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Aggregate Innovation Fluctuations and Complementary Ideas

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Abstract

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Aggregate Innovation Fluctuations and Complementary Ideas

Preliminary Analysis

March 20, 2012

Abstract

Patents are frequently used to measure innovation, but their dramatic increase since the mid-eighties has brought this claim into question. I argue they still serve this function, despite what appears to be a negative relationship between patents and a standard measure of patent quality. Surprisingly, patent number and quality are unrelated within industries. The aggregate and disaggregated relationships differ, because innovation is highly correlated across industries. A multi-sector innovation model with heterogeneous idea quality is constructed to explain these observations. New ideas in one sector alter the returns to developing ideas in complementary sectors, and endogenously change the marginal ideas used in innovation throughout the economy. Empirical support is provided that the relationships across industries strengthen with complementarities. Large innovation changes in less-innovative industries are found to be responsible for the negative aggregate relationship in the short-run. The model is calibrated to match cross-industry innovation differences and changes in patenting are argued to be significant for long-run economic growth.

1 Introduction

Patent rights are extended to reward innovation, and as a result the number of patents is argued to be a good innovation measure. There is increasing concern however, that recent changes to the U.S. intellectual property regime are actually discouraging innovation. Many scholars and practitioners believe the increased value of patents in legal disputes, have led to the filing of many low-quality patents. In order to assess the recent patenting surge though, one must consider the quality of ideas used in innovation. A negative relationship can also occur if the innovation process beings to select "lower-quality ideas" as demand increases. In either case, a negative relationship implies that measured innovation changes are larger than any actual changes. I find evidence of such a relationship, but argue instead that it results from innovation being correlated throughout the economy. More importantly, these results suggest that changes in patenting activity likely have important consequences for economic growth.

Although the aggregate number of patents and their average quality is negatively related at the aggregate level, this strong relationship disappears within industries. (See Figure 1 and Table 1.) This is puzzling, because the differing relationships cannot be attributed to an aggregate event. Suppose for example that patenting standards were changing, in this case the aggregate relationship would mirror the relationships within. This puzzle is also unexplained by changes to industry composition or trends. Instead, innovation is correlated across industries. In particular, patenting increases more substantially in some sectors while average quality declines in others. Because the aggregate relationship is actually an artifact of innovation being related across industries, patents remain a good innovation measure and any changes have important consequences for growth.

In order to study how innovation is related throughout the economy, I construct a multi-sector model of innovation where heterogeneous ideas serve as the key innovation input. It is well-known that patents vary in economic value,[1] and this is captured by ideas varying in the quality of an intermediate good they end up producing. The output from each sector is combined in the production of a final good, and as a result the ideas in one sector affect the value of ideas throughout the economy.

This trade-off between industry affects aggregate quality, when the availability of ideas changes. To see, consider the response to a complementary sector when the quality of all ideas improves in another sector. Because innovation becomes more productive in that industry, output increases as well. In the complementary sector, the returns to innovation also increase. Lower-quality ideas in the complementary sector will then be used as inputs to innovation. In this example, the number of patents will increase

[1] See Schankerman and Pakes (1986) for instance.

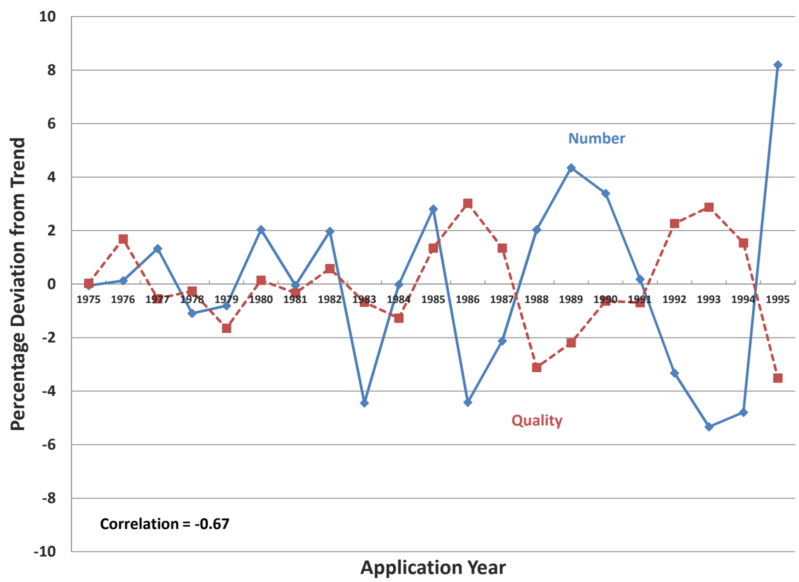

Figure 1: Patent Number and Average Adjusted Citations by Year

in both sectors, but the average quality of the innovations move in opposite directions. When there are enough[2] ideas to implement in the other sector, a large negative relationship between the number of patents in one industry and average quality in the other industry will preside.

The model can explain the key observations. The negative aggregate relationship emerges, because better ideas in less-innovative sectors lower average patent quality in the economy, when more-innovative industries have many near marginal ideas to innovate on. At finer classifications of industries, the number and quality relationship disappears because industries increasingly respond to the ideas of other sectors.

Empirical support is provided to verify predictions from the model. Using a spatial measure of sectoral complementarities, I find the negative relationship is much stronger when industries are in fact more complementary. I observe that innovation volatility is largest in less-innovative industries.[3] The timing of asymmetric changes to innovation corroborate the story that large changes ideas in the less-innovative industries are being transmitted throughout the economy. In particular, during periods were the negative aggregate relationship is the strongest, less-innovative industries simultaneously increase their output while more-innovative industries experienced larger quality drops.

[2]This notion will be made precise later.

[3]I use R&D/Sales, which Ilyina and Samaniego (2011) find is the best predictor of an industry's growth.

The model is calibrated to match cross-industry innovation differences. Simulations suggest that the changes in patenting have important consequences for long-run economic growth. This interpretation has important implications for growth and intellectual property regime design. In particular, better ideas can actually lower average patent quality, but not by too much, because selection is occurring across all industries. This is significant, because there is a substantial concern - for instance in Jaffe and Lerner (2004) - that a pro-patent legal system has led to the prevalence of low-quality patents which actually hinder innovation.

1.1 Related Literature and Previous Empirical Work

1.1.1 Innovation Determinants

Many papers analyzed how innovation is determined. Griliches' (1990) survey concluded that demand forces are likely to be more important than supply forces. In this paper, demand endogenously explains a substantial portion of aggregation innovation. A related branch of this literature, why research differs across industries. Very few papers have study short-run changes in patenting. A notable exception is Serrano (2007) who finds that patent transfers are directly linked to their usefulness and demand.

Ngai and Samaniego (2011) summarize the existing evidence. Research differs, because technological opportunities (factors that affect the efficiency of research), demand and appropriability (the extent to which R&D benefits the innovator). Only the first two determinants are considered here. This however is the first paper, to my knowledge, to explicitly model technological opportunity with multiple heterogeneous ideas being used within one sector.

1.1.2 Innovation Measurement

Patents are becoming the standard measure of innovation, despite being difficult to compare. In order to do so, they must be adjusted for quality, because a small proportion of patents account for the majority of their economic value.[4] Although noisy, the number of forward citations – cities by other patents – are typically the basis for this adjustment. Not only are they highly correlated with economic value, they are found to also be economically significant. Hall et. al. (2005) for example finds an extra citation per patent increases firm market value by 3%.[5]

[4] See Scherer and Harhoff (2000) for an example.
[5] Harhoff et al. (1999) echoes this result at the patent level.

1.1.3 Aggregate Patenting Activity and Patent Quality Overtime

Changes in U.S. patent grants have spurred much analysis. Their slow down during the 1970s, prompted concerns that research productivity was declining.[6] Lanjouw and Schankerman (2004) argue that research productivity – typically patents/R&D – was mismeasured, because the innovation output quality was changing. This explanation is plausible for this period,[7] because mean citations grew quite rapidly.[8]

Beginning in the mid-eighties, the number of patent applications "surged" despite modest R&D growth. Kortum and Lerner (1999) suggest that R&D productivity improved over this period. But since the number of patent examiners failed to keep up with the increased patenting, we should be suspicious, as argued by Hall (2007).[9] This is also at odds with numerous legal scholars and practitioners, who contend the filing of low-quality patents, are responsible for dramatic increase in patenting. In fact, some authors argue that patent quality increased.[10]

One study focusing on European data to note is Schankerman and Pakes (1986). They found that adjusting for quality explains the declines in European patenting that began in the late the 1960s. They also find that mean patent value is inversely related to patent number, but positively related market size.

1.1.4 Mixed Sectoral Trends

This paper argues the sectoral composition of industries affects the number and composition of aggregate patenting. In order make the argument that aggregate quality is a misleading indicator in the long-run, it will be helpful to understand the industry trends. In general, patenting increased in almost all sectors, but changes in quality within industries appear to be more disparate.

Kim and Marschke (2004) decompose the patent increase from 1983-1992 into three components: changes in R&D, changes in overall patent yield and change in the patent yield of individual industries. They attribute 70% of the patenting changes to R&D changes, but only offer conjectures as to why R&D was changing. They document that patenting increased in most industries. Patent yields generally increased as well, but especially in computers and computational equipment, electronic instruments and communication equipment, and optical and medical instrument industries. Patent yields appear to have declined, however, in pharmaceuticals and chemical products industries. The changes in patent yields are difficult to interpret, because by themselves they can either correspond to changes in demand or changes

[6] Griliches' (1990) explored several explanations, but they failed to account for the "slowdown."

[7] Their analysis actually focused on 1980-93 which, as discussed in the following paragraph, did not constitute a decline in research productivity.

[8] According to Figure 8 in Hall et. al. (2001).

[9] More recently, a new composite index from the OCED, suggests that patent quality has declined steadily in the last decade. It shows an average of a 20% decline between 1990-2000 and 2000-2010.

[10] See Hicks et. al. (2001).

in available ideas.

Although Hall's (2007) failed to find any hard evidence that patent quality declined, she suggests that patent standards might have been too low in some industries. Specifically as genomic and business methods applications at the USPTO became more stringent, their patent grants slowed.

Other industries failed to exhibit the decline in quality that might have been expected, given their increase in patenting. The semiconductor industry is particularly bizarre. When surveyed, its R&D managers indicated patents were actually declining in importance. Hall and Ziedonis (2001) argued that changes to patent management explained the "patent paradox." They argued that patents were being filed to withstand greater legal scrutiny. Because patent rights are often challenged for failing to cite prior work, the propensity to cite would actually increase and measured patent quality would increase. Preliminary work, however suggests that even by controlling for citation propensity,[11]patent quality still appears to have been increasing.

Although this paper does not study patents held by universities, the academic sector also had a rapid increase in patenting without a decline in patent quality. The Bayh-Dole Act of 1980 encouraged university entry into patenting and licensing. Sampat et. al. (2001) found that patent quality failed to decline, despite a significant increase in patenting.

Focusing a slightly earlier period, Lanjouw and Schankerman (2004) found patent quality actually increased from 1980 to 1993.[12] They developed a composite patent quality index using the number of citations, patent family size[13] and both backward and forward claims. In many industries they found patent quality actually went up, and patent number and quality were inversely related.

1.1.5 Micro Evidence

There is less work done at the firm or inventor level. In the U.S., patent number and quality appear to be unrelated within U.S. firms according to Lanjouw and Schankerman (2004). Furthermore, they conclude that variations in patent quality over time at the firm level are dominated by stochastic factors rather than any changes to R&D spending.

The evidence is mixed internationally. Francesco (2008) examines a regional sample of Italian inventors to find that patent number and average quality is unrelated at the inventor level. Using survey data from the European Patent Office, Rassenfosse and Guellec (2009) however find that a trade-off exists between the quantity and quality at the company level.

[11]These techniques are discussed in the next section.
[12]Hicks et al. (2001) also suggest patenting quality might have gone up during this period.
[13]Patent family size refers to the number of countries the same invention is patented.

1.1.6 Co-movement and Aggregation

Ouyang (2011) complements this work by finding a substantial portion of R&D cyclicality is explained by comovement. Specifically, she finds that only 5.67% of pro-cyclical aggregate R&D reflects within-industry timing of innovation and production, but 94.37% arises from inter-industry co-movement between R&D and output.

This paper argues that industry specific shocks can have aggregate implications. Informally, the draws from a skewed patent distribution have been argued potentially to have aggregate implications. Simulations in Nordhaus (1989) suggest that changes to the 0.01% of most valuable patents might be responsible for year-to-year fluctuations in U.S. economy-wide productivity changes.

This paper is also related to the aggregation of microeconomic shocks in the presence of sectoral linkages. Horvath (2000) and Conley and Dupor (2003) both suggest that sectoral shocks can have aggregate implications. More recently, Gabaix (2011) found that the idiosyncratic movements of the largest 100 firms[14] in the United States appear to explain about one-third of variations in output growth.

2 New Facts

2.1 Data

To document changes in patent counts at the industry level, I match patents and with their industry classification. The patent data is from the NBER patent database, which is described in detail in Hall et al. (2001). The third update to this dataset includes all utility patents granted in the USA between 1963 and 2006. I restrict the data to U.S. non-government organizations & individuals.

Citations themselves have to be adjusted, because there are concerns over changes to citation propensity. Lanjouw and Schankerman (2004) attribute a substantial proportion citations overtime to factors other than quality, such prior work becoming easier to find. Because alternative measure remain controversial and the NBER patent database provides an adjustment to control for citation propensity change, I use citations. To ensure average quality is comparable across time, I use the adjustments outline in Hall, Jaffe, Trajtenberg (2001) to adjust for citations.[15] The previous patent datasets, which included only patents until 1999 or 2001, demonstrates a quality decline 10 years prior to the last year granted patents collected. Examining newer data suggests that quality, in fact failed to decline. For this reason, I only consider patents from 1975-1995. This citation window is also consistent with Sampat et. al. (2001),

[14] He contends these effects could be expressed in terms of sectors.

[15] They estimate a 6 field specific obsolescence-diffusion model to adjust for citation inflation.

which argues that sufficient citation lags can cause misleading interpretations of quality when only five years of data are collected.[16]

For information on the industry, I utilize Standard & Poors' Compustat dataset. This includes data on all publicly traded U.S. firms, and more specifically the industry SIC industry classification. Hall et al. (2001) provides a correspondence between patents to their firms in the Compustat database. Unfortunately, the universe of firms consists only of firms that existed in 1989.[17] Because, I consider patents up until 1995, there might be a concern that smaller firms are underrepresented. Industry data is obtained by aggregating patent counts and average quality at the industry level. Throughout, I have dropped 3-digits industries with less than 10 patents in any year.

Input-output relations provide an economic distance, in terms of complementarities, measure that is used to characterize interactions between sectors. I follow Conley and Dupor (2003) in constructing my distance measure with the 1987 input-ouput table from the BEA. Denote by Φ the input-output table. Then the typical element $\Phi(i, j)$ is the dollar value of compensation to sector i for goods used in industry j. The distance measure is computed based on how similar a industries sales appear. That is, two industries are close if they sell goods to similar industries. This table contains industries such as agriculture, natural resources, wholesale and trade. I aggregate these sectors into a single industry, because it is not clear how this distance corresponds to complementarities in this case.

2.2 The Patenting Aggregation Puzzle

Number (N) is the number of patents per year and average quality (Q) is average number of future citations. Comparing quality across time is difficult, because their might be changes in the patenting rate, citation rate and data truncation. Total patenting and average patent quality countercyclical with each other from 1975 to 1995. To study this I remove the trends[18] from both series using a Hodrick-Prescott filter.[19] Figure 1 plots percent deviations of the total number of patents and their average number of adjusted citations these patents receive by application year.

As seen in the figure, cyclical variation in both patents and quality can be sizeable. The number of patents can vary by 6% in either direction and the change in the average citation can be as large as 3% - corresponding to nearly one citation difference for each patent. If 80,000 patents are granted a

[16] Henderson, Jaffe and Trajtenberg (1998) compared university patents to a random sample of all patents, finding that university patents were more highly cited prior to the act. They address two sources of truncation bias concerns: university and private patents differ in their citation levels or intertemporal distribution of citation.

[17] This is a non-trivial task, as outlined in Kim and Marschke (2004).

[18] The following holds if changes in growth rates are examined.

[19] A smoothing parameter of 6.25 is used.

Aggregation Level	Agg.	1-digit	2-digit	3-digit
Sectors (n)	1	4	25	92
$\sum_{i=1}^{n} w_i \text{corr}(N_i, Q_i)$	-0.67	-0.45	-0.30	-0.12

Table 1: Weighted Average Correlations of Patent Quality and Number at Different Aggregation Levels

year, this change could correspond to nearly a change in 5,000 patents a year. A 3% change in quality, corresponds to the average citation changing by nearly one third. According to Hall et. al. (2005), there is approximately a 3% change in the market value of the average patent. Thus the average market value could be changing by up to 1%.

This relationship is not being driven by a few key industries. To examine this, I considered the disaggregated relationships: that is, the series of quantity and quality for the one, two and three-digit SIC industries. Detrending them in the same fashion as the aggregate series, gives a surprising result - not a single series is as strong as the aggregate relationship demonstrated in Table 1. Here, each industry is weighted by the number of patents filed over this period. That is, w_i is the fraction of patents filed over the period. Notice the relationship dampens at finer aggregation levels.

2.3 Alternative Explanations

There are principally two explanations that could explain this relationship. The first is that low quality industries are responding more when there is a jump in patenting. To reject this as the principal explanation, I set $\tilde{Q} = \sum_{i=1}^{n} w_i Q_i$. Once this is done at the two-digit level, Corr $(N, \tilde{Q})$ reduces to only -0.58.

Another explanation is that the filtering technique is removing industry trends that could explain this. To test if this is the case, I set $Q'_{it} = (1+g_i^q)^t Q_{i,0}$ and $N'_{it} = (1+g_i^n)^t N_{i,0}$, where g_i^q and g_i^n are the growth rates for patents and quality in each industry and $Q_{i,0}$ and $N_{i,0}$ are their initially respective levels. In this case, the aggregate correlation coefficient is actually smaller in magnitude than the weighted average of all the correlation coefficients. Thus, trends are not responsible.

2.4 Decomposing the Correlation Coefficient

Notice the aggregate correlation coefficient can be decomposed into within industry variances and covariances. Here the subscripts denote specific industries. Notice that

$$\text{corr}(\sum_i N_i, \sum_i Q_i) = \frac{a+b}{\sqrt{cd}},$$

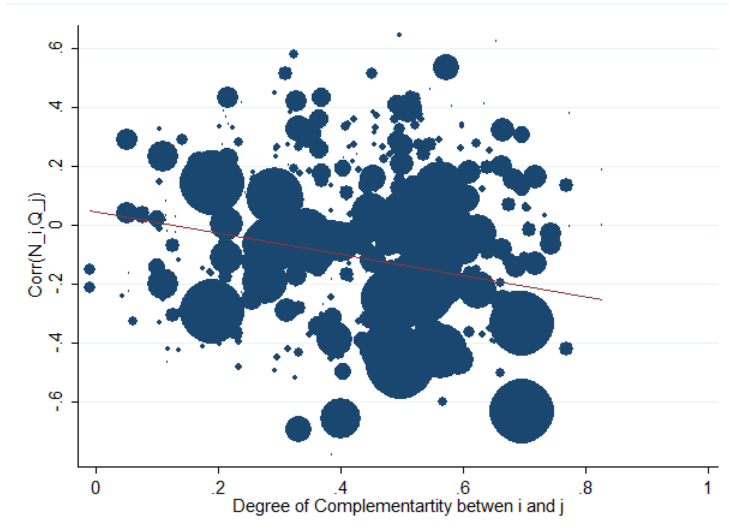

Figure 2: 2-Digit Cross-Industry Correlations between Patenting and Average Quality

where

$$a = \sum_{i=j} \text{cov}(N_i, Q_j)$$

$$b = \sum_{i \neq j} \text{cov}(N_i, Q_j)$$

$$c = \sum_{i} \text{var}(N_i) + \sum_{i} \sum_{j \neq i} \text{cov}(N_i, N_j)$$

$$d = \sum_{i} \text{var}(Q_i) + \sum_{i} \sum_{j \neq i} \text{cov}(Q_i, Q_j).$$

Mechanically the aggregate correlation coefficient is larger, because the average covariance terms between i and j are larger than the average variance terms in the numerator.

2.5 Complementarities

The negative relationship between patenting and quality grows between complementary sectors. A regression, weighted by w_i and w_j, demonstrates that the negative relationship strengthens with the complementary measure discussed above. (See Figure 2.) Specifically,

$$\underset{}{\text{corr}(N_i, Q_j)} = \underset{(0.07)}{-0.36}\text{Comp}(i, j) + \underset{(0.03)}{0.05}$$

where Comp(i, j) is less 1 less the spatial distance between industries i and j. Clearly these inter-industry relationships strengthen with a spatial measure of complementarities.

3 A Two-Sector Model of Innovation

To understand how innovation and innovation quality (productivity) are related across sectors, I develop a static model with two intermediate sectors. Each sector is endowed with a continuum of ideas, which are used to produce their respective intermediate good.

3.1 Innovation

Innovation is the selection of ideas. Whenever an idea is used, we assume it is costlessly patented. It is well documented that the returns to innovation differ substantially.[20] To capture this, ideas will be heterogenous in the quality of intermediate output they produce. Ideas in sector i are distributed by a continuous distribution the Pareto distribution $G(z_i)$ with shape parameter $k > 2$ over the support $[z_i, +\infty)$.[21]

3.2 Intermediate Production

Intermediate output X_i is produced by combining an idea with a unit of the final good. Each idea ϕ_i will produce $\phi_i \cdot 1$ units of the intermediate good i.

3.3 Final Good Production

The final good is produced by combining intermediate goods X_1 and X_2. Specifically,

$$Y = A(\theta X_1^{(1-\frac{1}{\epsilon})} + (1-\theta) X_2^{(1-\frac{1}{\epsilon})})^{\frac{\epsilon}{\epsilon-1}},$$

where $\epsilon \in (0, +\infty)$ represents the elasticity of substitution between industries. The degree of substitutability increases in ϵ. The parameter A represents the productivity of the final good technology. Finally, $\theta \in [0, 1]$ represents the share of intermediate good i used to produce the final good.

[20] See Scherer and Harhoff (2000) for a discussion.

[21] $k > 2$ ensures the first two moments exist.

3.4 Equilibrium

Because returns are increasing in idea quality – there is a cutoff idea ϕ_i^*– where developing an additional idea in sector i produces negative returns. The equilibrium is pinned down by ϕ_1 and ϕ_2. That is, sector i produces intermediate output:

$$X_i = \int_{\phi_i^*}^{\infty} \phi g(\phi) d\phi = \frac{k z_i^k}{(k-1)\, {\phi_i^*}^{k-1}}. \tag{1}$$

Then the number of patents in each sector is

$$N_i = \int_{\phi_i^*}^{\infty} g(\phi) d\phi = (\frac{z_i}{\phi_i^*})^k. \tag{2}$$

Dividing (1) by (2) gives the average quality for sector i :

$$Q_i = \frac{k\phi_i^*}{k-1}.$$

In the case of equal shares terms, the cutoffs are given by

$$\phi_i^* = \frac{2^{\frac{\epsilon}{\epsilon-1}}}{A} \big((\frac{z_j}{z_i})^{\frac{k(\epsilon-1)}{\epsilon+k-1}} + 1 \big)^{\frac{1}{1-\epsilon}}. \tag{3}$$

3.5 Relationships Within Sectors

Proposition 1 ($\frac{\partial \phi_i}{\partial z_i} > 0$)**.** *Better ideas in a sector imply that more ideas are patented, output increases and average quality increase within the sector.*

As ideas become more productive in a sector, its output increases. This has two effects. First, ideas are used in that sector, because income rises in the economy. Second, the social planner substitutes away from the good enough that the quality of the marginal idea rises. Because average quality depends only on the marginal idea, it rises in that sector.

3.6 Relationships Across Sectors

Proposition 2 ($\frac{\partial \phi_i}{\partial z_j} > 0$)**.** *Better ideas one sector imply that more ideas are patented, output increases and average quality declines in the other sector.*

Better ideas in one sector, have two effects. First, income rises in the economy so more ideas are produced in the other sector. Second, the social planner substitutes toward the other good. Both effects cause the quality of the marginal idea to decline, and in turn the average quality of the sector decline.

4 Aggregation

Denote by N the aggregate number of patents and denote by Q the average quality. Clearly,

$$N = N_1 + N_2$$

and

$$Q = \frac{X_1 + X_2}{N_1 + N_2} = \frac{N_1 Q_1 + N_2 Q_2}{N_1 + N_2}. \tag{4}$$

4.1 Aggregate Quality and Asymmetric Ideas

One of the most important results of this paper is that aggregate quality depends, not on the average quality of ideas, but on the relative quality of ideas across sectors in the economy.

Proposition 3 **(**$\frac{\partial Q}{\partial z_i} < 0, \frac{\partial Q}{\partial z_j} > 0$ if $z_i < z_j$**).** *Aggregate quality declines (increases) if ideas get better in the worse (better) sector.*

To understand Proposition 3 , consider the following example.

Example 1. *Cobb-Douglas*

Suppose that $\epsilon = 1$ and shares are symmetric. If factors are paid their marginal cost, the number of patents is identical in each sector. This happens, because the marginal cost is inversely related to the quality of the sector implying that $\frac{1}{\phi_i} X_i = N_i$, and thus

$$N_1 = N_2.$$

But this implies that aggregate quality is

$$Q = Q_1 + Q_2.$$

Furthermore, the ratio of factors shares imply that

$$\frac{\frac{1}{\phi_1} X_1}{Y} = \frac{k N_1}{(k-1) N_1 \sqrt{Q_1 Q_2}} = \frac{k}{(k-1)\sqrt{Q_1 Q_2}} = \frac{1}{2}.$$

Thus any change to average quality in one sector has an proportionally equal and opposite change in the other. The intuition as to why the level changes are larger in higher-quality sector, relies on the strength of the substitution effect relative to the income effect. The substitution effect is the largest when the high-quality sector becomes more productive. To see this affects aggregate quality, suppose that $z_l < z_h$. Consider the following two cases:

- $z_l \uparrow$: The increase in Q_l is small, because the income and substitution effects are offsetting each other. Conversely, increase in Q_h is large, because the income and substitution effects are working together.
- $z_h \uparrow$: The increase in Q_h is large, because the substitution effect is significantly greater than the income effect in sector h.

4.2 Aggregate Quality and Limiting Cases

Example 2. *Perfect Complements*

When $\epsilon = 0$, aggregate quality is invariant to idea distributions. To see this, I consider how aggregate quality changes by decomposing it into the contribution from each sector. Notice, a Leontif production function implies that the weighted quality of sector i equals

$$\frac{Q_i N_i}{N_i + N_j} = \frac{Q_i N_i}{N_i + \frac{Q_i N_i}{Q_j}} = \frac{1}{\frac{1}{Q_i} + \frac{1}{Q_j}}.$$

Then average aggregate quality is

$$Q = \frac{2}{\frac{1}{Q_i} + \frac{1}{Q_j}}.$$

Now, the distributional assumptions provide a stark implication. Since the average quality in each sector is proportional to marginal cost,

$$\frac{1}{\frac{1}{Q_i} + \frac{1}{Q_j}} = \frac{k}{k-1}\left(\frac{1}{\frac{1}{\phi_i^*} + \frac{1}{\phi_j^*}}\right) = \frac{k}{k-1}.$$

But

$$\frac{1}{\frac{1}{\phi_i^*} + \frac{1}{\phi_j^*}} = 1,$$

because the marginal benefit must equal the marginal cost. Therefore average aggregate quality is invariant to the idea distributions.

The intuition is that, any change in patent quality for a sector is exactly offset by its weight among patents. Thus the sector with worse ideas must produce more of them, because of complementarities.

Example 3. *Perfect Substitutes*

When $\epsilon = +\infty$, aggregate quality is also invariant to idea distributions. In this case, each marginal patent must be able to produce a unit of the final good. Thus

$$\frac{1}{\phi_i^*} = \frac{1}{2}.$$

This implies that the average quality for each sector is identical:

$$Q_i = \frac{2k}{k-1}.$$

Conversely to Example 2, in this case the sector with better ideas implements more of them.

4.3 Returning the Puzzle

The intuition developed in the two sector model can be used to explain the aggregation puzzle. The changes in average aggregate quality depend on the asymmetry between sectors. The patent number and quality relationship disappears with within industries, if they are either very substitutable or complementary.

5 Tentative Evidence of Innovation Shocks

This section presents tentative evidence that industry shocks to innovative productivity can explain an important fraction of the change in aggregate patents and their composition.

5.1 Innovation Shocks: Motivation and Definition

The key challenge to providing empirical support in the data is to identify sector specific shocks. Because we are concerned about changes in both the extensive and intensive margin this is a non-trivial task. I propose that innovation productivity shocks can be identified by changes in total innovation output. Because the output of all ideas in a sector may change when there is an innovation productivity shock, the productivity shocks will likely result in much larger changes in output compared to endogenous changes in innovative output.

Since R&D is fairly stable over the short-run, it is synonymous to innovation productivity. Innovative output is often defined as the weighted sum of all patents. Empirically output then is

$$X = \text{total citation weighted patents},$$

where I assign citation based weights following Hall (2005). Innovation shocks are then the change in log output from t to $t+1$.

5.1.1 Innovation Shocks Overtime

As we can see in Table 2, output is positively related to the number of patents and negatively related to the quality of patents. At the aggregate level, it appears that endogenous shocks dominate exogenous shocks, because output is negatively related to the average quality and positively related to the patent number.

Table 2: Aggregate Relationships

	corr(N,Q)	corr(X,N)	corr(X,Q)
All Years	-0.69	0.97	-0.52
1975-1986	-0.11	0.93	0.23
1987-1995	-0.92	0.98	-0.84

5.2 Innovation Asymmetries Overtime

The central hypothesis was that an increase in innovation in the low-opportunity sectors can reduce the average quality of all patents in the economy, because the high-opportunity sector responds along the extensive margin.

Although classifying industries by inventiveness is controversial,[22] it is common place to use R&D/Sales as a proxy for the inventiveness of a sector. I categorize all 2-digit sectors as either high- and low-opportunity using the median R&D/sales ratio.[23] Initially, I classify the top-four R&D/Sales industries as "high-opportunity" and classify the remaining industries as "low-opportunity."

Figure 3 shows the weighted productivity shocks for two sectors classified by R&D/sales. Two patterns emerge in the data. First, these sectors are positively correlated and then negatively correlated. Between 1975-1986 the correlation between the two series is 0.62 and after it becomes -0.29.

[22] See Von Tunzelmann and Acha (2005) for a discussion.
[23] Ilyina and Samaniego (2011) find this the best predictor of an industry growth

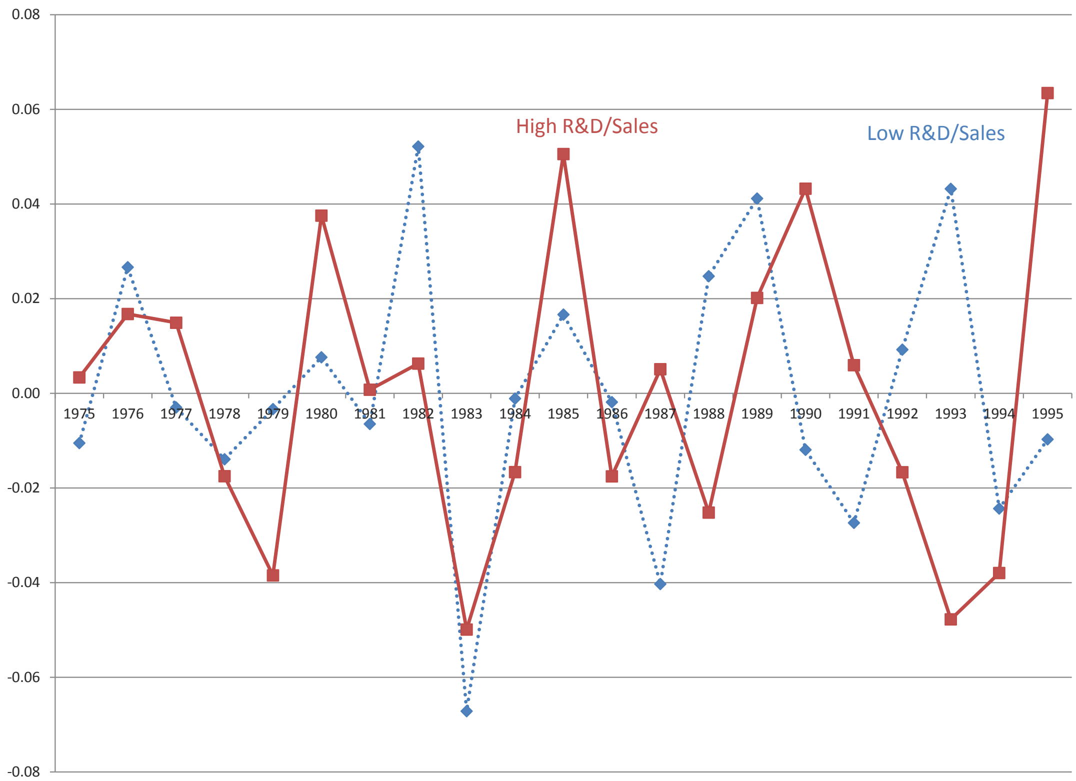

Figure 3: Weighted Output Shocks

These two periods will support the mechanism. Notice, from Table 2 the negative aggregate relationship between number and quality is the most prevalent during the second period. In addition to this, the cross relationship between the number of patents and quality - see Tables 4(a)-4(c). We can see that in the first period, these two sectors appear to be unrelated, but become related in the second period.

	N_L	N_H
Q_L	-0.27	-0.24
Q_H	-0.25	-0.65

(a) 1975-1995

	N_L	N_H
Q_L	-0.39	0.01
Q_H	0.04	0.23

(b) 1975-1986

	N_L	N_H
Q_L	0.05	-0.52
Q_H	-0.49	-0.86

(c) 1987-1995

Figure 4: Correlations Overtime

The first period can be explained by productivity shocks to both sectors, but with larger shocks to the high-opportunity and smaller shocks to the low-opportunity sectors. Furthermore, Figure 3 suggests simultaneous shock can explain the lack of co-movement in the cross-terms.

In the second period, these industries are now related in a very specific way. Here, a positive innovation shock in the low-opportunity sector occurs with a negative shock to the high-opportunity sector. It is however, only the increased return from developing an idea in the high-opportunity that can account for such substantial decline in the high-opportunity sector.

6 Benchmark Parameterizations and Results

6.1 Parameterizations

The general problem consists of I industries and S_i subindustries in each industry i. For simplicity, I assume the upper tier of the production function is Cobb-Douglas and that the lower tier takes the usual CES form.[24] That is, the social planners solves

$$\max A \prod_{i=1}^{I} \left(\frac{1}{S_i} \sum_{s=1}^{S_i} x_{i,s}^{1-\frac{1}{\epsilon_i}} \right)^{\frac{\theta_i \epsilon_i}{\epsilon_i - 1}} - \sum_{i=1}^{S} \sum_{s=1}^{S_i} N_{i,s},$$

where θ_i represents the expenditure share on industry i, each subindustry has symmetric shares and ϵ_i represents that intra-industry elasticity of substitution between the subindustries in industry i.

To calibrate the model, I set $I = 4$ to correspond to the number of industries at the 1-digit level. Initially, I consider only consider $S_i = 2 \, \forall i$. In order, to make the industry comparable in terms of demand

[24]Bernard, Redding and Schott (2007) specify an aggregate utility in a similar way.

I choose the largest subindustry for each industry[25] and consider all remaining subindustries as the other subindustry.

Model parameters are determined as follows. Each θ_i is set to capture the fraction long-run sales. Ngai and Samaniego (2011) use price-markup ratios to determine an average elasticity of 4.75 for a finer level of disaggregation. In the model research productivity is equivalent to patent quality, because R&D$= 1 \cdot N_i$. The z's can be determined by $\frac{kz_i}{k-1} = \frac{\text{Patents}}{\text{R\&D}}$.

6.2 Preliminary Numerical Results

We also see, empirically that innovative output is more volatile in the low-opportunity sectors. I consider idea shocks by adjusting the lower bound of the distribution. Each lowerbound at time t can be distributed by $z_{i,t} \sim (z_i, \frac{1}{1000 z_i^{\frac{1}{4}}})$. One std corresponds to a %10 change in the lower bounds.

Table 3: Different Levels of Aggregation - Data v.s. Simulation

	Data	Simulation
Corr(N,Q)	-0.67	-0.99
$\sum_i w_i \text{corr}(N_i, Q_i)$	-0.64	-0.08
$\sum_{is} w_{is} \text{corr}(N_{is}, Q_{is})$	-0.44	0.20

As can be seen in Table 3, this model has the potential to produce patenting aggregation puzzle. This preliminary exercise, suggests that larger shocks to low-tech sectors can explain this behavior. Table 4, however suggests that changes in quality of the most productive sector are more responsible for the aggregation relationship in the simulation than in the data. This may suggest the presence of aggregate shocks.

Table 4: Data v.s. Simulations Across Industries

	Data (R&D/Sales)	Simulation (Patents)
Std Q (%)	-0.48	-0.67
Corr(Q_i, Q)	-0.06	-0.66

[25] Specifically industries 13,29,38,48 are separated from their respective subindustries.

7 Discussion and Conclusion

This paper has argued that a change in one sector's inventiveness alters the return to developing previously unprofitable ideas in other sectors. This mechanism accounts for a variety of new facts about short-run changes in patenting. Furthermore, evidence was presented that larger volatility in the inventiveness of the less-innovative sectors can explain the negative patenting and average patent quality relationship that disappears with industry disaggregation.

Short-run changes in total patenting imply significant changes in innovative output. The patenting aggregation puzzle arises from the comovement between the interaction between supply and demand for across sectors of the economy. For this reason, there is little evidence of any substantial change in the composition of patents when patenting increases.

This result has consequences for intellectual property regime design, since it can reconcile the anecdotal evidence that patent quality has declined since 1985 and the absence of empirical evidence. Because increased inventiveness can led to a decline in average patent quality, the concerns about an increase in unnecessary patenting should be diminished. This is significant, because there is a substantial concern - for instance in Jaffe and Lerner (2004) - that a pro-patent legal system has led to the prevalence of low-quality patents which hinder innovation.

References

[1] Bernard, A., Redding, S., and Schott, P. Comparative advantage and heterogeneous firms. *Review of Economic studies 74*, 1 (2007), 31–66.

[2] Blind, K., Cremers, K., and Mueller, E. The influence of strategic patenting on companies' patent portfolios. *Research Policy 38*, 2 (2009), 428–436.

[3] Cohen, W. M., Nelson, R. R., and Walsh, J. P. Protecting their intellectual assets: Appropriability conditions and why u.s. manufacturing firms patent (or not). NBER Working Papers 7552, National Bureau of Economic Research, Inc, Feb. 2000.

[4] Commission, F. T. To promote innovation: The proper balance of competition and patent law and policy. Technical Report, 2003.

[5] Conley, T., and Dupor, B. A spatial analysis of sectoral complementarity. *Journal of Political Economy 111*, 2 (April 2003), 311–352.

[6] Cristiano, L., and Fitzgerald, T. The business cycle: it's still a puzzle. *Economic Perspectives*, Q IV (1998), 56–83.

[7] de Rassenfosse, G., and Guellec, D. Quality versus quantity: Strategic interactions and the patent inflation. Tech. rep.

[8] Dupor, B. Aggregation and irrelevance in multi-sector models. *Journal of Monetary Economics 43*, 2 (1999), 391–409.

[9] Gabaix, X. The granular origins of aggregate fluctuations. *Econometrica 79*, 3 (2011), 733–772.

[10] Gallini, N. The economics of patents: Lessons from recent US patent reform. *Journal of Economic Perspectives 16*, 2 (2002), 131–154.

[11] Griliches, Z. Patent statistics as economic indicators: A survey. *Journal of Economic Literature 28*, 4 (December 1990), 1661–1707.

[12] Hall, B. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. *RAND Journal of Economics 32*, 1 (2001), 101–128.

[13] Hall, B. Exploring the patent explosion. *Essays in Honor of Edwin Mansfield* (2005), 195–208.

[14] Hall, B., Jaffe, A., and Trajtenberg, M. The NBER patent citation data file: Lessons, insights and methodological tools. *NBER working paper* (2001).

[15] Harhoff, D. *Advancing Knowledge and the Knowledge Economy*, vol. 1. The MIT Press, 2006, ch. 19, pp. 331–351.

[16] Henderson, R., Jaffe, A., and Trajtenberg, M. Universities as a source of commercial technology: A detailed analysis of university patenting, 1965-1988. *Review of Economics and Statistics 80*, 1 (1998), 119–127.

[17] Hicks, D., Breitzman, T., Olivastro, D., and Hamilton, K. The changing composition of innovative activity in the US–a portrait based on patent analysis. *Research policy 30*, 4 (2001), 681–703.

[18] Horvath, M. Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks. *Review of Economic Dynamics 1*, 4 (1998), 781–808.

[19] ILYINA, A., and SAMANIEGO, R. Technology and financial development. *Journal of Money, Credit and Banking 43*, 5 (2011), 899–921.

[20] Jaffe, A., and Lerner, J. *Innovation and its discontents: How our broken patent system is endangering innovation and progress, and what to do about it.* Princeton Univ Pr, 2004.

[21] Kim, J., and Marschke, G. Accounting for the recent surge in US patenting: Changes in R&D expenditures, patent yields, and the high tech sector. *Economics of Innovation and New Technology 13*, 6 (2004), 543–558.

[22] Kortum, S., and Lerner, J. What is behind the recent surge in patenting? *Research Policy 28*, 1 (January 1999), 1–22.

[23] Lanjouw, J., and Schankerman, M. Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators*. *The Economic Journal 114*, 495 (2004), 441–465.

[24] Merrill, S. A., Levin, R. C., and Myers, M. B. *A Patent System for the 21st Century.* No. Committee on INtellectual Property Rights in the Knowledge-Based Economy, National Research Council of the National Academies. The National Academies Press, Washington, D.C., 2004.

[25] Ngai, L., and Samaniego, R. Accounting for research and productivity growth across industries. *Review of economic dynamics 14*, 3 (2011), 475–495.

[26] Nordhaus, W. Patents: Recent trends and puzzles - comment, 1989.

[27] Ouyang, M. Pro-cyclical aggregate r&d: A comovement phenomenon. *Working Paper* (2011).

[28] Sampat, B., Mowery, D., and Ziedonis, A. Changes in university patent quality after the Bayh-Dole act: a re-examination. *International Journal of Industrial Organization 21*, 9 (2003), 1371–1390.

[29] Schankerman, M., and Pakes, A. Estimates of the value of patent rights in european countries during the post-1950 period. *Economic Journal 96*, 384 (December 1986), 1052–76.

[30] Scherer, F. M., and Harhoff, D. Technology policy for a world of skew-distributed outcomes. *Research Policy 29*, 4-5 (April 2000), 559–566.

[31] Schmookler, J. *Invention and economic growth*. Harvard University Press, 1966.

[32] Serrano, C. Technology transfer and the business cycle: Evidence from patent reassignments. 2007.

[33] Van Pottelsberghe de la Potterie, B., and Van Zeebroeck, N. A brief history of space and time: The scope-year index as a patent value indicator based on families and renewals. *Scientometrics 75*, 2 (2008), 319–338.

[34] Von Tunzelmann, N., and Acha, V. Innovation in low-techindustries. *The Oxford handbook of innovation* (2005), 407–432.

[35] Ziedonis, A. *Advances in Strategic Management: Economic Institutions of Strategy*. 2009, ch. Intellectual Property Regimes and Firm Strategy: Putting Hall and Ziedonis (2001) in Perspective.