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Scale effect on endogenous growth: an evaluation

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Abstract

The aim of this paper is to empirically evaluate the “scale effect” as in Segerstrom (1998). To this end, we firstly build a new concordance table between SIC and USPCS codes. Then we analyze the difficulty index of each U.S. manufacturing industry using the patents forward citations data. Finally we evaluate by SUR method the relation between the difficulty index and the number of S&E by industry. Our investigation concludes showing that in the traditional sectors the “scale effect” is lower than in the new ones.

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1 Introduction

The idea of the endogenous growth with scale effect was generated in first neoschumpeterian articles (Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt(1992)). They suggest that an increasing number of scientists and engineers (S&E) employed in an country determines a proportional increase in its growth rate. Segerstrom (1998) contrasts this idea first using empirical evidences. For example, the growth of S&E employed never corresponded to growth rate in the US. In order to explain this phenomenon he introduces a new element, the *difficulty index*, that determines a less than proportional relationship among the number of S&E and the growth rate. No empirical evaluations of this intuition have been carried out so far. That is why we develop a new concordance table between SIC and USPCS industry codes using an USPTO concordance file. Then, we proceed defining how we evaluate the *difficulty index* . Finally we estimate the relationships among growth rate and the number of S&E (by industry) in order to provide the *dimension* of the scale effect absence, i.e. the difficulty index.

The article is organized as follows: in first section we propose a concordance table between USPCS (as December, 31 2002) and 1972 Standard Industrial Classification System (SIC) codes as the necessary methodological tool used to work on the original patent data file (NBER Patent Citations). Then, we describe the methodology to evaluate the difficulty index using the NBER 63_99 patent data file using forward citations variable. Thus, we obtain the historical series of the difficulty index by industry. In last section we evaluate the relation between the difficulty index of each industry and the number of S&E, drawing the scale effect role by industry.

2 Evaluating the Difficulty Index

Hirabayashi (2003) highlights the great difficulty which one researcher goes into when he needs to compare the available patent data to other economic variables: since they are classified by different industrial codes, they need to be homogenized before using in empirical analysis. Our principal aim is inquire on the quantitative relationship between the evolution of the difficulty index (that we derive from the NBER patent citations data file, as in Hall et al., 2001), classified in USPCS, and the number of the S&E employed in each sector, classified by NSF in SIC (1972); that is why we build a concordance table of these codes starting from the USPTO file[1]. In table 3 - see Appendix - we present the results.

After we homogenized our data, we proceed on empirically evaluating the "R&D races" as in Segerstrom (1998). The author defines the innovative success probability at time t as:

$$I(\omega, t) = \frac{AL_I(\omega, t)}{X(\omega, t)}, \tag{1}$$

[1]Available on the web at ftp://ftp.uspto.gov/pub/taf/sic_conc/;

where L_I is the number of S&E in the whole economy A is a given exogenous technological parameter and X is the *difficulty index* . Moreover he sustains that as industries do more R&D the difficulty index increases as:

$$\frac{\dot{X}(\omega,t)}{X(\omega,t)} = \mu I(\omega,t). \tag{2}$$

Substituting (1) in (2), and considering $A = 1$ without loosing of generality, we get the following relation that we want to test:

$$\dot{X}(\omega,t) = \mu L_I(\omega,t). \tag{3}$$

At this point of our analysis, to go further we need to define more than conceptually $X(\omega,t)$. In fact Segerstrom (1998) describes it as function of time and industry (ω).

Hall et al. (2003) underline that the patent data is the only instrument able to quantify the innovation process, since we cannot quantify the not-yet-patented ideas. That is why we use the NBER data patent citations (PAT63_99) to observe the difficulty index evolution in the last 30 years. The data on the mean forward citation lag has been fundamental in our work, since our idea is based on the number of citations received by a patent in the x periods of its "life". More simply, as we show in figure 1, generally the distributional form of the mean forward citation lag in each sector and in each year is firstly increasing and after decreases.

More deeply, our idea is that in the increasing side the patent has not reached the time of its obsolescence, since the number of its forward citations is yet increasing: on the contrast, the decreasing side shows that the patent has been substituted by another patented idea since its citations decline. The distribution peak represents the distribution mode.

From a first look, we could hypothesize that the higher is the number of citations until the distribution reaches its peak the higher is the difficulty index. In other words, the higher is the number of researchers that studies on this patent, do not discovering a patentable idea that completely overcome the original patent, the more complex is the original patented idea. But, since the aim consists in building each industrial index as in Segerstrom (1998), we need to standardize whole dataset by the relative dimension of each sector. Without this standardization, we should surely conclude that in the "new" or "high" tech (as in Cozzi and Impullitti (2004) classification) the difficulty index is the highest of the whole economy since they have the highest number of grant patents and, as a consequence, of citations received (see Schettino (2007a)): moreover, the instantaneous probability of innovative success would be similar in each industry because we should put both on the denominator (the number of forward citations) and on the numerator (the number of S&E) of the equation 1 the industry dimension. In that way finish loosing information on the *fishing out effect* that clearly appears if an exogenous and appropriate index is applied.

Thus, to eliminate this "sectoral dimension problem" we cumulate the forward citations frequencies (weighted by each sector mean forward citations) until the peak and we define them as the numerator of the difficulty index (from now on S). The idea is that the higher is the relative number of the scientists that research on the original patent until it reaches its peak, the more difficult is its substitution. In that way we go further the problem homogenizing the indexes.

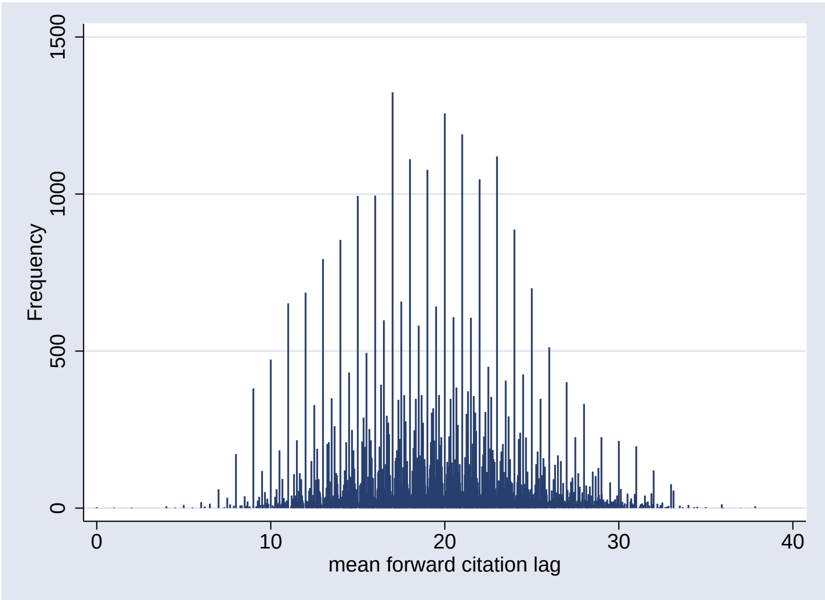

Figure 1: An Example of Distribution of the Weighted Mean Forward Citation

Here we go into the problem of the *truncation lag* as in Hall, Jaffe and Trajtenberg (2003). Obviously, the mean forward citation lags become lower and lower when we proceed through the last year of the data base (1999). We solve this problem in two ways. We firstly exclude last 8 years data: then we normalize S by dividing it with the square of the number of lags (a kind of "fixed effect" method):

$$X(\omega, t) = \frac{S}{y^2}. \tag{4}$$

Thus we obtain the time series (see table 1) of the difficulty indexes by each industry.

Now, we proceed evaluating the instantaneous probability of innovative success for each sector in each year (figure 2). We can observe that each series decreases in the whole period, confirming Segerstrom (1998) and that the "high tech" industries hold the highest probability of innovation in the first years, confirming the idea that the "first" innovations are easier to be discovered. Since the high tech industries innovation boom started on the 60s, they have to be considered as new sectors and, thus, their most obvious ideas are discovered in that period, instead of the low tech ones (called "traditional") whose most obvious ideas were discovered in the last part of the 19th century.

Table 1: Difficulty index serie

	Electron	Chemic	Fmp	Machinery	Transport	Food	Petroleum	Textile	Primary_met	Rubber	Stone_clay
1967	0.10	0.13	0.12	0.10	0.13	0.15	0.11	0.11	0.10	0.11	0.09
1968	0.15	0.13	0.13	0.13	0.14	0.13	0.14	0.16	0.14	0.12	0.13
1969	0.16	0.16	0.16	0.17	0.13	0.18	0.12	0.12	0.10	0.15	0.15
1970	0.18	0.16	0.18	0.17	0.20	0.17	0.13	0.12	0.17	0.17	0.17
1971	0.19	0.20	0.19	0.21	0.21	0.22	0.23	0.18	0.17	0.18	0.19
1972	0.23	0.24	0.24	0.25	0.25	0.27	0.26	0.25	0.26	0.22	0.24
1973	0.31	0.28	0.25	0.30	0.28	0.33	0.29	0.31	0.26	0.25	0.28
1974	0.34	0.32	0.31	0.34	0.33	0.35	0.36	0.29	0.28	0.30	0.32
1975	0.35	0.33	0.33	0.35	0.40	0.35	0.35	0.32	0.32	0.31	0.33
1976	0.39	0.37	0.36	0.36	0.38	0.37	0.40	0.35	0.37	0.35	0.37
1977	0.43	0.38	0.36	0.39	0.40	0.43	0.43	0.36	0.38	0.33	0.38
1978	0.45	0.40	0.37	0.41	0.43	0.45	0.44	0.37	0.40	0.40	0.43
1979	0.49	0.45	0.45	0.46	0.50	0.48	0.46	0.37	0.50	0.43	0.46
1980	0.51	0.49	0.44	0.48	0.49	0.54	0.54	0.49	0.43	0.46	0.49
1981	0.59	0.51	0.55	0.51	0.55	0.59	0.54	0.55	0.58	0.53	0.55
1982	0.63	0.58	0.55	0.60	0.60	0.65	0.65	0.61	0.60	0.58	0.57
1983	0.70	0.50	0.67	0.70	0.67	0.72	0.58	0.49	0.70	0.65	0.67
1984	0.74	0.77	0.76	0.70	0.73	0.85	0.82	0.71	0.65	0.73	0.71
1985	0.80	0.76	0.74	0.77	0.83	0.91	0.90	0.79	0.82	0.69	0.77
1986	0.95	0.91	0.94	0.93	1.02	1.13	1.06	0.96	1.02	0.86	0.95
1987	1.00	0.93	1.19	0.95	1.09	1.23	0.84	1.04	1.02	1.12	0.97
1988	1.29	1.23	1.33	1.23	1.40	1.41	1.22	1.25	1.25	1.23	1.38
1989	1.64	1.52	1.64	1.53	1.72	1.42	1.37	1.43	1.62	1.53	1.58
1990	1.85	1.69	1.89	1.73	2.02	1.89	1.47	1.53	1.82	1.70	1.75
1991	1.80	2.25	2.47	2.28	2.02	2.30	2.00	2.05	1.85	2.31	2.31
1992	2.64	2.52	2.72	2.43	2.93	2.80	1.97	2.59	2.60	2.51	2.46
1993	3.74	3.69	3.88	3.46	3.96	3.60	3.06	3.29	3.68	3.74	3.61
1994	4.52	4.79	4.96	4.33	5.01	4.86	3.97	4.34	4.69	4.85	4.66

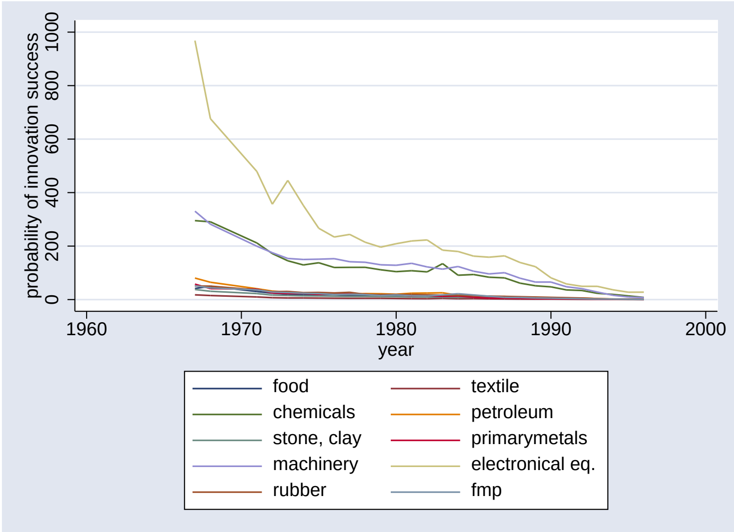

Figure 2: Istantaneous Probability of Innovative Success Trends

3 The Difficulty Index and the Innovation

Once we have defined the difficulty index as in table 1 we are interested to analyze the dynamical pattern. As we explained above we reduce our sample using data between 1969 and 1990. Thus we regress $X_{t+1} - X_t$ on $L_I(\omega, t)$ in each manufacturing sector. We use the $L_I(\omega, t)$ series created in SIC code by the NSF. In order to evaluate μ we use a GLS system applying the Seemingly Unrelated Regression method. The results are summarized in table 2.

Table 2: Estimations output: μ by sector

Sector	**Coefficient**	
Primary Metals	-0.063	
Chemical and Allied Products	0.020	***
Electrical Equipment	0.031	***
Machinery	0.031	***
Fabricated metal Products	0.054	
Rubber Products	0.059	
Petroleum refining and extraction	0.138	***
Stone, Clay and Glass products	0.463	***
Food, Kindered and tobaco products	1.148	***
Textile and Apparel	1.803	***

Results in table 2 evidence a high difference among manufacturing industries. As we can observe in equation 2, when μ is high, the higher the number of the S&E is, the greater the difficulty index grows and, thus, the higher the *fishing out* effect is. As a consequence, the high-tech (or new) industries present a lower

μ respect of the low-tech (or old) ones. That is, in low-tech sectors the difficulty in discovery new ideas is higher than in the high-tech ones, confirming that the innovation process in new sectors is more virtuous.

4 Conclusions

Empirically evaluating the Segerstrom (1998) model, specially the "R&D race", we tried to estimate the difficulty index. To do that, we use the mean forward citation lag of the U.S. patents (by NBER Patent Citations Data File). After we build a new concordance table between USPCS and SIC code we have evaluate the instantaneous innovation probability of success, finding that in each sector it is strongly decreasing. From that analysis we point out that in first years of the period (1969-1990) new sectors were discovering the most obvious ideas, while traditional industries have a constant low probability of find new patentable ideas in the whole period. Thus we evaluate the relationship between the difficulty index growth and the probability of innovate. Our results confirm Segerstrom (1998); moreover, estimating the parameter μ by using GLS model estimates by SUR methodology, we agree with the results in Dinopoulos and Segerstrom (1999) and Cozzi and Impullitti (2004), showing that there are notable differences among manufacturing sectors. Here we find different trends in innovation process among high and low industries: finally, we sketch out that the absence of scale effect (and the fishing out effect) is more clear in traditional sectors than in the high-tech ones.

Appendix

Table 3: Concordance table SIC to USPCS

SECTOR	SIC	USPCS
Food, kindred and tobacco products	**20,21**	83 127 205 426 428
Textiles and apparel	**22,23**	8 16 24 57 66 87 114 119 139 152 181 182 205 241 242 264 405 427 428 435 442 474 492
Chemicals and allied products	**28**	2 4 5 8 12 15 16 23 24 29 34 36 40 44 47 48 49 51 52 59 62 65 71 75 81 95 102 104 106 108 110 114 116 119 126 127 128 131 134 135 137 138 148 149 150 152 156 160 164 165 166 168 174 175 181 188 201 203 204 205 206 208 215 220 221 222 223 224 228 229 238 239 242 246 248 249 251 252 256 260 264 267 277 280 285 294 295 301 335 340 349 359 376 383 384 385 403 405 411 416 420 422 423 424 427 428 429 431 435 436 441 451 454 464 474 482 492 501 502 504 507 508 510 512 514516 518 520 521 522 523 524 525 526 527 528 530 532 534 536 540 544 546 548 549 552 554 556 558 560 562 564 568 570 585 588 604 607 800 930 968 976 987
Petroleum refining and extraction	**13, 29**	44 48 166 175 204 205 208 340 428 435 508
Rubber products	**30**	2 4 5 8 12 15 16 24 29 36 40 47 49 52 59 62 81 106 108 114 116 119 126 128 135 137 138 150 152 156 160 165 168 181 188 204 205 206 215 220 221 222 223 224 229 238 239 242 248 251 256 264 267 280 285 294 301 383 384 403 411 416 422 427 428 429 441 474 482 492 521 523 524 525 527 604 968
Stone, clay, and glass products	**32**	4 8 15 29 40 47 51 52 65 106 110 119 126 131 138 156 166 174 181 188 205 215 220 222 238 239 242 251 256 264
Primary metals	**33**	29 59 75 104 138 148 156 164 166 174 188 205 228 238 246 249 264 295 385 411 416 420 427 428 464
Fabricated metal products	**34**	2 4 5 7 14 15 16 24 28 29 30 37 38 40 43 47 49 52 54 56 59 62 69 70 72 75 76 79 81 99 104 105 109 110 111 114 116 119 122 125 126 131 134 135 137 138 140 141 144 148 156 160 165 166 168 172 180 181 182 185 186 188 193 204 205 206 211 215 220 221 222 223 224 232 237 238 239 242 244 245 246 248 249 250 251 254 256 258 261 267 269 280 285 289 292 293 294 295 296 297 300 301 310 312 359 376 403 404 405 407 410 411 413 414 416 419 427 428 431 441 454 464 474 482 492 968 976
Machinery	**35**	4 12 15 19 26 27 28 29 30 34 37 38 40 43 47 48 52 53 55 56 57 59 60 62 65 66 68 69 72 73 74 76 79 81 82 83 87 91 92 96 99 100 101 104 105 108 110 111 112 114 116 117 118 119 122 123 125 126 127 131 134 137 138 139 140 141 142 144 147 156 157 159 162 163 164 165 166 169 171 172 173 174 175 177 180 181 182 184 185 186 187 188 192 193 194 196 198 199 202 204 205 206 209 210 211 212 213 219 221 222 223 225 226 227 228 231 234 235 237 239 241 242 244 246 248 249 250 251 254 261 264 266 267 269 270 271 276 277 278 279 280 289 290 293 294 298 299 300 303 305 307 312 335 341 345 346 347 349 356 358 360 366 369 376 380 382 384 386 388 392 395 400 403 404 405 406 407 408 409 412 413 414 415 416 417 418 422 425 427 428 432 435 440 445 451 452 453 454 460 464 470 474 475 476 477 483 492 493 494 505 526 700 701 703 704 705 706 707 708 709 710 711 712 713 714 715 716 717 901 902 968 976
Electrical equipment	**36**	15 29 30 34 38 49 52 62 68 73 83 91 96 99 104 112 116 117 118 119 123 125 126 128 134 136 140 148 156 160 165 174 178 181 187 188 191 192 200 204 205 206 211 216 218 219 220 221 222 228 236 238 241 242 244 246 250 256 257 261 264 267 290 307 310 312 313 314 315 318 320 322 323 324 326 327 329 330 331 332 333 334 335 336 338 340 341 342 343 345 346 348 349 356 358 359 360 361 362 363 365 366 367 369 370 372 373 375 377 378 379 380 381 385 386 388 392 414 416 422 427 428 429 431 434 438 439 445 451 455 477 502 505 600 601 607 700 704 706 714 725 976
Tranportation equipment	**37**	14 15 29 37 42 49 52 60 62 73 74 86 89 91 102 104 105 110 114 116 119 123 124 126 135 137 152 157 160 165 166 169 175 180 181 182 184 186 188 191 192 213 219 220 237 239 242 244 246 254 258 264 267 278 280 291 293 295 296 297 298 301 303 305 307 315 359 384 405 406 414 416 428 431 434 439 440 441 454 464 474 475 476 477 505 701 706 976

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