Competition and Growth in Developing Countries: Evidence from Chile

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Abstract

This paper explores the impact of competition on productivity growth through innovation incentives. Using firm-level data from Chile, we estimate parameters from the model developed in Aghion et al. (2005) using Generalized Method of Moments. This allows us to quantitatively analyze the changes in growth coming from variations in competition intensity. Through this exercise we determine that higher rates of competition. through lower collusion, can accelerate economic growth and therefore country income convergence. Interestingly, we find an inverted-U pattern between innovation and the catch-up rate of lagagrd firms, something the original paper had not studied.

1 Introduction

One can trace the question of economic growth to 1776, when Adam Smith wrote his treatise, $The\ Wealth\ of\ Nations$. Recently, with the availability of new firm level data, the litterature has focused on firm dynamics and its contribution to growth. It is thus difficult to study the determinants of growth without considering competition. Most markets are far from the perfectly competitive benchmark assumed in most economic models. Some are even dominated by a couple of players strategically choosing prices, advertisement and output.

It would seem this pattern is even more salient in emerging economies. Large business groups diversify and become the leaders in several industries from manufacturing, retail and commodity extraction. This is the case of the Tata group in India or Samsung in the Republic of Korea. These are examples of dominating firms that face little or no competition within their respective countries. In some cases these conglomerates played an important role in economic and productivity growth, such as Korea's *chaebols*. However, a dominant position reduces the incentive to innovate as profits are guaranteed, specially within industries with large barriers to entry.

So far the litterature has identified two effects of competition on innovation. If we define the incentive to innovate as post-innovation rents, an increase in competition reduces these incentives as it negatively affects the profits incumbents enjoy. This is known as the "Schumpeterian effect", which we see in models developed by Salop (1977) and Dixit and Stiglitz (1977), where the entry rate represents innovation.

On the other hand, as competition increases firms are incentivized to distinguish themselves from competitors to capture a larger market share. The only way to do this is by innovating and reducing costs, which leads to productivity growth in the long run. This positive effect of competition on growth has been empirically tested in the international trade litterature. For example, using UK firm level data, Blundell et al. (1999) find that industries where the market share of the top five firms is high and import penetration is low, also exhibit lower levels aggregate innovation.

The main contribution of Aghion et al. (2005) is demonstrating that the direction of this effect is closely related to the industrial composition of an economy. The "Schumpeter" effect will dominate the "escape competition" effect, as they denote it, in industries where the leader possesses a significant technological advantage over rivals. On the other hand, the latter dominates the former in sectors where the technological gap is lower. In their paper they develop a model that formalizes these mechanisms and explain the existence of an inverted-U relationship between competition and growth.

While some papers look for furhter empirical evidence of an inverted-U using firm level data from other countries, so far none of them have estimated the model parameters directly. This paper carries this out using a Generalized Method of Moments approach using firm level data from Chile. We seek to understand what is the effect of competition as measured by a collusion parameter and a catch-up rate, on productivity growth. The paper is structured as follows. Section 2 provides an overview of the model developed by Aghion et al. (2005), Section 3 goes over the data as well as the estimation strategy and Section 4 concludes.

2 Theoretical Framework

The model we estimate in this paper is developed by Aghion et al (2005). Consider a unit mass of consumers with indentical preferences:

$$u = \int_t^{\infty} e^{-rt} \left(\ln y_t - l_t\right) dt$$

Within a time period, aggregate production y_t uses inputs from a continuum of intermediate sectors:

$$\ln y_t = \int_0^1 \ln x_{jt} dj$$

where x_{jt} is produced by two infinitely lived firms such that $x_{jt} = x_{Ajt} + x_{Bjt}$. In other words, both versions of good x_{jt} are perfect substitutes. We drop the time subscript t when it is not necessary.

Expenditure in x_j is $E = p_{Aj}x_{Aj} + p_{Bj}x_{Bj}$. However, given Cobb-Douglas preferences, in equilibrium consumers will spend the same share of income in each intermediate good x_j, which the authors normalize to 1. Wages w_t are therefore $w_t = 1$ in the paper as well. Nevertheless, we will not follow this normalization since including E as a parameter produces a better fit to the data.

Each duopolist i produces x_j according to:

$$x_{ij} = \gamma^{k_i} \cdot l_{ij}$$

where k_i is the technogical level of firm i and $\gamma > 1$. Firms therefore have constant marginal cost: $c_i = \gamma^{-k_i}$.

Thus the technological state of an industry j is characterized by the leader's technology l_j and the technological gap between the leader and follower m_j. The authors set $m_j = \{0, 1\}$. In other words, when $m_j = 0$, the two firms are in a $neck-and-neck$ situation. On the contrary, when $m_j = 1$ the sector is unleveled. Thus, the paper assumes innovations by the leader will be followed by immediate catch up from the follower, such that the gap remains at $m_j = 1$

Bertrand competition leads to limit pricing. Thus, the profits in each sector for each firm are given by:

$$\begin{aligned} \pi_1 &= E\left(1 - \gamma^{-1}\right) \\ \pi_{-1} &= 0 \\ \pi_0 &= \varepsilon\pi_1 \end{aligned}$$

where π_1, π_{-1} and π_0 are the profits of leaders, laggards and firms in $neck-$

$and - neck$ sectors respectively. Furthermore $\varepsilon \in \left[0, \frac{1}{2}\right]$ reflects the extent to which firms collude with $\varepsilon = 0$ and $\varepsilon = \frac{1}{2}$ representing perfect competition $(\pi_0 = 0)$ and collusion $(\pi_0 = \pi_1/2\ )$ respectively. Competitition is parametrized by $\Delta = 1 - \varepsilon$.

R&D costs $\psi(n) = n^2/2$, where n is the Poisson hazard rate at which a frontier firm moves one technological step ahead. On the other hand, h is the Poisson hazard rate at which a laggard firm catches up with the leader by copying its technology. This is also a measure of competition since higher values of h imply followers can acquire the leading technology faster, which allows them to compete with the leader in a $neck - and - neck$ situation. As a result of setting $m_j \leq 1$, the leader of an unleveled sector does not face any incentive to innovate. Thus, optimaly, $n_1 = 0$.

The authors find

$$\begin{aligned} n_0 &= -h + \sqrt{h^2 + 2\Delta\pi_1} \\ n_{-1} &= -(h + n_0) + \sqrt{h^2 + n_0^2 + 2\Delta\pi_1} \end{aligned}$$

where n_0 and n_{-1} are the equilibrium research intensities of neck-and-neck and laggard firms respectively.

As we can see from these expressions higher competition Δ produces faster growth in neck-and-neck sectors whereas it slows down growth in unleveled sectors. Let μ_1 and μ_0 be the share of unleveled and neck-and-neck industries respectively. In a steady state, inflow and outflow of the leveled state have to be equal:

$$\underbrace{\mu_1 \cdot (n_{-1} + h)}_{P(m_{t+1} = 0|m_t = 1)} = \underbrace{\mu_0 (n_0 + n_0)}_{P(m_{t+1} = 1|m_t = 0)}$$

and since $\mu_1 + \mu_0 = 1$ the innovation flow rate will be:

$$I = 2\mu_0 n_0 + \mu_1 \left(n_{-1} + h\right) = \frac{4n_0 \left(n_{-1} + h\right)}{2n_0 + n_{-1} + h}$$

In this model, the steady state growth rate is given by this innovation flow rate I.

3 Empirical Analysis

3.1 Data Description

As we will later see, to estimate this model we target moments related to firm profits and innovation activities. To carry this out we rely on two Chilean firm level datasets: the Longitudinal Survey of Firms (LSF) from 2007 and 2009, and the Sixth Survey of Firm Innovation (SFI) (2007-2008). Both datasets are produced by the Ministry of Economy in Chile.

The first covers a sample of formal firms that sold more than 3.9 USD in 2007 and 33,379 USD in 2009. [1]Furthermore, the Ministry of Economy conducted a third survey, for the year 2013. This database identifies firms included in the Panel and provides a unique identifier. We use this information to build a panel for the years 2007 and 2009, which we use to estimate TFP in the following section.

These surveys provide data on firm accounting, investment and employment among other variables. Sales are used to differentiate firms according to size, providing 6 categories in the 2007 survey. Furthermore, firm activity is classified

[1] To be considered in the Survey, firms need to have sold more than 0.1 UF in 2007 and 800.1 UF in 2008. The UF, or *Unidad de Fomento* is a unit of account used in Chile. Using the December 31st, 2007 and December 31st, 2009 exchange rates of 19,622.66 CLP and 20,942.88 CLP provided by the Internal Tax Service (SII in Spanish), this is equivalent to 1,962.27 CLP and 16,756,398.288 CLP. We use an exchange rate of 500 CLP for 1 USD to obtain amounts in dollars.

using the ISIC Rev 3 up to one-digit SIC code. Finally, a “Region” variable is included, which determines the geographic region where the headquarter of a firm is located at.

The second database we use is the Sixth Survey of Firm Innovation, also provided by the Ministry of Economy. It includes private firms with sales above 94,188 USD in 2007, and collects data on innovation activities and expenditures in R&D. It also classifies firms according to economic sector (one-digit SIC code), geographic region and firm size. For the latter classification, the survey provides only three categories “Small”, “Medium” and “Large” and does not consider “Micro” firms as the LSF does. However, the sales cutoffs are the same in both surveys, which will allow us to match industries, as defined below, in both datasets.

3.1.1 Sectors

The model assumes a continuum of sectors, which are later classified as leveled and unleveled. Since both the LSF and the SFI stratify firms using a one-digit SIC code, only 11 economic sectors are available. Therefore, to narrow the sector identification, we define a market as a group of firms of the same size, operating in the same geographic region in the same activity defined by the SIC code.

Thus we generate a new variable concatenating “Region”, “SIC” and “Size” which identifies these markets. The LSF identfies fewer SIC industries than the SFI thus we exclude “Fishing” firms as well as those in the “Social Services” sector. Furthermore, the paper seeks to understand the relation between competition and innovation in developing countries. Ideally, we would like to determine the competition level that produces the highest productivity growth rate. Therefore, we also exclude sectors that tend to natural monopolies such as “Utilities”, where multiple competitors cannot coexist due to economies of scale.

After identifying each sector and calculating average profits and R&D intensity in each using the LSF and SFI respectively, we merge both databases and obtaina set of 131 "markets".

3.1.2 Technological gap

The model distinguishes between leveled and unleveled sectors according to productivity. Thus we need a measure of productivity for each firm. To obtain this variable, we use the panel structure of the 2007 and 2009 LSF to estimate the following fixed effects regression:

$$\log\left(y_{it}\right) = \beta^{k}_{SIC}\log k_{it} + \beta^{l}_{SIC}\log l_{it} + \mu_t + \underbrace{\mu_i + \varepsilon_{it}}_{TFP}$$

where y_{it}, k_{it} and l_{it} are the sales, capital stock (fixed assets) and employment of firm i at time t. Firm sales and capital stock are in nominal values. However, to estimate this equation we require these variables in real terms. The LSF does not provide an investment deflator and therefore we use the Implicit GDP Deflator from the FRED to convert monetary values to 2010 CLP.

The model defines leveled industries as those where the technological gap between the leader and the follower is 0, whereas in unleveled industries this gap is exactly 1. Evidently this pattern does not hold in the data and therefore we need a adapted measure, which we obtain from Aghion et al. (2005). For each firm i in industry j define:

$$m_{ij} = \frac{A_{Fj} - A_{ij}}{A_{Fj}}$$

where A_{Fj} and A_{ij} are the estimated TFP of the leader in industry j and that of firm i respectively. Let m_j be the average of this variable across firms within each industry. We use this as a measure of technological spread for each sector as defined in the section above.

Thus we choose an arbitray threshold η, such that if $m_j < \eta$ then sector j is considered leveled. On the contray, if $m_j > \eta$ sector j is considered unleveled. For now we choose $\eta = 0.5$ and proceed with the estimation under this assumption. However, future work will have to check robustness of results under other specifications.

3.2 Model Predictions

After solving the model analytically, the authors make several predictions with respect to innovations, competition and the technological gap within an industry. Once states that, as competition in an industry increases, the average technological gap between leaders and followers should increase as well. We test this prediction by looking at m_j and the empirical measure of competition c_j they use in their paper:

$$c_j = 1 - \frac{1}{N_j} \sum_{i \in j} \frac{\pi_i}{y_i}$$

where π_i and y_i are the profits and sales of firm i, and N_j is the number of firms in sector j.

Figure 1 suggests this prediction holds towards higher levels of competition. As the authors explain, the dynamic positive effect of an increased innovation flow (to escape competition) on the technology spread dominates the static positive effect of competition on the exit rate of firms with lower technological levels.

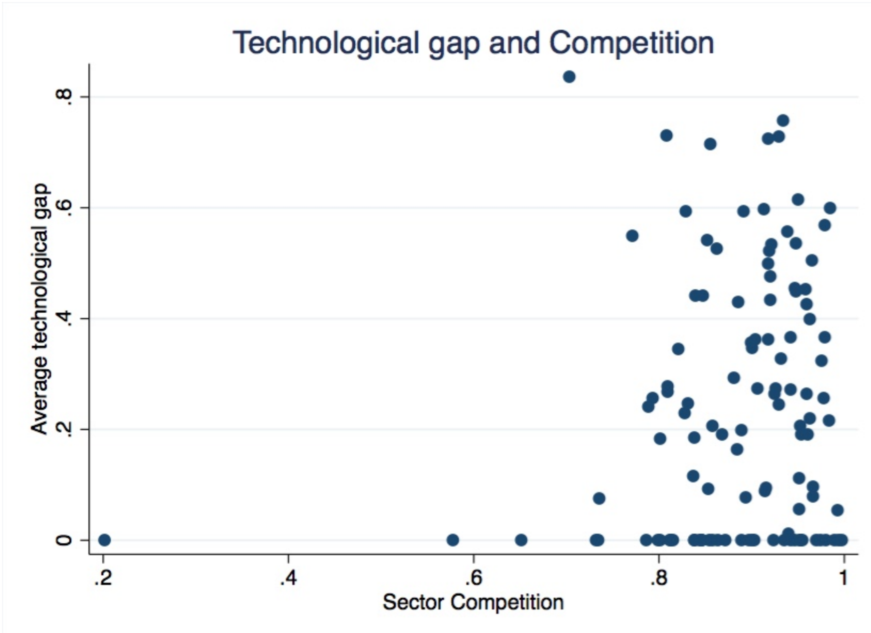


Figure 1: m_j and c_j

Recall the paper sought to explain the existence of an inverted-U relationship between competition and innovation. In this sense, the authors determine the conditions when this occurs and when the effect is strictly positive or negative. Figure 2 shows the relationship between R&D intensity and competition among Chilean firms. The figure suggests there is a positive relationship between competition and innovation.

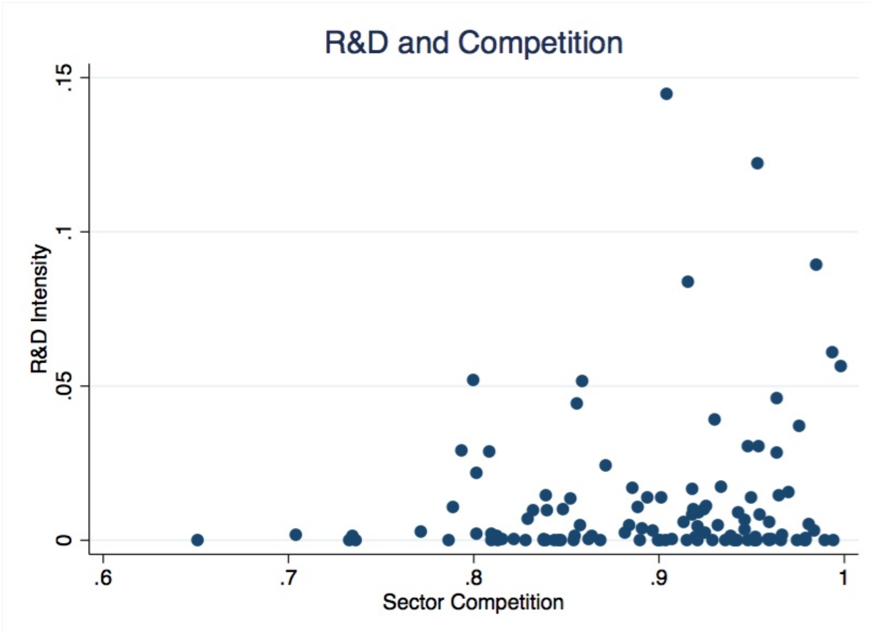


Figure 2: m_j and c_j

3.3 Estimation

3.3.1 Targeted Moments

The parameter vector we seek to estimate is $\Theta = (\rho, \varepsilon, h, E, \gamma)$. The macroeconomic litterature calibrates $\rho = 0.02$, which approximately matches a 97% annual discount factor. We estimate the remaining three parameters through GMM and use an optimal weighting matrix approach. For this we target the following moments:

Average R&D intensity in leveled sectors Recall the expression of R&D intensity in unleveled sectors is given by $n_0 = -h + \sqrt{h^2 + 2\Delta\pi_1}$. If we use the expression obtained in Section 2 for π_1 and Δ we obtain:

$$n_0 \quad = \quad -h + \sqrt{h^2 + 2\,(1-\varepsilon)\,E\,(1-\gamma^{-1})}$$

As we can see, this variable depends on all four parameters. We identify R&D intensity in the data as R&D expenditures over total sales. Thus the moment we target is average R&D intensity within leveled sectors: $\bar{n}_0$.

The endogenous growth litterature typically identifies n using R&D output (citation-weighted patent count) instead of input. However, the Innovation Survey only provides the total number of patents a firm possess at a given year, not the innovation flow. Furthermore, information on patent citations is also not available. Nevertheless, assuming an innovation production function exists, which maps R&D expenditures to patent production, targeting R&D expenditures over total sales approximates this output.

Average R&D intensity in unleveled sectors Similar to the previous moment, we target the average R&D intensity (defined as R&D expenditures over sales) for sectors where $\bar{m} > 0.5$. From the model we know

$$n_{-1} = -\,(h + n_0) + \sqrt{h^2 + n_0^2 + 2\,(1-\varepsilon)\,E\,(1-\gamma^{-1})}$$

where n_0 is given by the expression above. Thus this moment also depends on every parameter and there is not collinearity with n_0.

Profits in the unleveled sectors In any unleveled sector j, only the leader obtains profits $\pi_1 > 0$ since she possesses a higher technological level. From the model, these are given by

$$\pi_1 = E \cdot \left(1 - \gamma^{-1}\right)$$

As we previously mentioned, we do not normalize the scale parameter E to 1 and include it to produce a better fit of profits. The moment we target is therefore the average profits of unleveled sectors, where $\bar{m} > 0.5$. This will determine the parameter γ and the scale parameter E.

Ratio of unleveled to leveled profits In the model, profits in the leveled sectors π_0 are a fraction ε of profits in unleveled sectors π_1. Thus $\pi_0 = \varepsilon \cdot \pi_1$, which we rearrange to obtain:

$$\frac{\pi_0}{\pi_1} = \varepsilon$$

Hence we target the ratio of average profits from both types of sectors: $\frac{\bar{\pi}_0}{\bar{\pi}_1}$. This identifies the extent of competition $\varepsilon \in \left[0, \frac{1}{2}\right]$.

Ratio of industry shares As we saw above, in equilibrium the economy is in a stationary distribution such that $\mu_1 \cdot (n_{-1} + h) = \mu_0 2n_0$. We rewrite this and obtain the moment:

$$\frac{\mu_0}{\mu_1} = \frac{(n_{-1} + h)}{2n_0}$$

where n_{-1} and n_0 are given by the expressions above.

3.3.2 Results and counterfactuals

The estimation results are summarized in Table 1 and the value of the criterion function at the optimal is 2×10^{-16}. As we can see $\hat{\varepsilon} = 0.33$ reveals competition among Chilean firms is in between perfect competition $(\varepsilon = 0)$ and collusion $\left(\varepsilon = \frac{1}{2}\right)$. However, it does suggest a tendency to collusion, which could be explained by either low punishments or a low probability of catching anticompetitive behavior by regulatory agencies.

A catch-up rate of $h = 0.14$ reveals followers incorporate the leading technology very slowly. One of the explanations for this could be a long period of patent protection. However, other factors could affecting this results, such as low technology diffusion between firms due to lack of communication. Thus firms are able to keep information private more effectively.

Table 1: Parameter Estimates

#	**Parameter**	**Description**	**Value**
1.	ε	Extent of collusion	0.33
2.	γ	Size of leading edge innovation	1.14
3.	h	Catch-up rate	0.14
4.	E	Expenditure	0.45

To determine if this estimation and the model provide a reasonable explanation of the observed data, we examine the moments implied by these parameters, with the ones found in the data. As we can see, even if the criterion function reaches a low value, the distance between the observed and predicted moments is still high specially for profits in unleveled sectors. This could be due to multiple reasons. First, the theoretical model developed in Aghion et al. (2005) does not consider other elements we do observe in the data, such as firm entry and exit. Setting a maximum technological gap also limits the empirical predictions the framework can make. Second, R&D expenditures do not constitute a perfect determinant of innovation flow. Therefore matching n_0 with R&D intensity will not produce a reasonable estimate. Ideally one could use citation adjusted patent count, as the authors use in their empirical analysis.

Table 2: Model and Data Moments

#	Moments		Model	Data
1.	Average R&D intensity in leveled sectors	$\bar{n}_0$	0.16	0.01
2.	Average R&D intensity in unleveled sectors	$\bar{n}_{-1}$	0.04	0.016
3.	Average Profits in unleveled sectors	$\bar{\pi}_1$	0.054	109893.0
4.	Ratio of unleveled to leveled profits	$\frac{\pi_0}{\bar{\pi}_1}$	0.33	0.32
5.	Relative sector shares	$\frac{\mu_0}{\mu_1}$	0.56	5.27

We can still, however, construct some counterfactuals. Notably, we study the effect of competition ε and catch-up rate h on productivity, and therefore economic growth. The baseline growth rate implied by these estimates is $g\left(\hat{\rho}, \hat{\varepsilon}, \hat{h}, \hat{E}, \hat{\gamma}\right) = 0.23$. If we set $\varepsilon = 0$, growth increases to $g\left(\hat{\rho}, 0, \hat{h}, \hat{E}, \hat{\gamma}\right) = 0.27$ whereas if $\varepsilon = 0.5$, it falls to $g\left(\hat{\rho}, 0.5, \hat{h}, \hat{E}, \hat{\gamma}\right) = 0.2$. Similarly if we set $h = 0$ we obtain $g\left(\hat{\rho}, \hat{\varepsilon}, 0, \hat{E}, \hat{\gamma}\right) = 0.18$ whereas if $h = 1$, then it also decreases relative to the baseline to $g\left(\hat{\rho}, \hat{\varepsilon}, 1, \hat{E}, \hat{\gamma}\right) = 0.13$. This implies growth and the catch-up rate follow an inverted-U relationship, whereas it is decreasing in ε.

To confirm this we plot growth for different values of ε and h in figures 3 and 4. The inverted-U can be explained by the dual effect the catch-up rate has on growth. On the one hand, it directly increases the innovation flow of laggard firms and therefore raise the aggregate innovation rate of the economy. On the other, it decreases the incentives to conduct R&D by the laggards, as they can produce the same number of innovations with less effort. Thus in the first part of the graph, the first effect dominates the latter, whereas the latter dominates the former in the second part. Concerning the degree of collusion ε, it must be the case that Chilean firms are on aggregate in the increasing part of the inverted-U explained in Aghion et al. (2005).

Figure 3: Degree of Collusion and Growth

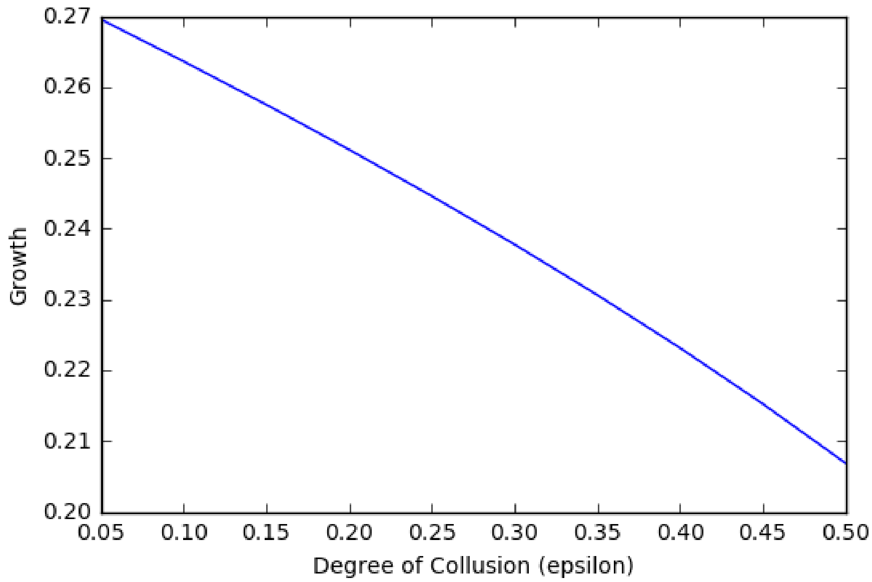
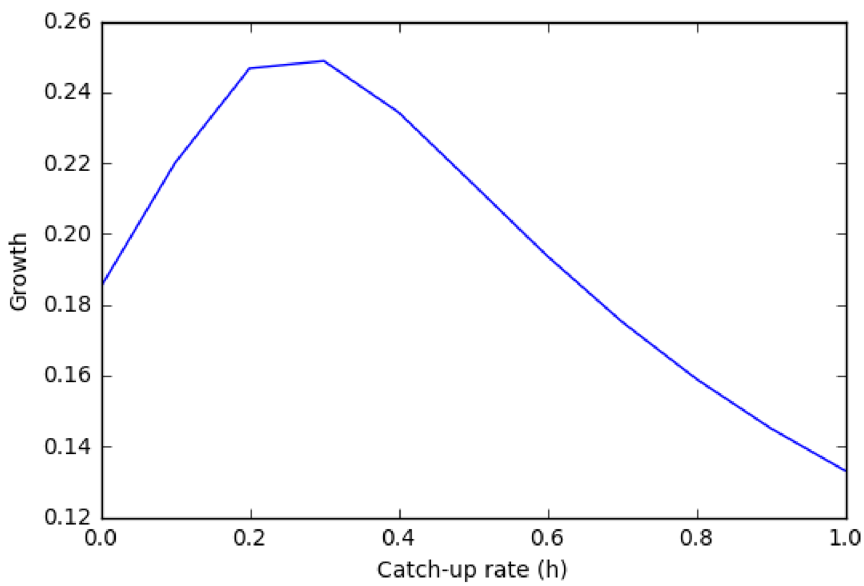


Figure 4: Catch-up rate and Growth



4 Conclusion

This paper expanded on the analysis carried out by Aghion et al. (2005) by estimating the model they develop using firm-level data from Chile. This yielded interesting new results, as we found a monotonic relationship between the degree of collusion and innovation unlike the inverted-U predicted by the model. Nevertheless, we did find an inverted-U relationship between the catch-up rate and productivity growth. Even though this is an aspect the original paper does not focus on, it is still important as it impacts growth and it can be shaped by policy decisions, such as patent length.

When comparing the moments, we realize the model did not provide a good fit to the data. There are two directions future research can take to improve these results. The first is to expand the model to include other elements found in the data, such as firm entry and exit. The second is to find more comprehensive data on patents as well as covering a longer time period. This can provide better predictions as well as determine the actions regulators can take to maximize productivity and economic growth in the long run.

5 Bibliography

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