Memo on Inventor Allocation

July 19, 2021

Abstract

Inventors are a scarce resource, whose skill sets can apply to R&D in disparate product markets. Motivated by this observation, I explore the impact of product market competition on the allocation of inventors, and its implications for growth. First, I delineate the boundaries of "inventor markets" , employing Compustat data and inventors flows assembled from USPTO PatentsView data to group NAICS sectors that employ the same inventors. Second, I analyze the relation between 4-digit NAICS sectors market concentration and the share of inventors employed in R&D projects relevant to these sectors. Two facts emerge from my preliminary analysis. First, the last thirty years saw a sizable increase in concentration of scientists across both patent (CPC) classes and their 4-digit sector of application. Second, over the period 1997-2012, increases in sector-level concentration are positively correlated with the share of inventors' market captured by each sector.

1 Rough project scheme

1. Data:

   (a) Sources:

      i. Compustat data matched with PatentsView through Arora et al's (2021) DISCERN dataset

      ii. all patents (PATSTAT), classified by Zolas et al. (2016) at the Census into NAICS 6d, who kindly shared non-published data with me,

      iii. Xwalk between PATSTAT and PatentsView (my main source), I can match 30% of patents to classification above

      iv. Census measures of concentration at NAICS 4d, unfortunately just about 60 sectors, and 5-year intervals

      v. Mercatus count of market restrictions at NAICS 4d to instrument for increase in concentration above (is the exclusion restriction satisfied?)

   (b) Data constructed:

      i. Grouping of sectors in inventor markets using observed inventor flows across Compustat firms

      ii. Inventor productivity on all patents assigned to companies, public or not, as the sum of inventor's patents per capita or their average over time

      iii. Inventor productivity as the inventor fixed effect α_i from either of the regressions:

$$\#\text{Patents}_{cfit} = \alpha_i + \alpha_{cft} + \varepsilon_{cfit} \tag{1}$$

$$\#\text{Patents}_{cfit} = \alpha_i + \alpha_{cf} + \alpha_{ct} + \alpha_{ft} + \varepsilon_{cfit} \tag{2}$$

      at the level of CPC (Cooperative Patent Classification) class, c, assignee/company, f, inventor i and year t. I prefer 1, but clearly 2 allows the identification of more fixed effects. All these measures are strongly correlated, which is reassuring.

      iv. Concentration measures of inventor productivity by Gini in different CPC classes and NAICS 4d as mapped from above

   (c) Findings:

      i. Inequality in effective inventors across CPC classes as well as NAICS 4d, as measured by the relevant Gini has increased substantially

ii. Long-difference regression for 1997-2012 for share of effective inventors (fixed effects) over Census concentration measure, with knowledge markets fixed effects, report positive and significant coefficients, weighted by sector sales. Similar finding when using Mercatus product-specific restrictions as instruments.

2. Theory:

   (a) Basic idea: concentration creates incentives to hoard inventors:

      i. Explored several alternatives: step-by-step, simple cournot, multi-sector growth models; here the mechanism is driven by individual firm's market size;

      ii. Currently thinking about a mechanism based on defensive patenting, whose incentive should grow with concentration; step-by-step is inadequate as it has the opposite prediction (more R&D in less concentrated markets).

3. Steps forward:

   (a) Empirical part:

      i. Control for the effect of sector size growth

      ii. Look at changes in dispersion of inventors within the sectors that become more concentrated: do inventors go to leaders or followers?

      iii. Explore effect on total innovation within these markets as well as individual patenting productivity

      iv. Link this concentration with forward citations?

   (b) Theory part:

      i. Check out/ build a model of defensive patenting (I found today Karam Jo's 2019 JMP which seems interesting in this respect)

2 Data updates

2.1 Data Sources

My new data consists of five main elements. The first is the complete set of PatentsView utility patents that have as assignee a company (I could do all but this seemed most reasonable). The second is a mapping constructed by Zolas et al. (2016) between PATSTAT patents and NAICS 6-digit sectors through text analysis. The third is a crosswalk between PATSTAT application ID and patent ID in PatentsView built by Gianluca Tarasconi in 2019 (http://rawpatentdata.blogspot.com/2019/). Thus is a ready-made alternative to digging into PATSTAT. I could not find the documentation but it does allow to match about 30% of the PatentsView patents to those analyzed by Zolas.[1] The fourth is the set of concentration measures for the US Economic Census for 1997-2002-2007-2012. I can extend to 2017 but have not done it yet. The fifth is the Mercatus QuantGov database of counts of product restrictions from legislative sources from 1970-2020.

2.1.1 Data limitations

There are two main issues with the data, which emerge primarily in the regression analysis. First, the time frame is strongly limited. Zolas et al. classified patents only to 2016, the closest available economic census is 2017, and most importantly, there are no NAICS 4d concentration measures before 1997 outside manufacturing, and even the ones available afterwards cover only a subset of around 80 sectors, which include predominantly manufacturing. Second, the QuantGov database covers a non overlapping subset of 4-digit sectors, so that I can do IV only on 39 observations, but that is perhaps ok. I tried using regulations at 3-digits, but that is a very poor instrument for concentration changes at 4-digit. I could recover 5 observations by re-building the knowledge markets on all patents, rather than the Compustat set.

[1] I suspect that the small matching rate is due to the fact that PATSTAT has all applications, even those that do not necessarily result in a patent, or that do so with substantial lag. Further the two dataset do not overlap fully in general. I shall contact the author and dig more into the details perhaps.

2.2 New computations of effective scientists

As discussed above, I compute inventor productivity as the inventor fixed effect α_i from either of the regressions:

$$\#\text{Patents}_{cfit} = \alpha_i + \alpha_{cft} + \varepsilon_{cfit} \tag{3}$$

$$\#\text{Patents}_{cfit} = \alpha_i + \alpha_{cf} + \alpha_{ct} + \alpha_{ft} + \varepsilon_{cfit} \tag{4}$$

at the level of CPC (Cooperative Patent Classification) class, c, assignee/company, f, inventor i and year t. I prefer 3, but clearly 4 allows the identification of more fixed effects. All these measures are strongly correlated, which is reassuring. I compute it for various levels of the CPC classification (1, 3, 4 digits). I also compute an alternative measure as in the presentation, that is the number of patents per capita by each inventor in each year. I compute both an average productivity as well as the total number of effective patents. The correlation between all these measures is quite high, which is reassuring. My preferred measure is the α_i from 3, at the CPC level 1, the most aggregate level for patents. The reason is that I still fully saturate, but I can identify a lot more fixed effects than narrower classification. From my checks the measures are pretty close when they are both computed.

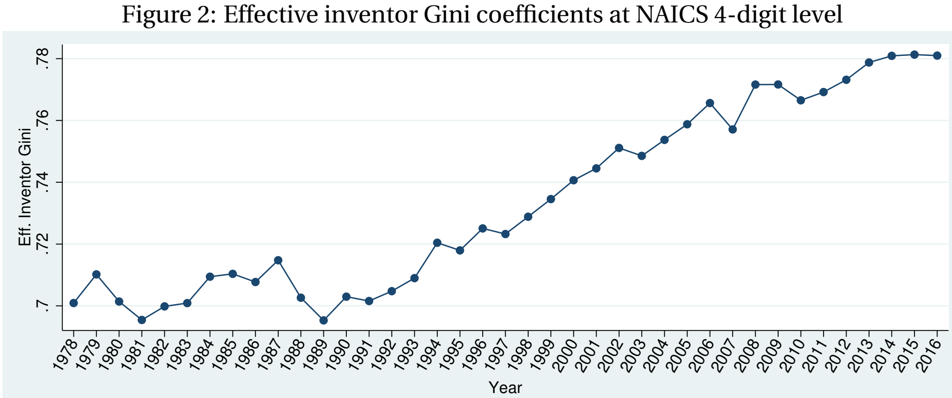
2.3 Increase in concentration across patent classes and Naics sectors

Given the above construction, I look at two things. First, I compute Gini coefficients of effective inventors, α_i (shifted to be nonnegative) across patent classes. This is reported in Figure 1. When looking outside Compustat only, the levels of concentration are more reasonable, and so is the increase.

Second, I use the subset of patents classified by Zolas (which ends in 2016) that I can match to PatentsView. This is shown in Figure 2. In both cases the coefficient increased by about 10% from 1978.

Figure 1: Effective inventor Gini coefficients at CPC-4 level

Figure 2: Effective inventor Gini coefficients at NAICS 4-digit level



2.4 Scatters and Regressions of Competition and Inventor share

The next step is computing the inventor shares of various sectors from above. To do so, I match the data above with the knowledge markets computed on NAICS 3-digits from Compustat. I see this as a first pass, while I construct more precise markets from the classified company patents, which will hopefully be at 4-digit. I then compute the share of effective inventors for each 4-digit NAICS, and run a long-difference specification between 1997-2012, weighted by Census-reported sales, and residualized by knowledge market:

$$\Delta \text{Share}_{pk} = f_k + \beta \Delta \text{Concentration}_p + \varepsilon_{pk}.$$

In a second analysis, I instrument the concentration change by the change in the number of NAICS 4-digit specific restrictions from Mercatus. I think the exclusion restriction is reasonable, although increase in product regulations might also increase the need to develop appropriate technologies and thus drive up the inventor share. However, I do not think that this effect ought to be major. Table 1 reports the results of the OLS ad IV regression. As I noted above, the Mercatus regulation measure is only available for a subset of sectors, so the sample is greatly reduced in the IV estimation. Two results stand out. First, the OLS specification shows a significant and positive effect, an increase of 1pp in the top 4 share in a NAICS 4-digit market results in an increase of 0.03pp in that sector's share of the relevant inventors.[2] Moving to the IV, the coefficient is reduced by about a third. I think this is reasonable in light of the reverse causality that logically exists between changes in concentration and inventors. The F-statistic is rather low, so I might want to look at Anderson-Rubin confidence intervals in the future. Graphically, Figure 3 displays a binscatter of changes residualized by knowledge market fixed effects (I made sure that the estimated slope holds when winsorizing at 1% as well).

Table 1: Long-differences specification, 1997-2012

	(1) OLS Change Share Inventors	(2) IV Change Share Inventors
Change Top-4 Sale Share	0.0338**	0.0201*
	(0.0164)	(0.0104)
Constant	-0.351*	
	(0.199)	
Observations	80	34
R-squared	0.212	0.032
K-market FE	Yes	Yes
First-stage F		12.75
AR Wald p-val.		0.0192

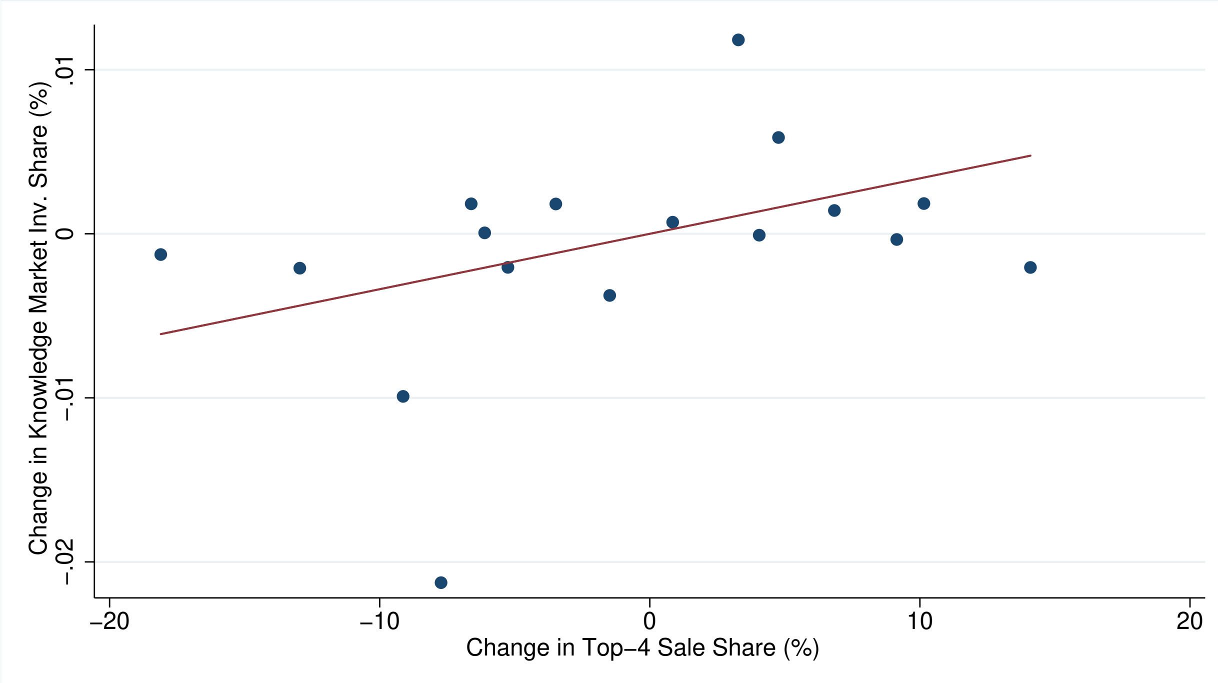
Regression weighted by total sales in 2012. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3 A simple cournot model

Here I present a very simple two Cournot-Nash game, where firms can choose quantity as well as hiring of R&D labor. The market size facing the individual firm seems to be the main driver of the results that more concentrated sectors hire more inventors. I also present a two-stage game where firms conduct extra strategic R&D, however this is not the defensive kind discussed above, and size remains the predominant factor.

[2] This effect might seem small, but it is important to consider that the largest inventor market can encompass as many as 40 sectors, in which case an even split of inventors across markets would result in a share of 2.5pp per sector. In this scenario a 1pp increase in the top-4 share would increase the inventor share by about 1%. Another way to get a sense of the magnitude is considering that the coefficient is 10% of the constant and that the (within) R-squared is around .21.

Figure 3: Binscatter of 1997-2020 change in inventor share over changes in NAICS 4-digit top-4 sale share



Note: Regression line estimated weighting by total sales in 2020.

In what follow, I solve the problem of a single sector with N firms that are Cournot competitors. I assume an isoelastic demand for the good produced by the sector:

$$Q = P^{-\varepsilon}, \quad \varepsilon > 1$$

The production function is linear in labor, so the firm i's operating profits are:

$$\pi_i = Pq_i - \tilde{c}_i w q_i,$$

where P is the good's price, w is the production wage and $\tilde{c}_i$ is the firm's labor requirement per unit of output. This labor requirement is determined as:[3]

$$\tilde{c}_i = \frac{c}{(1+x_i)^{\gamma}} \quad \gamma(\varepsilon - 1) < 1,$$

where x_i is the firm's R&D labor. Each R&D worker commands a wage w^{RD} so total profits are given by:

$$\pi_i - w^{RD} x_i.$$

There are two ways of setting the problem. The first assumes that R&D labor and quantity are set in the same period. The second assumes that the game has two stages. First, firms choose R&D spending taking other firms' spending as given, and then they play a Cournot quantity game. The resulting demands for R&D are different but both setups give the desired result.

[3]The condition on γ is required to have a downward sloping demand for R&D labor.

3.1 One-stage game

Firms choose R&D and quantities simultaneously, taking others' quantities and R&D as given:

$$\begin{aligned} \max_{q_i, x_i} \quad & q_i \left[P - \tilde{c}_i w\right] - w^{RD} x_i \\ \text{s.t.} \quad & \tilde{c}_i = \frac{c_i}{(1+x_i)^\gamma}, \; \gamma(\varepsilon - 1) < 1 \\ & P = \left(\sum q_i\right)^{-\frac{1}{\varepsilon}} \end{aligned}$$

This gives the system of equations:

$$P\left[1 - \frac{s_i}{\varepsilon}\right] = \tilde{c}_i w, \quad \forall i, \tag{5}$$

$$\sum s_k = 1,$$

$$\gamma \frac{c_i}{(1+x_i)^{1+\gamma}} w q_i = w^{RD}, \quad \forall i, \tag{6}$$

with $s_i = q_i/Q$. The set of equations 5 implies:

$$P^\star = \frac{\varepsilon}{\varepsilon N - 1} \sum_{i=1}^{N} \tilde{c}_i w \tag{7}$$

and corresponding quantities:

$$q_i^\star = P^{\star - \varepsilon} \left[\varepsilon - (\varepsilon N - 1) \frac{\tilde{c}_i}{\sum_{j=1}^N \tilde{c}_j}\right] \tag{8}$$

This general solution can be explored further assuming that the N firms are symmetric, $c_i = c$ for all i. In this case the equilibrium quantities and R&D are jointly determined by he system:

$$q^\star = \frac{1}{N}\left[\frac{\varepsilon N}{\varepsilon N - 1} \frac{c_i}{(1+x^\star)^\gamma} w\right]^{-\varepsilon}, \tag{9}$$

$$\frac{w}{w^{RD}} \gamma c_i q_i = \left(1 + x_i^\star\right)^{1+\gamma}. \tag{10}$$

Finally yielding:

$$x^\star = \left(\frac{\varepsilon N - 1}{\varepsilon N}\left[\frac{\varepsilon N}{\varepsilon N - 1} w c\right]^{1-\varepsilon} \frac{1}{N} \frac{\gamma}{w^{RD}}\right)^{\frac{1}{1-\gamma(\varepsilon-1)}} - 1 \tag{11}$$

In this model, equilibrium R&D labor is an increasing function of the quantity produced by the individual firm. Thus, ceteris paribus, it decreases with a larger markup, $\frac{\varepsilon N}{\varepsilon N - 1}$, and with the number of firms N. This inevitably gives rise to negative duplication effects in more competitive (larger N) markets, which mechanically results in R&D being more productive in less competitive environments. As a result, when doing simulations, I assume that aggregate R&D, X, spills over to individual firms, who take aggregate R&D as given :

$$\tilde{c}_i = \frac{c_i}{\left(1 + x_i + \alpha \frac{(N-1)^\xi}{N} X\right)^\gamma}. \tag{12}$$

In the simulations below I assume full spillovers, $\alpha = \xi = 1$, so that there is no waste from duplication. Solving the problem with this specification gives gives individual R&D:

$$x^\star = \frac{1}{N}\left[\left(\frac{\varepsilon N - 1}{\varepsilon N}\left[\frac{\varepsilon N}{\varepsilon N - 1} w c\right]^{1-\varepsilon} \frac{1}{N} \frac{\gamma}{w^{RD}}\right)^{\frac{1}{1-\gamma(\varepsilon-1)}} - 1\right],$$

so that aggregate R&D corresponds to individual R&D without spillovers.

3.2 Two-stage game

In this solution, firms play Cournot in period 2, and choose R&D strategically in period 1. The problem in period 1 is then:

$$\begin{aligned}
\max_{x_i} \quad & q_i \left[P - \tilde{c}_i w\right] - w^{RD} x_i \\
\text{s.t.} \quad & q_i = q_i^\star(x_i, x_{-i}),\; P = P^\star(x_i, x_{-i}) \\
& \tilde{c}_i = \frac{c}{(1+x_i)^\gamma},\; \gamma(\varepsilon - 1) < 1,
\end{aligned}$$

where $q_i^\star, P^\star$ denote the Cournot equilibrium price and quantities given R&D choices. Assuming symmetry and full spillovers we get individual R&D:

$$x^\star = \frac{1}{N}\left[\left(\left(\frac{\varepsilon N - 1}{\varepsilon N} + \frac{N-1}{N}\left[1 - \frac{1+\varepsilon}{\varepsilon N}\right]\right)\left[\frac{\varepsilon N}{\varepsilon N - 1} wc\right]^{1-\varepsilon} \frac{1}{N}\frac{\gamma}{w^{RD}}\right)^{\frac{1}{1-\gamma(\varepsilon-1)}} - 1\right] \tag{13}$$

Thus, firms conduct more R&D than in the one-stage game. This extra "strategic" R&D in equilibrium is governed by the term:

$$S \equiv \frac{N-1}{N}\left[1 - \frac{1+\varepsilon}{\varepsilon N}\right],$$

which is unsurprisingly 0 when the firm is a monopolist, $N = 1$, and increases towards 1 as N grows.

3.3 Simulation

The following graphs display the properties of main aggregates in a set of alternative economies with different numbers of firms. Note that here I am setting a given wage for production and R&D workers and looking at sector demands for R&D and ensuing equilibrium quantities, growth and marginal product of inventors, computed as:

$$MP(X^*) = \frac{\partial Q(X^*)}{\partial X},$$

further note that in this model, sector growth is just:

$$g = \mathrm{d}\log Q(X^*) = \gamma\varepsilon \log(1 + X^*).$$

Figure 4 displays the main quantities of interest relative to their value under monopoly, for both the one-stage and two-stage games. Both feature qualitatively similar features, although the two-stage game has a higher value of R&D due to the strategic interaction between firms. This strategic effect is reponsible for the hump in total R&D, output and growth in the respective panels. The concavity of sectoral R&D returns in turn implies that growth per inventor and marginal products increase with the number of firms, since demand for inventors falls with the number of firms. It is evident from the first-order condition 10 that R&D is decreasing in the number of firms due to a market-size effect. The more firms are active, the lower the fraction of the market captured by the individual firm, and the lower its incentive to conduct R&D. Figure 5 reports the case where I assume that there are no spillovers across firms. As is evident from the botton-middle panel here duplication kicks in after a point, reducing total growth per inventor. Of course all these results are for an illustrative calibration just to highlight the properties of the model and should not be taken too seriously.

Figure 4: Equilibrium Objects, Index Relative to Monopoly, No Duplication of R&D

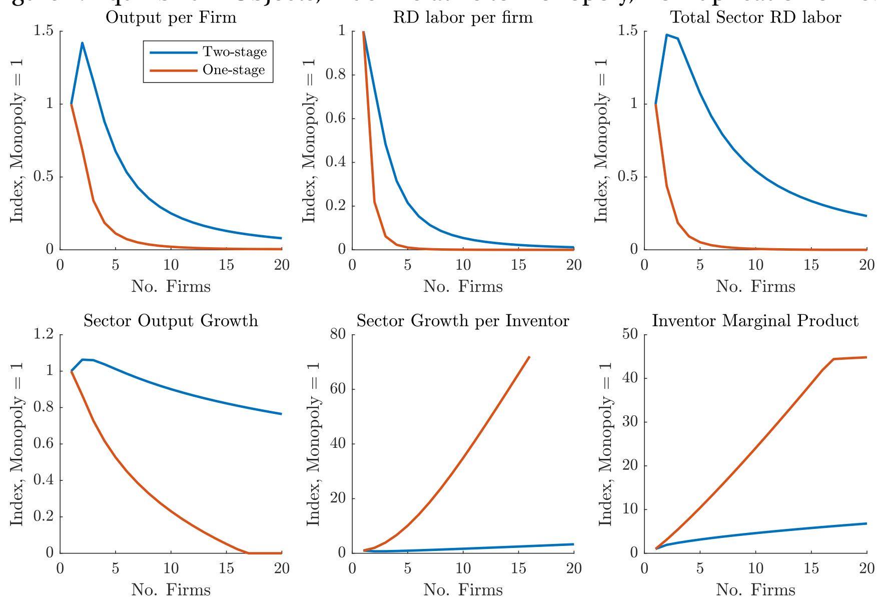


Figure 5: Equilibrium Objects, Index Relative to Monopoly, Duplication of R&D