Laboratory of Economics and Management
Sant'Anna School of Advanced Studies

LEM
Working Paper Series

Fingerprints of the Visible Hand.
Chandlerian Organizations and their Inward Looking Malaise

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2004/16   **September 2004**

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ABSTRACT

This paper investigates the relationships between firm organization attributes, namely a structure *á la* Chandler, and their inward looking or "exploitation" attitude in R&D and innovation. We argue that because of sunk costs and learning processes an inward looking behavior is a consequence of increases in firm size. However, it is also produced by an organizational model based on hierarchical managerial decisions, typical of the Chandlerian firms, that is not directly related to size. We find that the US States populated by larger firms show a higher share of patent self-citations normalized by their share of world patents. Even after controlling for firm size, a proxy for the extent of firm divisionalization in the States exhibits a significant effect on patent self-citations normalized by patent shares. This supports our point that the inward looking behavior of the Chandlerian firms is not just a consequence of size, but also of the Chandlerian organizational model. Among other things, this suggests that "exploration", which leads to the opening of new innovation trajectories, requires not only small firms, but also different organizational setups and decision processes.

1. Introduction

Alfred Chandler (1977) epitomized the modern corporation as the firm that relies on managerial direction − the "visible hand" − to allocate and coordinate information flows and resources inside the organization. More than 100 years ago, the Chandlerian corporation arose as the organizational innovation that allowed for the government of increasingly complex business operations. This was attained by an extensive specialization and division of labor inside the firm. As a result, the Chandlerian firm exhibits a considerable degree of divisionalization, that is a plethora of distinct operating units and divisions, along with layers of low, middle, and top managers organized under hierarchical relationships.

A common view in the literature is that the Chandlerian firms rely considerably on in-house resources and internally generated information and knowledge assets. A related feature is that they are more likely to "exploit" their existing business lines and R&D trajectories rather than "exploring" new ones (Levinthal and March, 1993). Several empirical studies have confirmed that the Chandlerian firms prefer exploitation to exploration investments (e.g. Henderson, 1993; Dougherthy and Heller, 1994; Christensen, 1997), unlike for instance small and young firms or more generally entrepreneurial environments in which there is greater use of knowledge and resources external to the individual organization (e.g. Saxenian, 1994). These features of the managerial firm are not less important today. According to the specialized press, the large divisionalized corporations are dedicating an increasing share of their R&D expenditures to the extension of existing business lines (e.g. The Economist, 2004; Business Week, 2004).

The goal of this paper is to show empirically that the Chandlerian organizations exhibit a greater propensity to rely on their own internal knowledge. Our analysis builds upon the seminal studies by Nelson (1961; 1982) and Arrow (1974; 1975) who highlighted how organizational forms − i.e. hierarchies of managers, layers of divisions − affect R&D

directions and economic outcomes. We discuss two propositions. The first proposition says that the propensity to use internal knowledge assets and information increases with the size of the firm. The rationale for this proposition is that the larger the firm the greater the sunk costs and the learning opportunities, which produce a greater bias towards improving existing trajectories rather than moving onto new ones. The second proposition is that a Chandlerian organizational structure, viz. a more extensive divisionalization and a greater reliance on hierarchical managerial layers, also induces a greater use of internal knowledge. Here we argue that, for an equal total investment in R&D, the Chandlerian corporation invests more resources per project than a set of independent firms. This implies greater scale and learning effects at the level of the individual projects or trajectories, which reinforces the bias in favor of established R&D or innovation lines. Moreover, it has been shown that the upper managers who select project and research trajectories have cognitive biases that favor activities in which they have greater experience.

To test these propositions, we employ data for 52 US States (50 States plus DC and Portorico). Our measure of the inward looking attitude of the Chandlerian firms is the share of patent self-citations (backward citations of patents by the same assignee) in a given State normalized by the share of world patents assigned to the State (the State of the first inventor is used to assign patents to States). We show that, after controlling for several factors, our normalized share of self-citations is positively correlated with measures of the States firm size distribution, which account for the presence of larger firms. It is also positively correlated with the average number of subsidiaries (divisions) of the firms divided by the firm sales, taken as a measure of the diffusion of Chandlerian organization models in the State. The latter result is important as it shows that there is an impact of an organizational structure *à la* Chandler that is not just implied by firm size.

We employed State-level data, instead of company data, because of the limitations in the availability of financial data and other controls for the smaller firms, and especially for the non-quoted ones. Chandlerian organizations are correlated with firm-size, and size is correlated with the availability of firm-level data. By selecting our sample of firms according to the availability of data, we would select it on the dependent variable, which would produce biased estimates of the impacts of the covariates unless one engages in complicated regression structures to account for the truncation. We wanted to avoid such a heavy statistical structure to pick patterns in the data without filtering them through elaborate statistical assumptions. Our aggregation at the level of States preserves the breadth of the sample of total patents, and particularly it does not entail a bias in favor of the large firms, while enabling us to employ a good set of controls in our regressions.

To summarize, we see the following contributions of this paper to the literature. First, it brings further evidence on the idea that "organization matters", and particularly that the R&D outcomes of one large Chandlerian firm can be different from the outcome of several entrepreneurial firms, even if the total R&D investment is the same.[1] Second, we try to explain the inward looking attitude and related inertial behavior of the Chandlerian firms (Hodgkinson, 1997). There is an empirical literature that correlates size with the attitude of firms towards exploitation (for a review see Krishnan and Ulrich, 2001), but to our knowledge there have been only few attempts, mainly based on case studies, to explain why we should observe it (Floyd and Wooldrige, 1997; Christensen, 1997; Trispas and Gavetti, 2000; Danneels, 2002). Moreover, we distinguish between the effects of size *per sè* vis-à-vis those of the organizational characteristics of the firm. Third, the paper sheds new light on some empirical regularity that until now have received little attention, namely the under-studied portion of patent citations, the self-citations, as instruments to proxy for intra-firm

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[1] Nelson (1961), Ghemawat (1991) and Henderson (1993) reached the same conclusions.

technological competences and spillovers. This could open new empirical trajectories in this field of study. Finally, this paper shows how organizational factors could be strictly interrelated with, and can be used to explain, some empirical regularity observed at the regional level.

Section II builds on the literature on Chandlerian corporations and R&D to derive our main propositions about the effects of size and organizational characteristics on the inward looking behavior of firms. Section III describes the data, while Section IV presents the empirical results. Section V concludes.

2. The Visible Hand and the Direction of R&D Outcomes

2.1 The effect of firm size on the use of internal knowledge

Large and complex managerial firms carry out many projects at once, and they have sunk costs in projects started in earlier periods. With sunk costs, existing business lines or research trajectories may be pursued over alternative opportunities in new areas even when the net profits of the latter are higher. This is a classical argument about sunk costs. Because the cost is sunk when the new opportunity arrives, it is not taken into account when comparing the two alternatives, which raises the current profitability of the trajectory whose costs are sunk. To fix ideas, suppose that there is a sunk cost K paid in the past, and that this produces current gross profit of a business line equal to $v > z$, where the latter is the net profit of a new business line whose sunk cost has not yet been paid. Because $v > z$, the firm will stay with its trajectory that produces net profits $v - K$ even if $v - K < z$. By contrast, if K was not sunk, and $v - K < z$, it would undertake the trajectory z. Larger and more complex Chandlerian firms, which have sunk costs in several activities, will then have a tendency to stick to their old businesses rather than moving onto new ones.

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The same applies if there is project- or trajectory-specific learning over time or if there are spillovers across concurrent projects or R&D trajectories rather than sunk costs (see e.g. Henderson and Cockburn, 1996). With learning, the profitability of an existing business line improves. Other things being equal, this makes it more advantageous to stay with the existing trajectories. Similarly, if a project benefits from spillovers from other projects of the firm, then other things being equal, it is more likely to be chosen vis-à-vis other trajectories in which the firm does not enjoy similar spillovers. The trajectories in which the firm enjoys economies of scope are typically those that are closer technically or from other perspectives (e.g. commercial, manufacturing). In turn, these are more likely to be trajectories that improve upon existing fields or areas of research than distant new fields or operations (see also Teece et al., 1994).

The foregoing arguments find confirmation in the literature. Arrow (1974) suggested that firms prefer to use existing information assets, even if they are less efficient, because of the costs of abandoning the old trajectories for the new ones. Henderson (1993) empirically confirms that incumbent diversified firms in photolithographic industry have a greater incentive to invest in incremental innovation. More generally, when the costs of using existing assets are lower than developing new ones, the incentives to remain in old well-defined research trajectories could be substantial (see for example Abernathy, 1978). At the same time, the magnitude of the sunk costs, the extent of the learning processes, or the number of projects with potential spillovers, are higher the larger the firm. Thus, larger firm are more likely to be affected by the factors mentioned above that induce them to persist in their established R&D trajectories. In turn, this means that the larger the firm the more likely it is that it relies on internal knowledge assets. This leads to our first Proposition.

Propostion 1. *Larger firms rely to a greater extent on internal knowledge assets.*

2.2 A logical outcome of the visible hand mechanism

Apart from size, hierarchies, division of labor and project selection offer a simple explanation of the Chandlerian tendency to expand investments on the projects that have already been launched. A stylized fact is that the Chandlerian corporations organize R&D in two phases: a preliminary phase where project proposals are assessed and selected, and a second phase where the selected projects are carried out (Nelson, 1961 and 1982; Loch et al., 2001). Typically, the upper managers are specialized in the supervision and selection of the projects, while hierarchically lower units composed of middle-low managers submit the proposals and carry out the projects. Chandler (1980) himself wrote that the modern divisionalized corporations separate "those who make the decisions about the firm's operations and those who own its means" (p.15).

This model of organizing R&D produces concentration of a given R&D budget on fewer projects and research trajectories. In fact, the most important task of the top-level managers is to avoid duplication in research trajectories and cannibalization among similar projects (Nelson, 1961; Loch et al., 2001). The selecting managers then try to pull together investments and researchers into selected project trajectories. It is straightforward that the unification of different efforts on restricted research paths increases the investments in each line of research. Another reason is that the specializations of the two types of managers lead to asymmetric information and related agency problems. Fewer projects are then selected compared to smaller firms in which the organizational distance between promoters and selecting managers is smaller (Arrow, 1983; Holmstrom, 1989). Finally, the very fact that another party checks a given project makes it less likely that it is approved simply because a second check can spot reasons why the project is not worth or drawbacks that the original proposing agent did not see: "two eyes are better than one" (see also Sah and Stiglitz, 1988).

As an example, take two firms with the same ex-ante fixed R&D budget denoted by R that have to choose among N different project proposals to fund. One firm behaves like the classical Chandlerian firm with the ex-ante project review and selection, and the other like N separated and independent divisions. The first one will chose $K < N$ projects to launch, investing on average R/K money in each project. The second firm will invest R/N. The underling assumption that the firm R&D budget is fixed before the selection decision is reasonable and it is confirmed empirically by the stability of the firm R&D intensity over time, especially for the large firms (see Halliday et al., 1997; Eberhart et al., 2004).

With fewer projects per unit of R&D budget, the Chandlerian mechanism implies greater concentration of the same amount of knowledge in a smaller number of areas than the equivalent set of independent firms. In addition, the concentration in fewer areas gives rise to scale economies and increasing returns on the launched project trajectories. For the reasons suggested when we discussed Proposition 1, this reinforces the tendency to stay with existing lines of business or research, and hence to rely on the knowledge base of the firm. While in the discussion of Proposition 1 the scale economies and increasing returns on existing projects stemmed from the size of the firm, in this case they are produced by the patterns of Chandlerian R&D selection, which produces a larger investment of the R&D budget per project. This leads to our second Proposition.

Propostion 2. *Firms organized under tighter Chandlerian models, viz. extensive divisionalization and hierarchical selection of projects, rely to a greater extent on internal knowledge assets.*

2.3 Cognitive biases of the visible hand

Given the hierarchical structure of the decision process in Chandlerian organizations, any cognitive bias of the visible hand should affects the directions of the firm R&D trajectories. Nelson (1982) and March (1988) have already highlighted the link between the knowledge of

the manager teams specialized in project selection and the R&D outcomes. Arrow (1974) stated that long-term patterns in an organization appear when "[new] information available somewhere in the organization [...] is not used by the authority". (p. 74). The cognitive biases of the selecting managers provide an additional argument for Proposition 2. Thus, without developing any new proposition, we do stress the cognitive biases of the selecting managers because, as we will see, they are an important part of the story why the Chandlerian firms use internal knowledge.

Recently, Kaplan et al. (2003) have stressed how the conservative attitude of mental models in high hierarchical levels of managers affect firm R&D directions. They have shown that the speed at which large pharmaceutical companies started to patent in biotechnology was influenced by the mental schemes of the top managers. The limitations in the cognitive maps of the coordinating managers could lead to inertial decisions, even when the potential project portfolio is heterogeneous. In this respect, the difficulties to cope with breakthrough innovations have found easy explanations (Hodgkinson, 1997; Floyd and Wooldridge, 1997; Trispas and Gavetti, 2000), especially when the coordination managers tend to be senior employees whose pool of knowledge is relatively aged. If the knowledge embedded in the selection managers is limited, their decisions will follow specific paths and they will be regular and predictable (Filkeenstein and Hambrick, 1988).

Burgelman (1994) provides an illuminating example. He analyzes the managers' attitude in Intel during the transition from the DRAM memories to microprocessor business. He shows how the microprocessor, an unplanned innovation, was hampered by the top managers who defended DRAMs as the Intel core business. They continued to fund DRAM projects as much as other more successful businesses. It was puzzling that the top management rejected at least two microprocessors project proposals to fund instead investments in DRAMs in the two years before Intel finally abandoned the DRAM business.

By contrast, the low-middle level managers were not in accord with the top management's view and lobbied for the Intel shift to microprocessors. Ex-post, the top-level managers mentioned that they found it difficult to deviate from their established criteria for internal project selection. They had established project evaluation criteria that by were designed to always favor existing R&D lines.

This attitude of the top managers can be cast in the framework of the previous section. The cognitive bias implies that, other things being equal, the selecting managers will exhibit a higher probability of accepting a project in an established field than a project in a new area. One explanation of this behavior is that the top managers develop specialized learning capabilities that enable them to have more information and a greater ability to assess existing product lines. Since they do not have experience in the new areas, they tend to reject new projects. In the previous section we cited Arrow (1983) and Holmstrom (1989) who stressed asymmetric information problems and agency costs in larger firms when it comes to launching new projects. A typical case widely emphasized in the literature is that the low-middle management has more information, relationships, and links with the users, while the selection manager team is more distant from the downstream source of knowledge (Floyd and Wooldridge, 1997).

In sum, the inward looking attitude of the Chandlerian firms could stem from the knowledge limitation of the top-level selecting managers who tend to replicate the same cognitive scheme. According to the view rooted in Levinthal and March (1993), inward looking stems from the bounded knowledge of the decision managers. It takes place even if the low-middle level project managers submit a wide portfolio of projects based on different source of information (external and internal). Of course, the cognitive limitation is only a necessary condition. If the organization of the firm were not based on a division of labor

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structured in layers of managers with different level of authority, this limitation would not affect the R&D trajectories.

3. Data and descriptive statistics

3.1 Data sources

We used patent data from the NBER US Patent Citation Dataset (Hall et al., 2001). To produce descriptive statistics we selected all the US patents granted from 1980 to 1999. For the regressions we employed the sub-sample of patents granted during 1995-99. We interpreted the US State of the first inventor as the "State" of the patent.

Patent self-citations are our proxy for intra-firm knowledge spillovers. Citations imply that the citing patent builds upon knowledge in the cited patent. There are backward and forward citations. Usually backward citations (citations made) are viewed by the literature as a proxy of knowledge spillovers, because if patent X cited patent Y this could indicate a flow of knowledge between the two innovations (Jaffe et al., 1993 and 1998; Mowery et al., 1998; Gittelman and Kogut, 2003, Ziedonis, 2004). Forward citations (citations received) are often used to analyze the importance and the value of the patents (Haroff et al, 1999). We employ backward citations. Self-citations take place when the previous inventions cited belong to the same assignee of the citing patent. According to Hall et al. (2001) self-citations "represent transfers of knowledge that are mostly internalized" (p.19). In this respect, a firm propensity to self-citation is a good proxy of the inward looking attitude of an organization, since it measures the propensity to create new knowledge from previously developed internal knowledge. So far, the only available evidence in this field is provided by Hall et al. (2001) who found a higher share of self-citations (about 20%) in the Chemicals and Drugs sector, which is dominated by large divisionalized firms. By contrast, Ziedonis (2004) observes that

in the semiconductor industry, which was recently characterized by an increasing division of labor and vertical disintegration, the average ratio of self-citations is 9.3%.[2]

The NBER database provides two measures of the ratio between self-citations and total citations, a lower bound and an upper bound. Since the assignee's name is not given for the patents granted before 1969, it is not possible to count the self-citations for these patents. Thus, we computed the share of self-citations either on the total sample patent (lower bound, LBC), or on the sub-sample of patents granted after 1969 (upper bound, UBC).

From the Bureau van Dijk's Orbis database, which contains data for more than one million US companies, we downloaded the number of employees of all the US firms by State. For each firm we counted its number of subsidiaries in the same US State, its turnover, and we identified the US State of location. The total number of firms in the sample is 1,382,732. The rationale for this data collection is to proxy for Chandlerian-ness with the fatness of the right tail of the firm size distribution of each US State. From the same database, we downloaded for each State the average book value of plants and propriety and the number of employees classified by sector (2 digit SIC code). Finally, from the database "State & County Quick-Facts" of the US Census Bureau we obtained several control variables by State for the year 2000, viz. population, income per capita, the share of employees with a Bachelor's degree, the State land area and the State R&D expenditures.

3.2 Descriptive statistics

Between 1980 and 1999 the US Patent Office granted 746,808 citing patents that cite 7,799,893 cited patents. The average percentage of self-citations in this period is 15.1% for UBC and 11.9% for LBC, with a standard deviation of 0.26 and 0.22 respectively. Graph 1 compares, for the sample period, the trends of the average UBC and LBC against the ratio

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[2] In other industries this percentage is much higher. For example, in the Coating industry the average rate of self-citations is over 50%.

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between citations and patents (citation intensity) and patent and assignees. The number of patents per assignee is constant throughout the period, while the number of citations per patent increases steadily. The share of self-citations decreases significantly until the end of the 80s, and then remains stable. This suggests that the share of self-citations was not strongly affected by the "explosion" in the number of citations per patent, especially in the most recent years. To check for the stability of self-citations, Graphs 2a and 2b report the first four moments of LBC and UBC. The two series look stable over time.

[Graphs 1, 2a and 2b about here]

Before moving to our regressions we perform some additional tests on our data to strengthen the importance of the issues that we want to focus upon in this paper. We first show that the share of self-citations exhibits a greater heterogeneity across firms than across technological fields. Technological fields could have different propensity to self-citation. For example, more codified knowledge bases are easier to transfer across organizations. As a result, the corresponding technological fields could exhibit fewer self-citations than others that rely on more tacit knowledge assets. To test technology *versus* firm effects, we performed an analysis of variance using the technological class dummies and the assignee dummies. Given that from 1995 to 1999 there are more than 16,000 assignees, we adopted a conservative approach and selected as dummy-assignees only those with patents in more than 5 different technological classes. We ended up with 673 firm and 408 technological class dummies. Our results show that firm effects overwhelm technological class effect. With an R^2 of 0.301 and UBC as the dependent variable, the percentage of the model variance explained by firm dummies is 26.6% *vs* 1.3% explained by technological class dummies (24.8% *vs* 1.11% for LBC).

To confirm these findings, we calculated for all the assignees the average LBC and UBC in every year to test for the extent of the heterogeneity of the share of self-citations

across firms. Table 1 summarizes the findings. Looking at the standard deviation, mean and skewness, the heterogeneity among the assignees is high and persistent over time. The average ratio between standard deviation and mean is 2.45 for the whole period. This implies that there are organizations that persistently cite their patents, and firms that do not rely much on self-citations.

[Table 1 about here]

One of the motivations of our work is that the large firms have a higher share of self-citation compared to the share of their patents, while this is not true for smaller firms that do not rely as much on tight Chandlerian organizations. Table 2 corroborates this evidence. We selected the 15 most important USPTO technological classes by number of patents granted, along with the assignee with the highest number of patents in each class. For these assignees and each USPTO class, we computed their shares of patents in the class over the total patents in the same class, and the share of self-citations of their patents in the class. If all the patents in a class were equally likely to be cited, the share of self-citations and the share of patents held over the patents in the same class ought to be roughly similar. But Table 2 shows that for the top patent holders the former is well higher than the latter. It also shows that the ratio between the average share of self-citations for all the assignees in the same class and their share of patents is smaller than for the top patent holder. Thus, not only are the leading firms more likely to cite themselves, but also this behavior is not similar to the average patent holder in the class. This provides evidence of the fact that the larger firms have a higher propensity to self-citations.

[Table 2 about here]

Finally, we provide some statistics by US State on the right tail of the firm size distribution. Table 3 shows that the US States differ considerably in terms of number of firms

with more than 2,500 employees. It also shows that they differ in terms of the number of

subsidiaries of these firms in the same State.

[Table 3 about here]

4. Empirical analysis

4.1 Methodology

As noted in the previous section, we want to assess the extent of the share of self-citations of

any given assignee beyond the unconditional probability to cite one of its own patents. A

company with more patents is naturally more likely to cite its own patents simply because

there is a higher base of patents to be cited. Our point is instead that, because of inherent

features of their organizational model, Chandlerian firms are more likely to use their internal

knowledge, and hence to self-cite, even after controlling for the fact that they may have more

patents (or a greater knowledge from which to draw new knowledge). The methodology that

we illustrate below rests on the idea that if all patents are equally likely to be cited, then the

share of self-citations by any firm should be equal to the share of patents of that firm over all

the patents. If self-citations are higher, then the firm has a higher propensity to self-cite,

while the opposite would be true if the share of self-citations was lower than their share of

patents.

Denote S_i to be the share of self-citations of the firm "i" and P_i the share of patents of

the same firm on total patents. Then

$$S_i = \eta_i \cdot P_i \qquad\qquad (1)$$

where η indicates any firm specific factor that alters the equal probability of citing your

patents. The proportionality factor η equals to 1 if there is no bias in self-citations.

Before moving to our State-level regressions, we assessed equation (1) empirically by

using 1995-1999 patent data and by running a robust OLS regression at the assignee level

with 9,333 observations. The form of the OLS regression is $S_i = \kappa + \eta \, P_i + \varepsilon_i$, where κ is the constant and ε_i is the error. The regression also controlled for technological class fixed effects. The estimated η is 3.75, and it is significant at the 5% level of significance. The F test (F=21.15) clearly rejected the null hypothesis that $\eta = 1$. This corroborates our assumption that there is a positive bias towards self-citations in the firm citing patterns. Unfortunately we could not expand this regression analysis further because of the lack of controls for several firms in our sample of assignees. As noted in the Introduction, we preferred to work by aggregating data at the level of US States where we could obtain better and more extensive controls that may affect the propensity to self-citations.

We structured our regression model as

$$S_i \,/\, P_i = \eta_i \ \text{ with } \ \eta_i = g(\boldsymbol{x}_i) \tag{2}$$

where **x** is the vector of predictors and controls. From this specification we can aggregate by summing over all the firms in a State. Given the additive functional form, we can use averages at the US State level

$$\int_{i \in \Theta} S_i \,/\, P_i = \int_{i \in \Theta} \eta_i \tag{3}$$

where Θ is the US State where the firm is located. We hypothesize that this linear aggregation from firm to US States does not introduce any significant bias.

Before we move further we would like to address another issue. A factor that may alter the rate of self-citations is the value of the patents. If the Chandlerian firms held more valuable patents, they could cite themselves to a greater extent not because of their inward looking attitude, but because their patents are more valuable. We think that this is not a serious problem in our analysis. First, as we shall see in Section 4.2 below, we use the State R&D intensity as a control for the value of the State patents. Second, if anything, the smaller firms hold more valuable patents on average. There are theoretical reasons, i.e. the costs of patenting (e.g. patent fees, administrative costs) are relatively higher for the smaller firms,

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which encourages them to patent only more valuable innovations. There is also empirical evidence. As discussed in Section 3.1, the number of forward citations by other patents is a common proxy for patent value. A recent study by the US Small Business Administration showed that for the small firm patents the number of forward citations averaged 1.53 compared to 1.19 for the large firms (SBA, 2003). Thus, the bias on self-citations produced by the heterogeneity of patent values across organizations could go even against the propensity of the Chandlerian firms to cite themselves.

4.2 Dependent variables and predictors

As dependent variables we employ the average share of patent self-citations by US State calculated on the patents granted from 1995 to 1999 standardized by the share of firm patent on total patents. We utilize a five-year average to smooth our measure with respect to year-to-year variations.[3] The differences among US States and the propensity to self-cite for each State are stable over time, as Table 4 shows. We have 52 observations. For simplicity, we report only the results obtained by using the upper bound self-citation measure (SELF) as the dependent variable. We obtained similar results with the lower bound measure.

[Table 4 about here]

Our four key covariates are: i) the estimated alpha parameter of a Pareto distribution fitted on each State firm size distribution of firm employees (ALPHA); ii) the average of State firm size distribution (AVG); iii) the skewness coefficient of the State firm size distribution (SKEW); and iv) the State average of the firm level ratios between the number of subsidiaries of the firms and their sales (DEPT). Each measure is calculated for 2000.

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[3] Our results, however, are consistent across different sample periods, like 1996-1999 and 1997-1999.

The Pareto distribution is utilized in the literature to estimate the firm size distribution because it is a heavy-tailed distribution (Axtell, 2001). The Pareto distribution has a density function of the form

$$P(x) = \alpha \beta^{\alpha} / x^{(\alpha+1)} \qquad\qquad (4)$$

where x is a random variable such that $x > \beta$, and α and β are the distribution parameters.[4] The parameter α is the "shape" parameter. Precisely, if α decreases the right tail of the Pareto distribution becomes fatter. So, in a preliminary step, we estimated for each State the parameter α of the Pareto distribution and we used it as a predictor. This was done by performing for each of the 52 States a non-linear OLS estimation of the cumulative distribution function of (4), which takes the form $F(x) = 1 - (\beta/x)^{\alpha}$. The observations for $F(x)$ are the relative frequencies of firms of size smaller or equal to x (where x is the number of employees), while the class x is the corresponding covariate in the right-hand side of the equations. The parameters α and β are then estimated. The regression results in Table 7 do not change when α was estimated using different size aggregation levels, precisely i) bins with width increasing in the power of three; ii) ten size classes according to distribution percentiles.[5] Compared to α, AVG and SKEW are less accurate proxies for the fatness of the right tail of the firm size distribution in the States, but all three covariates are intended to measure the presence of larger firms in the State. In this respect, we use them to test Proposition 1.

DEPT is instead a measure of Chandlerian-ness that is more independent of size. Argyres (1996) used the number of subsidiaries standardized by size as a proxy of the firm divisionalization intensity, viz. an organizational property of the firms with complex layers of managers and hierarchical relationships. To adopt a conservative approach, we selected only

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[4] The β parameter is the distribution position parameter and it allows for the estimation of α controlling for the distribution mean.

[5] See for more technical details Crovella et al (1998). As they show, different levels of aggregation tend to affect the β parameter, while they do not significantly influence α.

the subsidiaries in the same State of the parent company. This rules out subsidiaries that only promote and distribute firm products in distant markets, and hence avoids that our share of subsidiaries proxy for the internationalization or the spatial spread of the companies. We then use DEPT to test Proposition 2.

As control variables, we used the population (POP) of the States in 2000 as a proxy for its size.[6] We employed the percentage of the population with a Bachelor's degree (BACH), a measure of the State supply of skill, because States with a more educated population are more likely to produce technology-based products and innovations. State R&D intensity is another control. We use the ratio between State R&D expenditures and GDP in 2000 (R&D). As noted earlier, this controls for the value (quality) of the patents in the State. The State population density (DENS) accounts for local knowledge spillovers. Firms in highly populated areas can internalize external knowledge to a greater extent because of geographical proximity. To control for State industry characteristics, we follow Ziedonis (2004) who employed the US State average capital intensity (KAP) measured as the ratio of the book value of firm plants and property and the number of employees. Table 5 summarizes our description of variables, while Table 6 shows their basic statistics.

[Tables 5 and 6 about here]

The use of panel data would not add much to our analysis. Most of our variables, both the dependent and independent variables, do not vary substantially over time, and sizable longitudinal differences would only arise in the long run. In the regressions we use a log-log specification: Dependent and independent variables are in logs.

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[6] In unreported regressions, we observed that the State population and the State GDP play the same role. For the sake of simplicity, we show only the regression with POP.

4.3 Results

Table 7 reports our regression results. Our hypotheses are supported by the data. Our proxies for Chandlerian-ness, ALPHA, AVG, SKEW and DEPT, are significant and they have the expected sign. Specifically, a lower (higher) value of ALPHA (AVG or SKEW) yields a higher share of self-citations over the share of State patents. DEPT has a positive and significant effect even when we control for the fatness of the firm size distribution through ALPHA, AVG or SKEW (see Table 7, Models II, IV and VI). In short, there is an impact of divisionalization on the inward looking behavior of the firms that is not just equivalent to firm size. The organizational dimension matters. If we keep all the other variables at their mean values, a standard deviation increase (from the mean) in ALPHA, AVG, SKEW and DEPT in models I, III, V and VII of Table 7 produce an increase in SELF of 9.6%, 4.5%, 5.4% and 2.8% respectively.

[Table 7 about here]

All the other covariates do not need any special discussion; they are employed just as controls. But one interesting result, when significant, is that the share of population with a bachelor degree, as a proxy for human capital in the State, has a negative impact on the dependent variable. One explanation is that people with higher human capital are more likely to search for knowledge inputs from external sources rather than looking primarily at their experience within their organizations. Interestingly enough, the R&D intensity has a slightly significant impact on self-citations only in one regression out of seven. This suggests that there is no strong impact of a measure of the potential value of patents on the dependent variable. Probably, the aggregation at the State level flattens the effects of the value of patents on self-citations.

5. Conclusions

This paper investigated the relationships between firm organization attributes, namely a structure *á la* Chandler, and their inward looking/exploitation attitude in the development of innovations. By using US State level data, we found that the US States with a fatter right tail of their firm size distribution display on average a higher share of patent self-citations normalized by the patents attributed to the State. Moreover, even after controlling for the effects of firm size, a proxy for the extent of the divisionalization of the firms in the State displays a significant effect on patent self-citations, which suggests that organizational factors are also important.

By building upon previous studies in the literature, we provide some explanations for these stylized facts. First, size implies greater sunk costs at the level of individual projects, and a greater number of projects that can give rise to economies of scope in related trajectories of diversification. Scale economies, learning processes, and spillovers across similar projects provide a greater encouragement to persist on similar product or technological trajectories. Second, the Chandlerian decision process, based on managerial hierarchies, is such that the decision to carry out projects in known areas tends to be favored vis-à-vis the decision to launch new projects. Thus, our results strongly support the view that organization design shapes the long run behavior of firms. Especially for the large firms this is key to understand the question of their inertia pointed out by the literature. Incidentally, the government of the firm human resources should deal with the top managers overly dependence on their consolidated mental models (e.g. through top managers rotation, or training), especially in organization that are vertically structured (Hodgkinson, 1997). The paper also sheds new light on some empirical regularity that until now have received little attention, namely the under-studied portion of patent citations – self-citations – as instruments to proxy for intra-firm technological competences and spillovers.

Our findings encourage additional research in several directions. We could not perform a firm level analysis because of the lack of data especially for small unquoted firms. But relating self-citation intensity with firm size and firm-level organization measures and controls is the direction to go, provided that suitable data at this level can be collected. Moreover, we proposed two explanations to motivate the inward looking attitude of Chandlerian firms. Future work matching firm controls, along with patent, inventor and regional data, could provide a better assessment of these two explanations, along with greater and more specific details about them. It can also provide a richer set of explanations than we were able to do in this paper.

References

Abernathy, W.J. (1978). *The Productivity Dilemma*, John Hopkins University Press, Baltimore.

Argyres, N. (1996). 'Capabilities, technological diversification and divisionalization, *Strategic Management Journal*, **17**(5), 395-410.

Arrow K.J. (1983) 'Innovation in large and small firms', in Ronen J. (ed.) *Entrepreneurship*, Lexington MA: Lexington Books.

Arrow, K.J. (1974). *The Limits of Organization*. Norton&Company, New York.

Arrow, K.J. (1975). 'Vertical integration and communication', *Bell journal of Economics*, **6**, 173-183

Axtell R.L. (2001) 'Zipf distribution of US firm sizes', *Science*, 293 (5536): 1818-1820.

Burgelman R.A. (1994). 'Fading memories: a process theory of strategic business exit in dynamic environments', *Administrative Science Quarterly*, **39**(1), 24-56.

Business Week. (2004). 'What Big Pharma Could Learn from the Pipsqueaks', **38**(84),6-7

Chandler, A.D. (1977). *The Visible Hand: the Managerial Revolution in American Business*, Cambridge University Press, Cambridge, MA.

Chandler, A.D. (1980). 'The United States seedbed of managerial capitalism', in Chandler A.D. and Daems H. (eds), *Managerial Hierarchies*, Harvard University Press, Cambridge, MA

Christensen, C. (1997). *The Innovator's Dilemma* Harvard Business School Press, Boston.

Crovella M.E., Taqqu M.S., Bestavros A. (1998) 'Heavy-Tailed probability distributions in the World Wide Web', in Adler R., Taqqu M. S. and Feldman R (eds), *A Practical Guide to Heavy Tails*. Birkhauser Boston, 3–25

Danneels, E. (2002). 'The dynamics of product innovation and firm competences', *Strategic Management Journal*, **23**(2), 1095-1121

Dougherthy, D. and Heller, T. (1994). 'The illegitimacy of successful product innovation in established firms', *Organization Studies*, **5**(2), 200-218.

Eberhart A.C., Maxwell W.F. and Siddique A.R. (2004). 'An examination of long-term abnormal stock returns and operating performance following R&D increases', *Journal of Finance*, **59**(2), 623-650

Economist (the). (2004). 'Fixing the drugs pipeline', 4 March, 88-89

Finkelstein S., Hambrick D. 1988. *Strategic Leadership: Top Executives and Their Effects on Organizations*, West Minneapolis.

Floyd S.W. and Wooldridge B. (1997). 'Middle management's strategic influence and organizational performance', *Journal of Management Studies*, **34**(3), 465-485.

Ghemawat P. (1991). 'Market incumbency and technological inertia', *Marketing Science*, **10**, 161-171

Gittelman M. and Kogut B. (2003). 'Does good science lead to valuable knowledge? Biotechnology firms and the evolutionary logic of citation patterns', *Management Science*, **49** (4), 366-382

Hall, B. H., A. B. Jaffe, and M. Tratjenberg. (2001). 'The NBER patent citation data file: lessons, insights and methodological tools'. NBER Working Paper 8498.

Halliday R.R.G., Drasdo A.A.L., Lumley C.C.E., Walker S.S.R. (1997) 'The allocation of resources for R&D in the world's leading pharmaceutical companies', *R&D Management*, 27(1): 63-77.

Harhoff D., Narin F., Scherer F.M., Vopel K. (1999). 'Citation frequency and the value of patented inventions', *Review of Economics and Statistics*, **81** (3), 511-515

Henderson R., Cockburn I. (1996) 'Scale, scope, and spillovers: The determinants of research productivity in drug discovery', *Rand Journal of Economics*, 27 (1): 32-59

Henderson, R. (1993). 'Under-investment and incompetence as responses to radical innovation: evidence from the photolithographic alignment equipment industry', *Rand Journal of Economics*, **24**(2), 248-270.

Hodgkinson G.P. (1997). 'Cognitive inertia in a turbulent market: The case of UK residential estate agents', *Journal of Management Studies*, **34**(6), 921-945.

Holmstrom, B. (1989) 'Agency costs and innovation', *Journal of Economic Behavior and Organization,* **12** (3), 305-327

Jaffe A.B., Trajtenberg M., Henderson R. (1993). 'Geographic localisation of knowledge spillovers as evidenced by patent citations', *Quarterly Journal of Economics*, **10**, 577-598.

Kaplan S., Murray F. and Henderson R. (2003). 'Discontinuities and senior management: assessing the role of recognition in pharmaceutical firm response to biotechnology', *Industrial and Corporate Change*, **12** (2), 203-233.

Krishnan V. and Ulrich K.T. (2001). 'Product development decisions: A review of the literature', *Management Science*, **47** (1), 1-21

Levinthal, D. and March, J. (1993). 'The myopia of learning', *Strategic Management Journal*, **14**, 95-112.

Loch C.H., Terwiesch C. and Thomke S. (2001). 'Parallel and sequential testing of design alternatives', *Management Science*, **47**, 663-678

March, J. (1988). *Decisions and Organizations*, Basic Blackwell, New York.

Mowery D.C., Oxley J.E. and Silverman B.S. (1998). 'Technological overlap and inter-firm cooperation: implications for the resource-based view of the firm', *Research Policy*, **27** (5), 507-523.

Nelson R.R. (1961). 'Uncertainty, learning and the economics of parallel research and development efforts', *Review of Economics and Statistics*, **43**, 351-364

Nelson R.R. (1982). 'The role of knowledge in R&D efficiency', *Quarterly Journal of Economics*, **13**, 453-470

Sah R. and Stiglitz J. (1988). 'Committees, hierarchies and polyarchies', *Economic Journal*, 98: 451-470

Saxenian A. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*, Harvard University Press, Boston MA

SBA –United Stated Small Business Administration. (2003). 'Chi-Research's report: small serial innovators: the small firm contribution to technical change', **225** (3) February.

Teece, D.J., Rumelt, R., Dosi, G., and Winter, S. (1994) 'Understanding corporate coherence: theory and evidence', *Journal of Economic Behavior and Organization* 23, 1-30.

Trispas M. and Gavetti G. (2000). 'Capabilities, cognition, and inertia: evidence from digital imaging', *Strategic Management Journal*, **21**, 1147-1161

Ziedonis, R. (2004). 'Don't fence me in: fragmented markets for technology and the patent acquisition strategies of firms', *Management Science*, **50**(6), 804-820.

Table 1: Share of self-citations per assignee, 1980-99

Year	Upper bound			Lower bound		
	Average	Stand.Dev	Skewness	Average	Stand.Dev	Skewness
1980-89	0.075	0.177	0.019	0.045	0.111	0.013
1990	0.060	0.151	0.014	0.041	0.108	0.012
1991	0.067	0.161	0.014	0.046	0.117	0.012
1992	0.063	0.148	0.014	0.043	0.106	0.012
1993	0.065	0.154	0.013	0.045	0.112	0.011
1994	0.062	0.145	0.012	0.044	0.108	0.010
1995	0.064	0.142	0.011	0.045	0.107	0.010
1996	0.065	0.151	0.011	0.047	0.113	0.010
1997	0.066	0.146	0.010	0.047	0.110	0.009
1998	0.061	0.143	0.011	0.045	0.109	0.010
1999	0.062	0.143	0.010	0.046	0.110	0.009

Source: Our elaboration on NBER Patent Database

Table 2: Top assignee in the largest 15 USPTO technological classes in terms of patent granted, their share of self-citations in the class, and the average share of self-citations of all the assignees in the class (averages 1995-1999)

USPTO Class	Top assignee (1)	Patent share of (1) on total patents in the class	Self Upper Bound of (1) in the class	Self Lower Bound of (1) in the class	Self Upper Bound, all assignees in the class	Self Lower Bound, all assignees in the class
73	General Electric	0.019	0.361	0.326	0.086	0.071
210	Pall Corp.	0.021	0.263	0.212	0.110	0.090
257	IBM	0.092	0.260	0.249	0.130	0.126
280	Morton Int.	0.075	0.178	0.167	0.107	0.085
340	Motorola	0.056	0.323	0.308	0.116	0.099
345	IBM	0.148	0.230	0.209	0.098	0.093
361	IBM	0.061	0.260	0.249	0.109	0.100
424	Procter & Gamble	0.044	0.327	0.292	0.146	0.132
428	Minnesota Mining	0.063	0.380	0.315	0.173	0.153
435	Incyte Pharma	0.029	0.121	0.120	0.119	0.103
438	Micron Tech.	0.130	0.182	0.178	0.122	0.119
514	Eli Lilly	0.059	0.461	0.437	0.224	0.211
600	H&P	0.025	0.338	0.326	0.084	0.071
604	Procter & Gamble	0.049	0.327	0.292	0.110	0.087
606	US Surgical Corp.	0.048	0.247	0.190	0.087	0.063
	Average	0.055	0.288	0.262	0.122	0.108
	Stand. Dev.	0.030	0.090	0.083	0.035	0.037

Source: Our elaboration on NBER Patent Database

Table 3: Firms with more than 2,500 employees by US State in 2000

	Average	Dev. Stand.	Skewness	Min	Max
Number of firms	140.66	169.15	1.71	0	686
Number of subsidiaries	1260.17	1943.13	2.36	0	9,697

Source: Our elaboration on Bureau van Dijk's ORBIS Database

Table 4: Average share of self-citations by US State, 1995-1999

	Years					
	Upper Bound					
	1995	1996	1997	1998	1999	1995-99
Average	0.115	0.116	0.121	0.112	0.11	0.114
Dev. Stand.	0.046	0.049	0.053	0.041	0.114	0.038
Max	0.251	0.242	0.333	0.229	0.214	0.234
Min	0.008	0	0.019	0.011	0.028	0.038
	Lower Bound					
Average	0.095	0.098	0.103	0.096	0.094	0.097
Dev. Stand.	0.044	0.043	0.045	0.038	0.038	0.035
Max	0.224	0.218	0.285	0.21	0.203	0.21
Min	0.007	0	0.024	0.011	0.032	0.033

Source: Our elaboration on NBER Patent Database

Table 5: Description of variables

Label	Description
Dependent variables	
SELF	Average share of self-citations calculated on 1995-1999 patents granted by US State divided by the average share of State patents on total patent (upper bound). (State patent = first inventor located in the State.)
Predictors	
ALPHA	Estimated alpha parameter of a Pareto distribution for each State firm size distribution measured by employees
AVG	First moment of the State firm size distribution measured by employees in 2000
SKEW	Skewness coefficient of the State firm size distribution measured by employees in 2000
DEPT	State average of the ratio between the number of subsidiaries in the same State and the sales of the firm, in 2000
Controls	
POP	State population in 2000
DENS	State population per square mile in 2000
KAP	State average industry capital intensity, measured as the ratio between book value of plant and property and number of employees in 2000
BACH	Share of State population with a Bachelor degree in 2000
R&D	State R&D expenditures over GDP in 2000

**Table 6: Dependent variables and predictors, basic statistics**

Variable	Obs.	Mean	Std. Dev.	Min	Max
SELF	52	61.51	30.70	2.69	197.42
ALPHA	52	0.511	0.022	0.453	0.574
AVG	52	119.17	47.45	49.17	296.18
SKEW	52	23.54	3.52	14.93	32.26
DEPT	52	0.008	0.005	0	0.02
POP	52	5,317,631	6,239,022	493,792	35,100,000
DENS	52	365.64	1,289.93	0.55	9,378.02
KAP	52	4.12	1.17	1.45	15.07
BACH	52	0.24	0.04	0.14	0.39
R&D	52	0.018	0.016	0.00	0.086

Table 7: Regression results, dependent variable share of self-citations upper bound, robust OLS (52 observations)

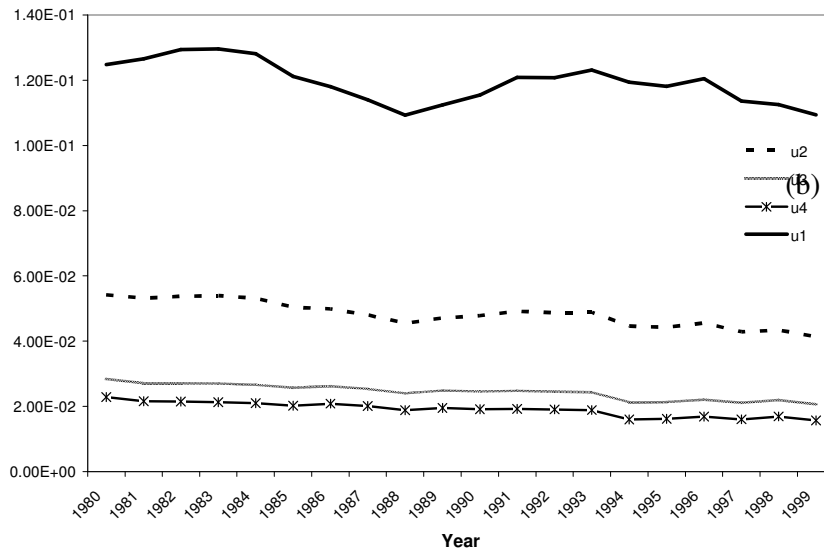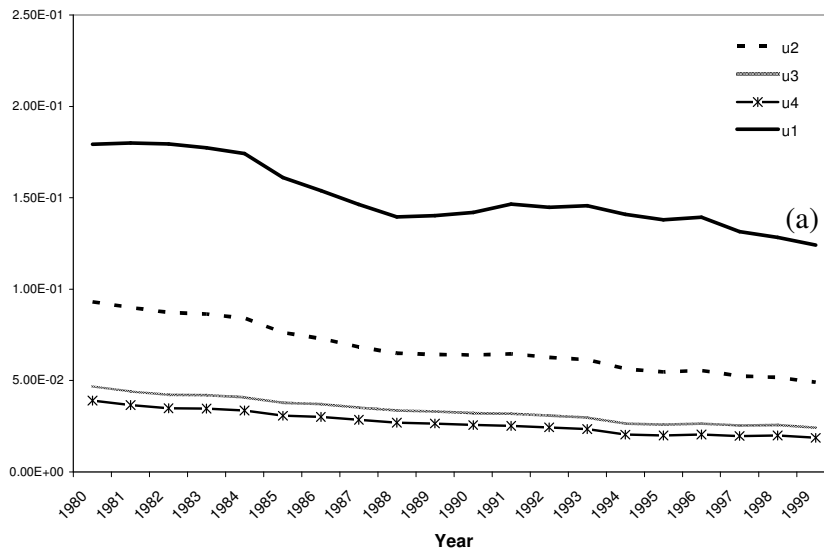|	Models						
	I	II	III	IV	V	VI	VII
ALPHA	-2.727**	-2.439**					
	(0.821)	(0.840)					
AVG			0.223**	0.205**			
			(0.096)	(0.094)			
SKEW					0.426**	0.377**	
					(0.162)	(0.162)	
DEPT		134.513*		185.76**		164.414*	206.73**
		(78.834)		(91.672)		(88.220)	(103.234)
BACH	-1.830	-2.757*	-2.706 *	-3.827 **	-2.811 *	-3.812 **	-4.354 **
	(1.501)	(1.635)	(1.539)	(1.615)	(1.510)	(1.603)	(1.662)
DENS	0.048	0.039	0.018	0.011	0.042	0.033	0.004
	(0.036)	(0.036)	(0.036)	(0.035)	(0.037)	(0.037)	(0.037)
KAP	-4.354	-1.843	4.994	5.930	1.617	3.610	21.453**
	(10.311)	(10.380)	(10.130)	(9.875)	(10.369)	(10.252)	(7.102)
R&D	0.063	0.073*	0.029	0.049	0.038	0.054	0.028
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
POP	0.132**	0.119**	0.028	0.023	0.009	0.009	0.057
	(0.052)	(0.053)	(0.053)	(0.052)	(0.055)	(0.053)	(0.052)
CONS	-7.023**	-6.569**	-4.839 **	-4.525 **	-4.781 **	-4.514 **	-4.576**
	(0.998)	(1.044)	(0.819)	(0.815)	(0.808)	(0.810)	(0.848)
R-Sq.	0.304	0.396	0.300	0.350	0.321	0.359	0.280

Notes: Heteroskedastic-consistent standard errors in parentheses. * 0.10 and ** 0.05 level of significance.

Graph 1: Share of self-citations (upper and lower bound), patent per assignee and total citations per patents, 1980-1999
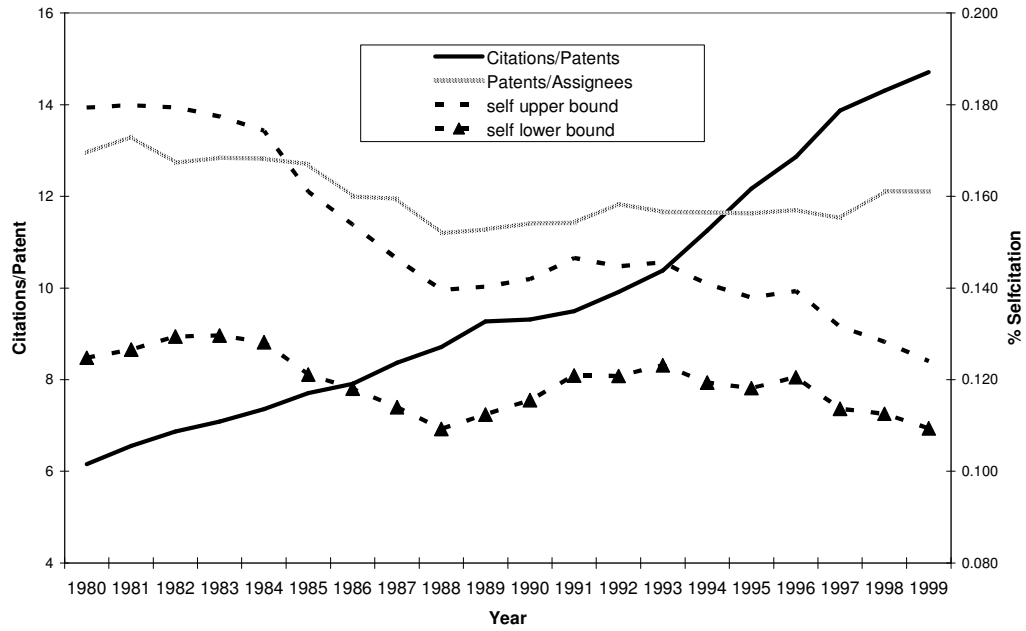
Source: Our elaboration on NBER Patent Database

Graph 2: First four moments for upper bound (a) and lower bound (b) share of self-citations

Source: Our elaboration on NBER Patent Database