters help firms' competitiveness by facilitating the diffusion of tacit knowledge through cooperation and by facilitating product differentiation through local competitive pressure. As clusters grow, the supply-side agglomeration benefits might decrease because of numerous firms competing for the same pool of specialized suppliers and skilled labor. The increased local rivalry brings its own benefits for regional and country performance by encouraging company innovation to survive in the market. It is this combination of competition and cooperation that spurs cluster growth.

This mix of competition and cooperation is best formalized in Porter's (1990) *diamond framework*. In this model, supply-side and demand-side factors interact and shape the strategy and competitiveness of firms, regions, and countries. The materialization of cluster benefits requires a complex interaction among input conditions, the context in which rivalry takes place, local customers sophistication, and the availability of related and supporting industries. A key determinant of the clusters' sustained growth is local rivalry. The proximity helps monitor the competitors' and suppliers' performance, and this evaluation facilitates both differentiation-based competition and collaboration.[9]

Based on social and spatial models of competition (ecology theory), Sorenson and Audia (2000) propose a related mechanism to explain the growth of clusters. The organizational ecology studies predict that organizations located near competitors are more likely to fail because companies compete for the same set of resources and firms' capabilities might become similar. Sorenson and Audia (2000) and Stuart

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[9] Some regional studies emphasize more the cooperation than the competition effects that take place within clusters. In these studies clusters (industrial districts) are nexus of untraded interdependencies such as personal trust and fewer conflicts of interest between the cluster members (see e.g., Becattini et al. 2003, Storper, 1995 1997).

and Sorenson (2003) test this prediction for U.S. shoe-manufacturing plants and U.S. biotechnology firms, respectively. They find that clusters had higher rates of founding new firms, but new plants located near other plants had higher rates of failure than isolated plants. Thus, they argue that greater firm performance does not seem to be the determinant of cluster growth. Instead, they argue, clusters survive by promoting greater entrepreneurial opportunities. The idea is that the cost of creating a new venture is lower in a cluster because it offers "a better social structure of opportunity," including social networks, reputation and venture capital.

I have analyzed different mechanisms that explain how industrial clusters could *promote* innovation-based competition and *respond* to changes in the degree of competition by adjusting the network relationships among their firms and promoting entry of new firms. Prior studies support that clusters promote differentiation strategies and innovation and adjust to changes in the market. The Schmitz (2001) analysis of the shoe cluster in Sinos Valley, Brazil shows that bilateral supplier-buyer networks increased substantially during the 1990s in response to greater competition in the cluster's foreign markets. Branstetter (2000) finds evidence that the manufacturers and specialized suppliers in Japanese vertical keiretsu groups share the risk involved in the creation of new products; and these network relationships with specialized suppliers have a positive influence on companies' R&D efforts and patenting. At the country level, Furman, Porter and Stern (2001) and Porter and Stern (2003) find a significant relationship between cluster attributes and countries' international patenting.

While some prior empirical studies measure the effect of clusters on the innovation of firms, regions and countries, there is very little systematic empirical work on the relationship between location externalities and firm strategy (versus performance). One notable exception is Furman (2003). In the paper, the adoption of more science-oriented strategies by firms will depend on (regional, sub-national, and national) location specific supply-side factors. In particular, he finds that the strength of the local scientific and technological base positively influences the science-oriented strategies of global pharmaceutical firms.[10]

In contrast with previous studies that focus on supply-side location factors, in this paper the adoption of quality strategies will depend on both supply- and demand-side cluster attributes in a country. Because both company competitive strategy and the cluster environment adjust to changes in the market, I control for unobserved market shocks in the proposed econometric model (Section 4).

3. Sources of Endogeneity

The empirical cluster literature is largely descriptive. These studies make a relevant contribution by gathering data at the regional level and identifying subtle correlations between firms' competitiveness and cluster attributes. They often focus on the isolated relationships between specific cluster attributes and performance measures, without addressing potential endogeneity problems. The goal of this paper is to offer a more systematic empirical analysis of the effect of clusters on the quality-differentiation strategy of a country's companies, controlling for the institutional and the macroeconomic environments in the country. The main challenge is that cluster attributes are not exogenous. The positive relationship between cluster and company quality strategy could be driven in part by two sources of bias: a selection effect; and contemporaneous correlation between the cluster environment and unobserved country factors driving company strategy.

The selection effect (or country heterogeneity). At the company level, the selection effect means that companies with some level of quality differentiation may be more likely to participate in clusters with better attributes, such as a higher quality of local suppliers and a higher level of product and process collaboration among the cluster agents. Interestingly, the selection effect could be negative for the high-end performance companies. That is, companies with the best specific assets (e.g., multinational firms)

[10] Furman (2003) addresses the simultaneity problem of high-science locations attracting science-oriented companies by offering qualitative evidence that the location choice was made prior to the strategy decision; and controlling for the initial differences in location-specific characteristics.

may decide not to participate in clusters to avoid having their management and technological capabilities spill over to their competitors (Flyer and Shaver 2000, Chung and Alcacer 2002).

On average the selection effect will be positive at the country-level. If innovative clusters tend to attract quality-differentiated companies, then those countries with a higher number of innovative companies (i.e., advanced countries) are more likely to have a higher prevalence of clusters and better cluster attributes. In order to control for the pool of differentiated companies existing in a country, I include country fixed effects in the econometric model (Section 4). The country dummies will take into account countries' initial conditions that impact the strength of clusters and the innovation orientation of national companies: including the communication and research infrastructures, cultural assets, innovation policies to attract FDI and the economy openness. At the same time, the country fixed effects capture the sector specialization of the country.

Contemporaneous correlation: unobserved country idiosyncratic market shock. In the paper, I assume that having controlled for a country's initial conditions, the only mechanism by which changes in the quality orientation of companies may affect the cluster environment (i.e., reverse causality) is through a country idiosyncratic market shock (ω_{ct}). The term "market shock" is used as a synonym for fluctuations in demand, provoked by new competitors and changes in local customers' habits. A positive shock in a country means that local customers are more sophisticated and competitive pressure in the domestic market is greater. More generally, the shock includes supply-side changes that affect the market structure.[11] Importantly, since I am using Survey data, the country market shock could also be interpreted as Survey respondents' expectation about the economic outlook of their countries. For example, when Survey companies expect a boom (recession), they might overestimate (underestimate) the innovation orientation of national companies and cluster attributes. While the unobserved country shock may have two interpretations (market shock and Survey respondents' bias), in both cases an increase in the shock (ω_{ct}) may have a positive influence on companies' quality strategy and on the cluster environment.

[11] For instance, technological changes may induce demand of more sophisticated inputs and products by buyers and consumers.

As mentioned in Section 2, clusters respond to changes in the intensity of competition and in consumer sophistication (Porter 1998, 2000; Schmitz 2001; Bonte, 2004). Helper, MacDuffie and Sabel (2000) offer additional empirical evidence on how companies' network structures adjust to changes in the intensity of competition. They explain that automakers in the U.S. moved away from vertical integration to create flexible agreements with independent suppliers in response to the entry of new competitors in the market (including used cars and international competition).[12]

Kranton and Minehart (2000) offer a theoretical framework to explain the benefits of supplier-buyer networks under uncertainty in demand provoked by new competitors and by changes in consumer taste. They analyze whether buyers will improve their products by developing network relationships with specialized suppliers or by vertical integration. They conclude that, as buyers face more demand uncertainty, buyer-supplier networks are the equilibrium outcome. The buyer-supplier network reduces the costs for buyers as they share the capacity of suppliers, who also benefit from producing for various buyers.

The above discussion suggests that market shocks contemporaneously change the cluster environment and company competitive strategy. Certain responses by clusters to these shocks occur in the short term. For example bilateral supplier-buyer networks, the rate of entry of new firms and consumers' tastes change in the short term, while improvements in horizontal and multilateral networks take longer. I abstract from long-term effects in the analysis.

I expect that a positive market shock in a country (e.g., economies in boom) will improve company quality-orientation and the strength of clusters in the country. In response to better demand opportunities and competitive pressure companies will find it more beneficial to increase quality differentiation, even if they do not participate in clusters. Simultaneously, the cluster strength might improve because clustered firms respond to the increased demand sophistication and competitive pressure

[12] They explain internal firm practices in the automotive industry that allow buyers and suppliers to improve their joint products and processes without the need for vertical integration.

by splitting up the innovation process and by strengthening the network relationships among them. In addition, the strength of clusters could improve due to the entry of new firms in clusters.

4. The Econometric Model

The relationship between the type of competitive strategy of the representative company in a country and the country's cluster attributes is modeled using a balanced panel of 74 countries over the 2001-2004 period. The core econometric specification is:

$$y_{ct} = \beta_0 + \beta_X' X_{ct} + \delta_p p_{ct} + \alpha_T T_t + \alpha_c + \omega_{ct} + \eta_{ct} ; \qquad (1)$$

where the dependent variable y_{ct} is the extent to which the average company in country c at year t prioritizes innovation-oriented strategies (unique products and/or processes) versus low-cost strategies; X_{ct} is a vector that includes the country's cluster attributes (such as the prevalence of clusters and the level of cluster collaboration) and economy-wide innovative factors (such as supporting institution and access to foreign technologies); and p_{ct} is the GDP per capita (lagged one period) to control for the economic outlook of the country (see Section 5 for a detailed explanation of the dependent and explanatory variables). In addition, the model includes year dummies (T_t) that control for common time trends; and country-fixed effects (α_c). The use of country-fixed effects prevents the effect of clusters on company competitive strategy from being driven by the number of innovative companies existing in a country. Finally the error term has two components: (1) η_{ct} is an i.i.d. error term and (2) ω_{ct} is the unobserved country market shock (or Survey respondents' bias) that could be positively correlated with the dependent variable and the explanatory variables.

In order to control for the endogeneity effects, I use a semiparametric, country-fixed effect model. In the absence of proper instrumental variables, I use the semiparametric method developed by Olley and Pakes (1996) and implemented by Levinsohn and Petrin (2003) to condition out the country market shock. This approach consists of finding an observable proxy variable (p_{ct}) that increases monotonically with the unobserved shock (ω_{ct}). In this case, the proxy function is invertible and the unobserved market shock can be expressed as a function of the proxy variable: $p_{ct} = p(\omega_{ct}) \rightarrow \omega_{ct} = \omega(p_{ct})$. The unobserved shock is then conditioning out by including in the econometric specification a non-parametric function of the proxy variable: $\phi(p_{ct}) = \phi(p_{ct}, \omega(p_{ct}))$.[13]

In this paper, the main proxy variable is the log of GDP per capita (lagged one period). I then transform equation (1) into a semiparametric (SP) country-fixed effect model, and obtain a consistent estimator of the coefficients of the cluster attributes (β_X):

$$y_{ct} = \beta_X' X_{ct} + \phi(p_{ct}) + \alpha_T T_t + \alpha_c + \eta_{ct}\,, \tag{2}$$

$$\phi(p_{ct}) = \beta_0 + \delta_p p_{ct} + \omega(p_{ct})\,. \tag{3}$$

In order to estimate equation (2), I extend the 2-stage estimation procedure by Levinsohn and Petrin (2003) to solve for country-fixed effects (α_c). I implement two alternative within-country transformations of the function $\phi(p_{ct})$ (see Appendix B). First, based on Pagan and Ullah (1999, Chapter 3) and Ullah and Roy (1998), I use a local linear approximation of $\phi(p_{ct})$ and the resulting time-demeaned function is $\tilde{\phi}(p^*_{ct}) = \frac{\partial \phi}{\partial p}(p)\, p^*_{ct}$. The within-country transformation of equation (2) then becomes:

<u>SP Model 1</u>: $$y^*_{ct} = \beta_X' X^*_{ct} + \frac{\partial \phi}{\partial p}(p)\, p^*_{ct} + \alpha_T T_t \; + \eta^*_{ct}\,, \tag{4}$$

where variables with an asterisk are time-demeaned ($V^*_{ct} = V_{ct} - \frac{1}{T}\sum_{t=1}^{T} V_{ct}$). The Second SP model assumes that the time-demeaned proxy variable (p^*_{ct}) is monotonic in the time-demeaned shock ($\omega^*_{ct} = \omega(p^*_{ct})$). The resulting simpler semiparametric model to solve for is:

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[13] Olley and Pakes (1996) study the relationship between firm production and the choice of inputs, allowing for firm productivity shocks that vary over time (ω_{it}). The OLS model is inappropriate because firm unobserved productivity is correlated with the choice of inputs. To address this problem, they specify the productivity shock as a monotonic function of investment and capital (observable variables). Alternatively, Levinsohn and Petrin (2003) use as a proxy variable an intermediate input (materials or electricity), which is also an explanatory variable. The idea is that the use of materials will increase monotonically with the productivity shock.

SP Model 2: $$y^*_{ct} = \beta'_X X^*_{ct} + \phi^*(p^*_{ct}) + \alpha_T T_t + \eta^*_{ct}, \quad (5)$$
$$\phi^*(p^*_{ct}) = \beta_0 + \delta_p p^*_{ct} + \omega^*(p^*_{ct}); \quad (6)$$

where $\phi^*(p^*_{ct})$ is a non parametric function whose argument is the variable p^*_{ct}.

Estimators of the Coefficients of the Cluster Variables. The main estimators of the coefficients of the cluster attributes is Robinson's (1988) semiparametric estimator ($\hat{\beta}^{SP}_X$), which solves the equation:

$$y^*_{ct} - E(y^* \mid p^*_{ct}) = \beta'_X (X^*_{ct} - E(X^* \mid p^*_{ct})) + \alpha'_T (T_t - E(T \mid p^*_{ct})) + \eta^*_{ct}. \quad (7)$$

Note that the $\hat{\beta}^{SP}_X$ estimators will be the same for the two SP models proposed above (equations 4 and 5).[14] Second, to reinforce the SP results and offer a better understanding of how the model works, a discrete semiparametric estimator is also calculated ($\hat{\beta}^D_X$). I compute $\hat{\beta}^D_X$ by transforming the continuous p^*_{ct} variable into a uniform discrete variable taking values 1 to 7 (p^{*D}_{ct}). The discrete SP estimator is obtained by specifying $\phi^D(.)$ as a step function that includes an intercept and a dummy for each (but one) value of p^{*D}_{ct}, solving the following equation:

$$y^*_{ct} = \beta'_X X^*_{ct} + \delta_1 + \sum_{j=2}^{7} \delta_j I(p^{*D}_{ct} = j) + \alpha_T T_t + \eta^*_{ct}; \quad (8)$$

where *I*(.) is an indicator function that takes value one when p^{*D}_{ct} is equal to *j*. I refer to the discrete SP estimator from now on as the dummy estimator.[15]

Consistency of the SP Model. The key assumption in obtaining a consistent estimator of the effect of a country's cluster environment on the competitive strategy of national companies is the monotonicity of the unobserved country market shock ($\omega_{ct} = \omega(p_{ct})$). The coefficient I am most interested in is $\hat{\beta}_X$, but I need to identify the coefficient of the GDP per capita variable ($\hat{\delta}_p$) to test for

[14] However, the estimators of $\phi(.)$ and δ_p will differ in model 4 versus model 5 (See the Appendix B).

[15] See Figure 1 for a comparison between the continuous and discrete estimator of $\phi(.)$.

monotonicity. This coefficient the GDP per capita is estimated in a second stage by solving a semiparametric nonlinear least squared model using GMM (using the first stage SP estimators of $\hat{\phi}(.), \hat{\beta}_X$, and $\hat{\alpha}_T$).[16,17]

Testing for monotonicity. While Olley and Pakes (1996) prove that the monotonicity condition holds in their model, Levinsohn and Petrin (2003) assume monotonicity and then test for it. Following Levinsohn and Petrin's (2003) approach, I test whether the estimated country shocks ($\omega(p_{ct})$ in SP-Model 1 and $\omega^*(p^*_{ct})$ in SP-Model 2) increase with GDP per capita (lagged one period). In the SP Model 1 (equation 4), we can only recover the slope of the market shock: $\widehat{\frac{\partial \omega}{\partial p}} = \widehat{\frac{\partial \phi}{\partial p}}(p_{ct}) - \hat{\delta}^{SP}_p$; while in the SP Model 2, we can estimate the shock $\hat{\omega}^*(p^*_{ct}) = \hat{\phi}^*(p^*_{ct}) - \hat{\delta}^{SP}_p p^*_{ct}$. Figure 2 illustrates that in the empirical analysis monotonicity holds for most of the range of the GDP per capita variable, supporting the consistency of the SP coefficients.

5. Data

The main source of data for the empirical analysis is the *Executive Opinion Survey* (EOS) developed by the World Economic Forum in collaboration with the Institute for Strategy and Competitiveness, at the Harvard Business School. This Survey data are used to evaluate the competitiveness of countries and elaborate the *Global Competitiveness Reports* (see Porter and Stern 2003 and Cornelius 2003). The EOS meets the need for up-to-date data, providing valuable qualitative information for which hard data sources are scarce or nonexistent. An important attribute of the Survey is that the respondents are executives of companies, and they are the actual decision makers that ultimately determine economic activity. These business leaders report their perceptions about a variety of country

[16] The programs used for the econometric estimation are MATLAB and Stata. See the Appendix B and Levinsohn and Petrin (2003, p. 340) for a detailed explanation of the semiparametric GMM procedure.

[17] To get a consistent estimator of $\hat{\delta}_p$ requires the following two additional assumptions: (1) the shock follows an exogenous first-order Markov process; and (2) the previous year's GDP per capita is not contemporaneously correlated with unexpected changes in the shock ($\omega_{ct} - E(\omega_{ct} \mid \omega_{ct-1})$).

competitiveness factors, including the strategies and operations of national companies, the quality of the national cluster environment, and innovation policies. Survey respondents evaluate each question using 7-point Likert-scale ratings. The Survey also includes a very few attributes of the respondents, such as their size and foreign ownership.[18]

This paper uses the 2001-2004 EOS Surveys. The number of countries covered and the number of respondents for each country vary over time (with the coverage improving in later years). For the empirical analysis, I focus on a balanced panel of 74 countries for the years 2001-2004, resulting in 296 observations. I compute the average response by country-year using the over 20,789 individual responses (this represents an average of 70 respondents per country-year).[19] This detailed Survey data allow me to be the first testing the impact of clusters on the way companies competes across a large set of countries.

Dependent Variable. The dependent variable (TYPE OF COMPETITIVE STRATEGY) measures whether "the competitiveness of your nation's companies in international markets is due to low cost (or local natural resources) or unique products/processes." This variable indicates the degree to which company competitive advantage depends on introducing unique goods and services. While both types of competitive strategies are valuable ways to compete, the dependent variable will capture which strategy is the predominant.[20]

A first order question is whether companies in practice prioritize one type of strategy: low-cost or quality strategies. The strategy theory suggests that most companies need to focus on one type of strategy to develop a sustainable competitive advantage (Porter, 1996). Indeed, the company level data also support that in practice companies will prioritize either cost or innovation strategies. Specifically, using data on Survey companies' own strategies (questions available only in the 2002 Survey instrument), I find that surveyed companies that report greater quality orientation (unique products, better consumer

[18] The rate of response of the Survey varies by Partner Institute and by year, with an average rate of response of around 40%.
[19] The Survey data is mainly collected during the first quarter of the specific year. See Cornelius (2003) for further information on the Survey.
[20] Table 1 shows the definition and descriptive statistics of the dependent and explanatory variables.

services and greater marketing services) tend to report that they have worse cost performance than their competitors (in terms of overall costs, material costs and wages).

Additionally, if firms were indifferent between cost and quality strategies, most Survey respondents would report a value of 4 to the dependent variable. However, the distribution of the type of competitive strategy variable reveals that this is not the case: around 25% of company responses take a value of 2 or less, and an additional 25% of the observations take a value of 5 or greater.

Another validation exercise for the dependent variable is to analyze its correlation with hard data on a country's innovation orientation, such as international patents (utility patents in the USPTO). The correlation between the countries' international patents and their type of competitive strategy is positive and highly significant.[21]

Cluster Environment. The main cluster variables are overall measures of the strength of clusters in a country, such as the prevalence and depth of clusters (EXTENT OF CLUSTERS), the level of collaboration in clusters among suppliers, partners, local customers and institutions (CLUSTER COLLABORATION), and the average of these two variables (AVERAGE CLUSTER STRENGHT).[22] Table A1 in the Appendix shows that the top five countries based on AVERAGE CLUSTER STRENGTH are Finland, the United States, Taiwan, Japan, and Italy. Indeed, these countries have well-known clusters and numerous cluster policy initiatives at the regional and national level (Van der Linde, C. 2002; Sölvell, et al, 2003). This reinforces that the Survey indicators are capturing meaningful information on a country's cluster environment

In addition to the indicators of the overall cluster strength in a country, drawing on Porter's (1990) diamond framework and on Porter and Stern's (2003) cluster subindex, I include in the model supply- and demand-side factors of the cluster environment. These variables of the cluster environment are the local availability of high quality process machinery (LOCAL MACHINERY), local customers'

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[21] The correlation is above .70, and the relationship between these two variables remains significant after controlling for a country's GDP and stock of patents

[22] In the Survey the concept of a cluster refers to the concentration of firms in a particular field, with their suppliers, specialized service providers and the supporting institutions located within the country.

sophistication (DEMAND SOPHISTICATION), and the intensity of rivalry (INTENSITY OF COMPETITION). Ideally I would like to complement the Survey-based cluster indicators with hard data indicators on the number and size of clusters in a country and the linkages and complementarities among clusters (e.g; Italy specializes in fashion-related clusters that may share skills, industries and/or consumers). Countries that specialize in clusters that are linked may benefit from greater cluster-driven agglomeration benefits. However, the EOS Survey indicators seem to be the only measures of clusters available across a large set of countries.

Controls. The econometric model controls for the institutional and macroeconomic environment in the country. Supporting institutions such as universities and standard setting agencies are important drivers of firm-level strategies and competitiveness (Mowery and Nelson, 1999). In the empirical analysis, the variable UNIVERSITY-INDUSTRY measures the R&D collaboration between companies and local universities. The variable REGULATORY STANDARDS refers to the existence of demanding standards with respect to product and service quality, energy and other regulations. This type of regulatory characteristics could induce innovation-oriented competition.[23]

The econometric model also takes different types of access to new technology (ABSORPTION OF TECHNOLOGY and LICENSING FOREIGN TECHNOLOGY). Finally, the model incorporates the GDP per capita to control for the overall productivity and prosperity existing in a country. As I explain below, this explanatory variable is also used to control for unobserved market shocks (and Survey respondents' expectations on country performance).

Proxy Variable. I look for a proxy variable that increases with market shocks and affect the dependent variable and the cluster variables. As mentioned earlier, the proxy variable (p_{ct}) has to vary monotonically with the unobserved market shock (ω_{ct}) (Section 4). The empirical analysis uses the (log of) GDP per capita adjusted by purchasing power parity and lagged one period as the proxy variable (LOG $GDPpc_{t-1}$). This macroeconomic variable measures the sophistication of the domestic demand (i.e.,

[23] There are other indicators of a country's innovation policies and supporting institutions in the Survey. We have chosen the most relevant ones. Alternatively, we could use some aggregation of all the indicators using principal components factor analysis.

consumers with higher income tend to buy based on product quality). At the same time, countries with higher GDP per capita tend to be more open economies and face higher competitive pressure in their domestic markets. These two factors suggest that GDP per capita increases with positive market shocks. Higher GDP per capita is also synonym for differentiated markets, and so it has a positive effect on company innovation orientation and increases the incentive for companies to participate in clusters.

The *Absorption of New Technology* is another candidate proxy variable used in the sensitivity analysis. This variable measures companies' interest in absorbing new technology. In response to new competitors or to a boom companies might be more aggressive in using new technology.

Attributes of Survey Respondents. In Section 4, I discussed that we could interpret the market shock (ω_{ct}) as the respondents' expectation on economic growth of their countries. These expectations will reflect in part the real economic conditions (previous GDP), and the semiparametric model will correct for it. Additionally, in the robustness analysis, the average employment size of the respondents within a country-year is included in the econometric specifications to further control for variations across country and year in the type of company answering the Survey.[24]

Another potential Survey bias (or measurement error) is that the dependent and explanatory variables may be biased towards the respondents' own strategy and business environment. Some descriptive analysis reveals that this respondent-bias problem is small. In particular, there is a small correlation (below 0.1) between respondents' own-strategies and their perception about the type of strategy of national companies. Additionally, the Survey sampling method is designed to get a representative sample that takes into account the sector composition of a country.

[24] Note that Survey respondents may vary by year, but overall there is a relatively high continuity across years of a country's Survey respondents. Unfortunately, the dataset does not include company identifiers.

6. Results

This section analyzes the effect of cluster attributes on companies' type of competitive strategy (unique product/process versus low-cost strategies). First, I discuss the consistency of the semiparametric estimators. I then explain the impact of clusters on company quality-orientation using the whole sample (Section 6.2). The main findings refer to the country-fixed effect semiparametric models, but I also explore cross-country variations. Finally, I apply the econometric model to sub-samples of countries to assess how the benefits from clusters differ across groups of countries (Section 6.3).

6.1 Evaluation of the Semiparametric and OLS Estimators

I specify different set of regressions to better evaluate the significance of the strength of cluster variables. Table 2.1 shows the simplest models. Alternative measures of the strength of clusters are used: the EXTENT OF CLUSTERS, CLUSTER COLLABORATION, and their average. In these specifications, the only control variables are the year dummies, the country dummies and the proxy variable (lagged GDP per capita). Table 3 includes key supply-side and demand-side cluster characteristics as explanatory variables (LOCAL MACHINERY, DEMAND SOPHISTICATION, and INTENSITY OF COMPETITION). Finally, Table 4 shows the most comprehensive models, which measure the effect of cluster attributes on companies' competitive strategy, controlling for supporting institutions and access-to-technology variables.

In Tables 2.2 and 4.2, the SP estimators are compared to the OLS estimators. I expect the OLS coefficients to be biased due to the unobserved market shock (ω_{ct}). Following Levinsohn and Petrin (2003), I apply the following "bias test": I generate 200 pseudo samples by sampling countries with replacement.[25] For each of these samples, the bootstrap OLS, SP and Dummy coefficients are estimated ($\hat{\beta}_{X,j}^{OLS}, \hat{\beta}_{X,j}^{SP}, \hat{\beta}_{X,j}^{D}$, where *j* refers to the specific pseudo sample).[26] I count then the number of times the

[25] I use a blocked re-sampling approach where each draw is a country across all years.
[26] The 200 boostrapped SP coefficients are used to compute the standard errors and confidence interval of the SP coefficients.

difference between the OLS and SP estimates is greater than zero. The bias analysis shows that the OLS coefficients, as opposed to the dummy and SP estimators, tend to overestimate the effect of the cluster strength variables.[27] For example, about 80% of the times, the OLS coefficient of cluster collaboration is higher than the SP coefficients (Table 2.2), but the differences between the OLS and the SP estimates are insignificant.[28] In contrast, the difference between the OLS and SP coefficients is statistically significant in the models without country fixed effects (Table A3).

Consistency tests. I apply two specification tests implemented by Levinsohn and Petrin (2003, p.11 and pp. 16-17). First, and most importantly, I implement the "monotonicity test," and show that the estimated shock increases with GDP per capita in 80%-90% of the range of the variable (Figure 2).[29] Figure 2 shows that the estimated market shock ($\hat{\omega}^*(p^*_{ct})$) increases with the (de-meaned) proxy variable in 80% of the GDP range. In the SP Model 1 (equation 2), I can only recover the slope of the market shock, which is positive in 90% of the GDP range. Second, I implement the "choice of the proxy test." If the semiparametric model is correct, any valid proxy variable should give similar coefficients of the non-proxy variables. Indeed, I find insignificant differences in the $\hat{\beta}^{SP}_X$ coefficients when Absorption of Technology is the proxy variable instead of the GDP per capita (not reported). Overall, the monotonicity test, the bias test, and the choice of the proxy test support the specified semiparametric model.

6.2. The Effect of Cluster Attributes on Companies' Competitive Strategies

The semiparametric, country-fixed effect models specified in Tables 2 to 4 reveal that there is a positive and significant relationship between a country's cluster environment and companies' innovation

[27] I find, as expected, that the sign of the bias of the OLS estimators relative to the semiparametric ($\hat{\beta}^{SP}_X$) is the same than the bias relative to the dummy estimator ($\hat{\beta}^{D}_X$).

[28] One possible explanation is that the relationship between GDP per capita and the unobserved market shock could be kind of linear. In this case, the GDP variable will directly control for the market shocks. Second, we only have four consecutive years of data, and after including country and year fixed effects there may be little variation in the data. Interestingly, there are significant differences between the OLS and SP coefficients after dropping the country-fixed effects.

[29] These results hold for all the econometric specifications in Tables 2-to-4. The monotonicity test fails for some outlier values of the GDP. However, since the GDP outliers do not affect in a significant way the estimators, I have decided to keep outliers to preserve the balanced panel.

orientation. In the simplest SP models specified in Table 2, the alternative cluster strength variables (prevalence of clusters, cluster collaboration among suppliers, buyers and institutions, and the average cluster strength) induce national companies to prioritize quality-oriented rather than low-cost strategies. Table 4 (models 4-1 and 4-2) shows that, having controlled for supporting institutions and access-to-technology variables, there is a significant positive influence of cluster strength on company quality strategy. Interestingly, the local availability of specialized process machinery seems a key factor of the cluster environment (Tables 3 and 4).[30]

Not surprisingly, the GDP per capita has the greatest positive relationship with national companies' quality-orientation in international markets. The university-industry R&D collaboration has also a high positive influence on the innovation strategy of companies. Precisely, the collaboration between companies and local research institutions is more likely to happen in clusters since companies tend to concentrate close to the science and technological base.

Absorption of technology has the expected positive effect, but the type of access to new technology matters. The local availability of specialized inputs (versus imports) facilitates higher levels of quality differentiation. In contrast, the licensing of foreign technology induces primarily low cost strategies. While licensing might help companies face increased competition, it does not guarantee countries' innovativeness.

Exploring cross-country variations. To further analyze the importance of country heterogeneity and the difference between the OLS and SP estimators, I specify a semiparametric model without country fixed effects (pooled SP model), using the same specifications than in Table 4 (Appendix A, Table A2). The cross-country analysis shows that the OLS coefficient of the prevalence of clusters is significantly biased upward as compared to the SP coefficient. The difference in coefficients is also significant for the variables of regulatory standards and licensing of foreign technology. While the bias is reduced after the OLS model is augmented by adding a square term on the (log of) GDP per capita, the gap between the SP

[30] These results are robust to the inclusion of Survey respondents' employment size (not reported). The negative coefficient of this variable suggests that large companies are more conservative in their evaluation of national companies' quality strategies.

and OLS coefficients remains significant (at 10% level). Overall these findings suggest that the SP model is preferred to the OLS model.[31]

When excluding the country-fixed effects from the specifications in Table 4, the strength of cluster variables and demand sophistication have a positive and significant influence on companies' innovation orientation, while the variable local availability of qualified suppliers becomes insignificant. Overall, the semiparametric country-fixed effect model is preferred because country heterogeneity influences the relationship between the cluster environment and the strategy choice of the companies located in the country.

Finally, for robustness, I use company individual responses (company-country level panel with more than 20,000 observations) and run the models specified in Tables 2-4, including *country-year* fixed effects (α_{ct}) to directly control for the unobserved time-varying country shocks (ω_{ct}). The OLS estimates show that all attributes of the cluster environment have a positive and significant relationship with the quality strategy of companies, reinforcing that the strength of the cluster environment in a country induces companies to develop competitive advantages based on unique products and services.[32] While this is a useful robustness exercise, this is not the core econometric specification because more meaningful indicators of country competitiveness are obtained by aggregating all individual responses within a country-year.

6.3 Country Sub-sample Analysis: By Country Income and Cluster-Orientation

The type of cluster benefits could vary for different groups of countries. Particularly, developing versus developed countries, and low- versus high-cluster strength countries, might benefit from cluster attributes in different ways. The extent of clusters and cluster collaboration could be very beneficial for developing countries. However, companies in developing countries may be poorly equipped to generate and absorb knowledge spillovers. For example, the lack of specialized local suppliers often induces big firms to vertically integrate the production of its inputs or to import them (Porter, 1998). More generally,

[31] In the pooled SP model the monotonicity condition does not hold.

[32] The variables with a greater impact are the demand-side variables (demand sophistication and regulatory standards) and the strength of cluster variables (both the extent of clusters and the collaboration in clusters).

developing countries tend to have a weaker cluster environment. To analyze these issues, countries are classified into low and high level of GDP per capita (ppp adjusted) based on whether they are below or above the median of the GDP per capita; and into low and high cluster strength based on whether they are below or above the median AVERAGE CLUSTER STRENGTH over the 2001-2004 period. Maybe not surprisingly, the means of the dependent and explanatory variables are all significantly lower for the groups of countries with low income or low cluster strength. For low- versus high-income countries, the variables that are relatively lower are the regulatory standards, the sophistication of demand, and the quality orientation of companies (see Table A1 in the Appendix for a list of the 37 countries include in each of the four categories).

I apply the semiparametric, country-fixed effect model described above to the alternative groups of countries.[33] The subsample analysis reinforces previous results. Specifically, the average cluster strength of a country has a positive and significant effect on the quality-orientation of companies for all groups of countries, even after taking into account supporting institutions and access-to-technology variables (Table 5). Not surprisingly, R&D collaboration between universities and firms is a key driver of companies' innovation strategies, for all groups of countries (to a lower extent for developed countries).

It is noteworthy that the influence of specific cluster attributes on company quality strategy changes across groups of countries. In particular, local availability of process machinery seems the key cluster attribute for low cluster-oriented and, especially, for developing countries.[34] This finding suggests that cluster policies focusing on improving the availability of local suppliers may be especially effective to improve the innovation orientation of less advanced countries. More research is needed to understand to what extent the impact of cluster attributes depends on the stage of development of a country and its clusters. In clusters' earlier stages of development (i.e., informal clusters), cluster collaboration may be

[33] The monotoinicity test holds for the sub samples of developing and low-cluster oriented countries.

[34] The Chow test indicates that the coefficient of the availability of local suppliers is statistically higher for the group of developing countries, while the effect of the average cluster strength is significantly greater for developed countries. These findings also hold when we compare countries with weak versus strong clusters (although in this case the differences in the coefficients are not statistically significant).

more likely to promote cost reductions than innovation strategies. Once clusters become more organized, the strength of cluster networks may prioritize innovation strategies.

7. Conclusion

This paper examines whether stronger clusters in a country induce national companies to compete primarily on the basis of quality differentiation rather than low cost strategies. After a careful validation of the Survey data, the empirical analysis disentangles the effect of clusters on national companies' competitive strategies by controlling for country heterogeneity and contemporaneous correlation between the cluster environment and unobserved factors driving company strategy (such as unobserved market shocks or Survey respondents' bias). A semiparametric, country-fixed effect model is used to address the endogeneity problems.

The empirical analysis reveals a robust and positive relationship between the strength of clusters in a country and national companies' adoption of quality strategies in global markets. This result holds in both the within-country and cross-country analyses.Maybe not surprisingly, university-industry R&D collaboration is especially relevant in explaining the innovation orientation of companies. With regard to the access-to-new-technology variables, the results suggest that the source of new technology matters for companies' strategy choice. While the availability of specialized local suppliers facilitates primarily quality strategies, licensing of foreign technology seems to promote cost-reduction strategies.

Finally, this paper assesses whether the influence of cluster attributes differs across groups of countries with different levels of economic development and growth. The average cluster strength of a country is positively associated with the quality-orientation of companies for all sub-samples of countries. Interestingly, local availability of specialized process machinery (versus imports) seems the key cluster attribute for the groups of low GDP per capita, low-cluster-oriented countries, and low growth countries. More research is needed to understand how a cluster's and a country's stage of economic development influences the relationship between strategy choice and the cluster environment.

Overall this paper suggests that domestic linkages continue to play a key role in improving the innovation strategies of companies. In response to the increased globalization, countries and regions compete to offer the best business environment to attract firms in specific fields. Cluster policies could help countries to identify their competitive advantage and attract companies to complementary activities that support the existing and nascent clusters (Porter 2000, Ketels and Memedovic 2008).

Due to data limitations, I abstract from the cluster composition of countries. A country specializing in inte-related clusters (e.g., Italy specialization in fashion-related clusters, including shoes, apparel, and eye-glasses) and interacting with neighboring countries (e.g., BioValley biotechnology cluster is co-located in neighboring regions of France, Germany and Switzerland) may be more able to innovate than a country with weak clusters and/or specialized in poorly related clusters. The relationship between country competitiveness and the cluster composition of countries and regions will be analyzed in future research.

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Table 1: Variables' Definitions and Descriptive Statistics

Variables	Definition	Mean	Std Dev
TYPE OF COMPETITIVE STRATEGY	Companies' strategy in global markets: Unique product/process vs. low cost	3.77	1.23
CLUSTER ENVIRONMENT			
EXTENT OF CLUSTERS	Prevalence and depth of clusters	3.48	.86
CLUSTER COLLABORATION	Product/process collaboration between the cluster's agents	3.90	.82
AVERAGE CLUSTER STRENGHT	Average of the Extent of Clusters and Cluster Collaboration variables	3.69	.81
LOCAL MACHINERY	Availability of world-class process machinery in the cluster (vs. imports)	3.16	1.02
DEMAND SOPHISTICATION	Buyers buy based on superior attributes vs. based on the lowest prices	4.23	1.05
INTENSITY OF COMPETITION	Intensity of competition in local market	4.95	.65
ECONOMY-WIDE FACTORS			
REGULATORY STANDARDS	High standards on product/service quality, energy, and other regulations	4.58	1.10
UNIVERSITY-INDUSTRY	University-industry R&D collaboration	3.66	1.00
LICENSING FOREIGN TECH.	Extent of licensing of foreign technology	4.69	.70
ABSORPTION TECHNOLOGY	Companies' new technology absorption	4.95	.76
LOG GDPpc$_{t-1}$	Logarithm of GDP (PPP adjusted) per capita	9.20	.89

Note: All the indicators are sourced from the Executive Opinion Survey; with the exception of the GDP variable which is sourced from the World Development Indicators.

Table 2.1: The Effect of the Strength of Clusters on National Companies' Innovation Orientation

	TYPE OF COMPETITIVE STRATEGY (Obs. =296)					
	OLS	SP	OLS	SP	OLS	SP
	(2-1)	(2-2)	(2-3)	(2-4)	(2-5)	(2-6)
EXTENT OF CLUSTERS	**.278**	**.264**				
	(.087)	**(.091)**				
CLUSTER COLLABORATION			**.260**	**.244**		
			(.073)	**(.087)**		
AVERAGE CLUSTER STRENGTH					**.368**	**.350**
					(.094)	**(.103)**
LOG GDPpc$_{t-1}$	**2.274**		**2.106**		**2.137**	
	(.498)		**(.481)**		**(.486)**	
CONSTANT	**-18.019**		**-16.548**		**-17.169**	
	(4.558)		**(4.399)**		**(4.442)**	
COUNTRY FEs	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
YEAR FEs	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Adjusted R-Squared	**.949**		**.949**		**.951**	

Note: Bold and bold-italic numbers refer to coefficients significant at 5% and 10% levels. Robust standard errors (OLS models) and bootstrap standard errors (SP Models) are given in parentheses.

Table 2.2: Evaluating the bias of the OLS Estimators in Table 2.1: Percentage of Times the OLS Coefficients are larger than the SP Coefficients

	OLS vs. SP Coefficients	
	Difference in Coefficients	% of Times $(\hat{\beta}^{OLS}_{X,j} - \hat{\beta}^{SP}_{X,j}) > 0$
EXTENT OFCLUSTERS	.014	.61
CLUSTER COLLABORATION	.012	.82
AVERAGE CLUSTER STRENGTH	.018	.71

Note: Percentages of times that the OLS bootstrapped coefficients are higher than the SP bootstrap coefficients. The analysis is based on 200 simulations.

Table 3: The Effect of the Cluster Environment on National Companies' Innovation Orientation

	TYPE OF COMPETITIVE STRATEGY N=296			
	OLS	SP	Discrete SP	SP
	3-1	3-2	3-3	3-4
EXTENT OF CLUSTERS	***.134***	.120	.122	
	(.075)	(.082)	(.089)	
AVERAGE CLUSTER STRENGTH				***.165***
				(.091)
LOCAL MACHINERY	**.187**	**.185**	**.180**	**.167**
	(.060)	**(.068)**	**(.067)**	**(.065)**
DEMAND SOPHISTICATION	***.180***	***.181***	***.181***	***.173***
	(.093)	***(.117)***	***(.112)***	***(.117)***
INTENSITY COMPETITION	***.154***	***.149***	***.142***	.138
	(.093)	***(.106)***	***(.108)***	(.104)
ABSORPTION TECHNOLOGY	.084	.078	.086	.077
	(.082)	(.082)	(.084)	(.082)
LOG $GDPpc_{t-1}$	**1.727**	**1.787**		**1.703**
	(.444)	**(.624)**		**(.636)**
CONSTANT	**-15.075**			
	(4.039)			
COUNTRY FEs	**Yes**	**Yes**	**Yes**	**Yes**
YEAR FEs	**Yes**	**Yes**	**Yes**	**Yes**
Adjusted R-Squared	**.955**			

Note: Bold and bold-italic numbers refer to coefficients significant at 5% and 10% levels. The notes in Table 2.1 apply to this table. The SP coefficients of the GDP per capita are obtained from the second stage estimation of the SP Model 2 (SP Non Linear Least Squared with Normal kernel).

Table 4.1: The Effect of Clusters on National Companies' Innovation Orientation (SP Models)

	TYPE OF COMPETITIVE STRATEGY			N=296
	(4-1)	(4-2)	(4-3)	(4-4)
EXTENT OF CLUSTERS	**.176**		.093	
	(.077)		(.072)	
AVERAGE CLUSTER STRENGTH		**.194**		.073
		(.094)		(.090)
LOCAL MACHINERY			**.156**	**.162**
			(.059)	**(.061)**
DEMAND SOPHISTICATION			.105	.102
			(.122)	(.122)
INTENSITY COMPETITION			.053	.054
			(.095)	(.096)
REGULATORY STANDARDS	.174	***.184***	.123	.133
	(.106)	***(.109)***	(.117)	(.117)
UNIVERSITY-INDUSTRY	**.372**	**.346**	**.327**	**.321**
	(.068)	**(.069)**	**(.074)**	**(.077)**
LICENSING FOREIGN TECH.	-.132	-.113	***-.120***	-.110
	(.077)	(.079)	***(.078)***	(.079)
ABSORPTION TECHNOLOGY	**.178**	**.163**	***.140***	***.133***
	(.070)	**(.072)**	***(.078)***	***(.079)***
LOG GDPpc$_{t-1}$	**2.017**	**1.905**	**1.542**	**1.702**
	(.730)	**(.706)**	**(.653)**	**(.623)**
COUNTRY FEs	**Yes**	**Yes**	**Yes**	**Yes**
YEAR FEs	**Yes**	**Yes**	**Yes**	**Yes**

Note: Bold and bold-italic numbers refer to coefficients significant at 5% and 10% levels. In the SP model, the coefficients of the GDP variable are obtained from the second stage estimation using SP Model 2.

Table 4.2: Bias of the OLS Estimators: Percentage of Times the OLS Coefficients are larger than the SP Coefficients

	TYPE OF COMPETITIVE STRATEGY N=296 OLS vs. SP Coefficients: % of Times $(\hat{\beta}^{OLS}_{X,j} - \hat{\beta}^{SP}_{X,j}) > 0$					
	(4-1)		(4-2)		(4-4)	
	Diff.	%	Diff.	%	Diff.	%
EXTENT OF CLUSTERS	.018	.72				
AVERAGE CLUSTER STRENGTH			.025	.79	.027	.70
LOCAL MACHINERY					-.000	.63
DEMAND SOPHISTICATION					.005	.49
INTENSITY COMPETITION					.007	.51
REGULATORY STANDARDS	.004	.64	.003	.57	.005	.58
UNIVERSITY-INDUSTRY	-.003	.45	-.008	.39	-.014	.35
LICENSING FOREIGN TECH.	.017	.26	.017	.30	.005	.48
ABSORPTION TECHNOL.	-.014	.32	-.016	.31	.001	.50

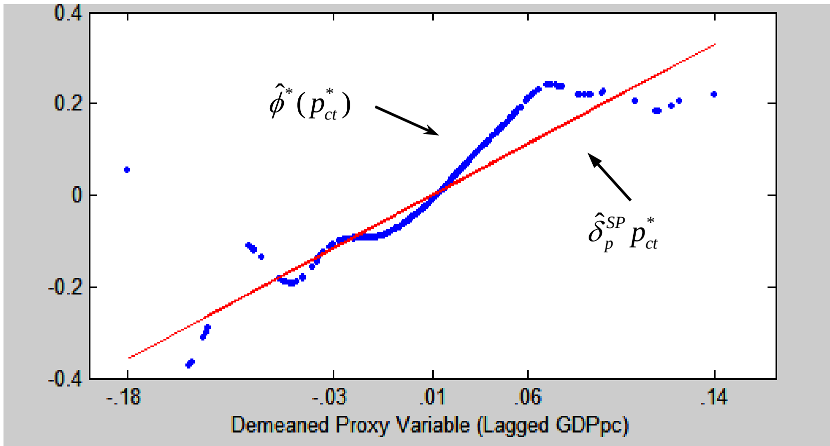
Note: See notes in Table 2.2.

Table 5: Country Sub-sample Analysis. The Effect of Clusters on Company Innovation Orientation (Semiparametric Models)

	Dep. Variable: TYPE OF COMPETITIVE STRATEGY						N=148	
	GDP per capita		**Cluster Strength**		**GDP per capita**		**Cluster Strength**	
	Low	High	Low	High	Low	High	Low	High
AVERAGE CLUSTER	.223	**.218**	***.226***	**.210**	-.023	**.211**	.072	.161
STRENGTH	(.151)	**(.099)**	***(.139)***	**(.104)**	(.139)	**(.113)**	(.136)	(.106)
LOCAL MACHINERY					**.371**	-.038	**.220**	.118
					(.087)	(.071)	**(.109)**	(.076)
DEMAND					***.316***	.001	.229	.056
SOPHISTICATION					***(.187)***	(.114)	(.179)	(.144)
INTENSITY COMPETITION					.044	.087	.069	-.060
					(.095)	(.098)	(.140)	(.101)
REGULATORY	.155	-.078	-.019	**.377**	-.009	.062	-.126	***.317***
STANDARDS	(.159)	(.149)	(.136)	**(.143)**	(.171)	(.168)	(.157)	***(.143)***
UNIVERSITY-INDUSTRY	**.507**	***.108***	**.370**	**.308**	**.377**	.091	**.330**	**.297**
	(.091)	***(.072)***	**(.100)**	**(.110)**	**(.107)**	(.074)	**(.095)**	**(.110)**
LICENSING FOREIGN	-.073	-.030	-.015	**-.205**	-.105	-.034	-.051	***-.180***
TECH.	(.122)	(.107)	(.118)	**(.121)**	(.108)	(.105)	(.119)	***(.120)***
ABSORPTION	.117	**.209**	.174	.094	.028	**.210**	.106	.097
TECHNOLOGY	(.130)	**(.094)**	(.144)	(.121)	(.138)	**(.097)**	(.154)	(.132)
COUNTRY FEs	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
YEAR FEs	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Note: Bold and bold-italic numbers refer to coefficients significant at 5% and 10% levels. Country-fixed effect Semiparametric models. Bootstrap standard errors are given in parentheses. The proxy variable is LOG $GDPpc_{t-1}$

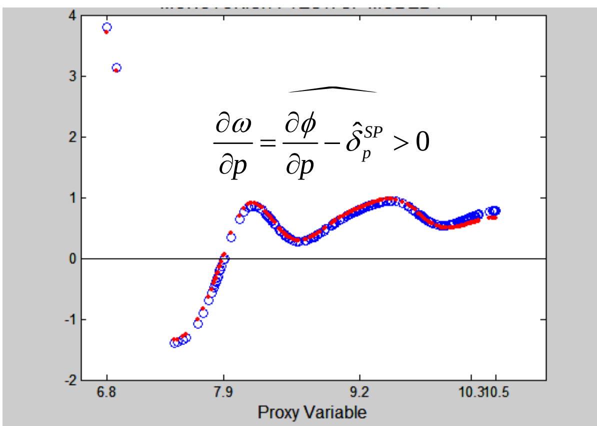
Figure 1: The Estimator of $\phi^*(p^*)$ and δ_p^{SP} for the Model (4-1) (Table 4.1)



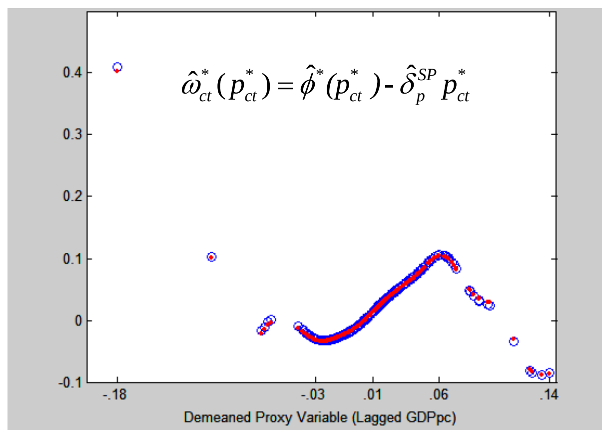
Note: The *x* axis' ticks are the minimum, 10th, 50th and 90th percentiles, and the maximum of the demeaned LOG $GDPpc_{t-1}$.

Figure 2: Monotonicity Tests for the Specifications in Table 4.1

MONOTONICITY TEST: SP MODEL 1



MONOTONICITY TEST: SP MODEL 2



Note: The blue and red graphs correspond to the specifications (4-1) and (4-2), respectively. The *x* axis' ticks are the minimum, 10th, 50th and 90th percentiles, and the maximum of the proxy variable (or demeaned proxy variable). In the SP Model 1, monotonicity implies that the slope of the estimated market shock is positive. The monotonicity test holds for 90% of the GDP range ($\hat{\delta}_p^{SP}$ is 1.958 in Model 4-1 and 1.899 in Model 4-2). In SP Model 2, the monotonicity test holds for 80% of the GDP range ($\hat{\delta}_p^{SP}$ is 2.017 in Model 4-1 and 1.905 in Model 4-2).

Appendix A: Additional Descriptive and Empirical Analysis.

Table A1: List of Countries by Income Level and Cluster Strength (Countries are ranked from the highest value to the lowest)

GDPpc		AVERAGE CLUSTER STRENGTH	
LOW	**HIGH**	**LOW**	**HIGH**
Chile	Norway	Poland	Finland
Trinidad & Tobago	United States	Mexico	United States
Malaysia	Denmark	Lithuania	Taiwan
Mexico	Iceland	Latvia	Japan
Costa Rica	Switzerland	Romania	Italy
Latvia	Austria	Czech Republic	Germany
Uruguay	Canada	Ukraine	Singapore
Russia	Netherlands	Philippines	Sweden
Brazil	Ireland	Chile	United Kingdom
Bulgaria	Australia	Sri Lanka	Korea
Thailand	Belgium	Panama	Canada
Dominican Repub.	Germany	Trinidad & Tobago	Austria
Romania	Japan	Mauritius	Ireland
Colombia	Hong Kong	Jamaica	Hong Kong
Turkey	France	Vietnam	Denmark
Panama	Italy	Slovenia	Switzerland
Venezuela	Finland	Hungary	Netherlands
Peru	United Kingdom	Jordan	France
El Salvador	Sweden	Estonia	Brazil
Ukraine	Singapore	Costa Rica	Belgium
Paraguay	Taiwan	Colombia	Norway
China	New Zealand	Dominican Repub.	India
Philippines	Spain	Greece	Israel
Jordan	Israel	Bulgaria	Thailand
Guatemala	Greece	Guatemala	China
Jamaica	Portugal	Bangladesh	South Africa
Sri Lanka	Slovenia	Zimbabwe	Iceland
Ecuador	Korea	Argentina	Malaysia
Indonesia	Czech Republic	Peru	Portugal
India	Hungary	Ecuador	Australia
Honduras	Slovakia	El Salvador	Spain
Nicaragua	Estonia	Honduras	New Zealand
Bolivia	Argentina	Uruguay	Indonesia
Vietnam	Mauritius	Venezuela	Russia
Zimbabwe	Poland	Nicaragua	Nigeria
Bangladesh	Lithuania	Bolivia	Turkey
Nigeria	South Africa	Paraguay	Slovakia

Note: Low (High) GDP countries correspond to an average GDPpc below (above) 9,784 US $.

Table A2: Cross-Country Analysis: The Effect of Clusters' on Companies' Innovation Orientation (All control variables included and without country fixed effects)

	Dependent Var.: TYPE OF COMPETITIVE STRATEGY (N=296)		
	OLS (A2-1)	SP (A2-2)	OLS (A2-3)
EXTENT OF CLUSTERS	**.417**	**.238**	**.314**
	(.070)	**(.111)**	**(.069)**
REGULATORY STANDARDS	**.217**	.104	.076
	(.109)	(.151)	(.108)
UNIVERSITY-INDUSTRY	**.258**	***.206***	**.261**
	(.099)	***(.123)***	**(.093)**
LICENSING FOREIGN TECH.	**-.399**	**-.267**	**-.325**
	(.068)	**(.097)**	**(.065)**
ABSORPTION TECHNOLOGY	**.263**	**.294**	**.263**
	(.099)	**(.153)**	**(.098)**
LOG GDPpc$_{t-1}$	**.374**		**-3.733**
	(.082)		**(.773)**
SQUARED LOG GDPpc$_{t-1}$			**.237**
			(.046)
CONSTANT	**-2.519**		**15.648**
	(.593)		**(3.361)**
COUNTRY FEs	**No**	**No**	**No**
YEAR FEs	**Yes**	**Yes**	**Yes**
Adjusted R-Squared	.760		.778

Notes: Models without country fixed effects. All columns include year effects. Bold and bold-italic numbers refer to coefficients significant at 5% and 10% levels, respectively. In the OLS models, robust standard errors are given in parenthesis. In the semiparametric model, the bootstrap standard errors are given in parentheses.

Appendix B: Semiparametric Estimators: GMM Procedure

The econometric model that I need to solve for is:

$$y_{ct} = \beta_o + \beta_X' X_{ct} + \delta_p p_{ct} + \alpha_T T_t + \alpha_c + \omega_{ct} + \eta_{ct} \qquad \text{(B1)}$$

where the proxy variable p_{ct} is a monotonic function of the unobserved country idiosyncratic shock $p_{ct} = p(\omega_{ct})$. Drawing on Olley and Pakes (1996) and Levinsohn and Petrin (2003) the unobserved country shock is conditioning out using a non-parametric function of the proxy variable:

$$y_{ct} = \beta_o + \beta_X' X_{ct} + \phi(p_{ct}) + \alpha_T T_t + \alpha_c + \eta_{ct} \qquad \text{(B2)}$$
$$\phi(p_{ct}) = \beta_0 + \delta_p p_{ct} + \omega(p_{ct})$$

To estimate equation (B2), I extend the 2-stage estimation procedure by Levinsohn and Petrin (2003, p. 340) to solve for country-fixed effects (α_c). I implement two within-country transformations of the function $\phi(p_{ct})$. First, based on Pagan and Ullah (1999, Chapter 3) and Ullah and Roy (1998), I use a local linear approximation of $\phi(p_{ct})$ and the resulting time-demeaned function is $\tilde{\phi}(p^*_{ct}) = \frac{\partial \phi}{\partial p}(p) p^*_{ct}$.[35] The within-country transformation of equation (B2) then becomes:

<u>Semiparametric Model 1</u>:

$$y^*_{ct} = \beta_X' X^*_{ct} + \frac{\partial \phi}{\partial p}(p) p^*_{ct} + \alpha_T T_t + \eta^*_{ct} \qquad \text{(B3)}$$
$$\phi(p_{ct}) = \delta_p p_{ct} + \omega(p_{ct}),$$

where variables with an asterisk are time-demeaned. Second, I assume that the time-demeaned proxy variable is monotonic in the time-demeaned shock ($\omega^*_{ct} = \omega(p^*_{ct})$), and the resulting model to solve for is:

<u>Semiparametric Model 2</u>:

$$y^*_{ct} = \beta_X' X^*_{ct} + \phi^*(p^*_{ct}) + \alpha_T T_t + \eta^*_{ct} \qquad \text{(B4)}$$
$$\phi^*(p^*_{ct}) = \delta_p p^*_{ct} + \omega^*(p^*_{ct})$$

First Stage Estimation: $\hat{\beta}_X, \hat{\alpha}_T$, $\hat{\tilde{\phi}}(p^*_{ct}) = \widehat{\frac{\partial \phi}{\partial p}} p^*_{ct}$, and $\hat{\phi}^*(p^*_{ct})$.

The Robinson's (1988) estimator of $\beta = \begin{bmatrix} \beta_X \\ \alpha_T \end{bmatrix}$ is based on a normal kernel, and solve by non intercept OLS the following equation:

$$0 = n^{-1} \sum_i^n [(y^*_i - \hat{E}(y^* / p^*_i)) - (V^*_i - \hat{E}(V^* / p^*_i))\hat{\beta})] \hat{I}_i (V^*_i - \hat{E}(V^* / p^*_i)) \qquad \text{(B5)}$$

$I_i = I(|\hat{f}(p^*_i)| > b)$ and $V^*_i = [X^*_i \ T_i]$

Note that the $\hat{\beta}_X$ estimators will be the same for the two SP models proposed above (equations B4 and B5); and I use $\hat{\beta}_X$ and $\hat{\alpha}_T$ to identify $\tilde{\phi}(p^*_{ct})$ (in SP Model 1) and $\hat{\phi}^*(p^*_{ct})$ (in SP Model 2).

---

[35] Specifically, $\phi(p_{ct}) - \phi(\bar{p}_c) = \left(\phi(p) + \frac{\partial \phi}{\partial p}(p)(p_{ct} - p)\right) - \left(\phi(p) + \frac{\partial \phi}{\partial p}(p)(\bar{p}_c - p)\right)$.

In SP Model 1, the estimator of $\tilde{\phi}(p^*_{ct})$ solves:

$$\hat{y}^*_{ct} = y^*_{ct} - \hat{\beta}'_X X^*_{ct} - \hat{\alpha}'_T T_t = p^*_{ct}\frac{\partial \phi}{\partial p}(p) + \eta^*_{ct} \qquad \text{(B6)}$$

The Local Linear Estimator of $\widehat{\frac{\partial \phi}{\partial p}}(p)$ is obtained by regressing $\sqrt{K_{ct}}\,\hat{y}^*_{ct}$ on $\sqrt{K_{ct}}\,p^*_{ct}$ using least squares (the weights $K_{ct} = K\left(p_{ct} - p/h\right)$ are computed using normal kernels). In SP Model 2, I compute two related estimators of $\hat{\phi}^*(p^*_{ct})$: (1) the Normal kernel and (2) a Local Linear estimator, which solve, respectively, the following 2 equations:

$$\hat{y}^*_{ct} = \phi^*(p^*_{ct}) + \eta^*_{ct} \qquad \text{(B7)}$$

$$\hat{y}^*_{ct} = \phi^*(p) + (p^*_{ct} - p)\frac{\partial \phi^*}{\partial p}(p) + \eta^*_{ct} \qquad \text{(B8)}$$

where $\hat{y}^*_{ct} = y^*_{ct} - \hat{\beta}'_X X^*_{ct} - \hat{\alpha}'_T T_t$. The $\phi^*(.)$ estimator is obtained by regressing $\sqrt{K_{ct}}\,\hat{y}^*_{ct}$ on $\sqrt{K_{ct}}$ (in equation B7), and regressing $\sqrt{K_{ct}}\,\hat{y}^*_{ct}$ on $\sqrt{K_{ct}}$ and $\sqrt{K_{ct}}\,p^*_{ct}$ (in equation B8) using least squares (weights $K_{ct} = K\left(p^*_{ct} \text{ - } p/h\right)$ are computed using normal kernels).[36]

Second Stage Estimation. I need to identify the coefficient of the GDP per capita variable ($\hat{\delta}_p$) to estimate the shock $\hat{\omega}$ and test for monotonicity. Assuming that the shock follows a first order Markov process, the equation to solve for is

$$\hat{y}^*_{ct} = y^*_{ct} - \hat{\beta}_X X^*_{ct} - \hat{\alpha}_T T_t = \delta_p p^*_{ct} + E(\omega^*_{ct} / \omega^*_{ct-1}) + \tilde{\eta}^* \qquad \text{(B9)}$$

Where the transformed error term is $\tilde{\eta}^*_{ct} = \xi^*_{ct} + \eta^*_{ct}$ and $\xi^*_{ct} = \omega^*_{ct} - E(\omega^*_{ct} / \omega^*_{ct-1})$. The parameter δ_p is an argument of the nonlinear function *E(.)*, and I estimate it using Non Linear Least Squares following Levinsohn and Petrin (2003). The main step is to estimate $E(\omega^*_{ct} / \omega^*_{ct-1})$. The Kernel estimator of $E(\omega^*_{ct} / \omega^*_{ct-1})$ depends on whether I use SP Model 1 or SP Model 2. Thus, I obtain different $\hat{\delta}_p$ for each model ($\hat{\delta}^1_p, \hat{\delta}^2_p$). In the SP Model 1 $\hat{\tilde{E}}(\omega^*_{ct} / \omega^*_{ct-1}) = s(\hat{\tilde{\phi}}(p^*_{ct-1}), \delta_0 p^*_{ct}, \delta_0 p^*_{ct-1})$:[37]

a. $\widehat{\omega^*_{ct} + \eta^*_{ct}} = \hat{y}^*_{ct} - \delta_0\, p^*_{ct}$;

b. $\hat{\omega}^*_{ct-1} = \hat{\tilde{\phi}}_{ct-1} - \delta_0\, p^*_{ct-1}$

c. $\widehat{\omega^*_{ct} + \eta^*_{ct}} = s(\hat{\omega}^*_{ct-1}) + \varepsilon_{ct}$

where $E(\widehat{\omega^*_{ct} + \eta^*_{ct}} / \hat{\omega}^*_{ct-1}) = \hat{\tilde{E}}(\hat{\omega}^*_{ct} / \hat{\omega}^*_{ct-1}) = \hat{s}(\hat{\omega}^*_{ct-1})$ is obtained from (c) using a kernel function. The estimator δ^1_p minimizes the sum of squared residuals from equation (B10) by iterating on steps (a) to (c). In the SP Model 2, the estimation process is the same, but I use $\hat{\phi}^*(.)$ instead of $\hat{\tilde{\phi}}(.)$; and the expected demand shock is $\hat{E}^*(\hat{\omega}^*_{ct} / \hat{\omega}^*_{ct-1}) = s(\hat{\phi}^*(p^*_{ct-1}), \delta_0 p^*_{ct}, \delta_0 p^*_{ct-1})$. I use $(\hat{\delta}^1_p, \widehat{\frac{\partial \phi}{\partial p}}(p))$ and $(\hat{\delta}^2_p, \hat{\phi}^*(p^*_{ct}))$ to test for the monotonicity of $\hat{\omega}(p_{ct})$ and $\hat{\omega}^*(p^*_{ct})$, respectively (see Figure 2).

[36] For more details on these kernel estimators, see Pagan and Ullah (1999, Chapter 3) and Ullah and Roy (2002). In this paper, the empirical results are robust to using these alternative estimates of $\hat{\phi}^*(.)$.

[37] The initial value of the coefficient δ_0 is the OLS estimate.