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What is the Effect of Technological Shocks? : A Natural Experiment from Manufacturing Industry in the United States of America from 2000 to 2010

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Abstract

This research studies from a firm level experiment in which we explored an exogenous technological change in firm's productivity. We present evidence from the manufacturing industry in the United States of America from 2000 to 2010, when the artificial intelligence are widely introduced across manufacturing sector. The result suggests that positive technological shocks affect the productivity in a positive way. Analysis of the data shows that the sector effect and the geographical effect exist but both are limited. These results highlight the universal impact of technological shocks and the interplay among innovations, firms and employees.

Key Words: Technological Shocks, Firm Data, Manufacturing Industry, Effect on Productivity

1 Introduction

With the boom in technology nowadays, we are heading into a new era with humans' labors can be replaced by the artificial intelligence. Statistics show that one out of twenty-five workers in Japan is robot (Lin et al, 2012). Shareholders nowadays begin to decide to hire a person or a machine in the next few years. There are more and more cases and studies on this kind of substitution.

The real business cycle (RBC) paradigm are proposed by Kydland and Prescott (1982) with the introduction of the technological shocks, the short-run fluctuations to capture the exogenous changes in the real economic environment, supported with the data from the postwar US economy. Kydland and Prescott suggested that only technology shocks, random fluctuations in the productivity level, could shift the constant growth trend up or down. Moreover, the RBC theory points out the positive correlation between technology shock and labor employment. But some scholars were skeptical on the observations on the RBC theory with the absence of the independent evidence to track technological shocks. Prescott only posts the data of oil shocks but not the whole industry, which means that this model strategy has little empirical foundation. The most powerful argument (Gali, 1996), combined the data from the G7 countries, stresses the apparent contract to the patterns of RBC model. The data reflect a downward shift in the labor employment schedule caused by technology shocks for a majority of countries. However, similar to the studies of Gali, Christiano (2003) suggested a specification error in the way that Gali presented. And after the correction, the relationship between the technology and per capita hours worked is actually positive.

In sum, these researches are all presented technological shocks in the macroeconomics level and there are little study concerning the microeconomics empirical research. The major reason for this lack is that it is hard to define technology and collected the relevant data due to the technological revolution is transforming time to time. This research tries to solve this problem and seek another way to track the development of technology.

From the U.S. Bureau of Economic Analysis, an official data website, there is boom in productivity output in manufacturing industry during the period of 2000 to 2010. On the other hand, from this website, there is also an obvious sign of manufacturing job loss. From the previous studies, it is mainly accounted for the new artificial intelligence that robots replace human labors. This research therefore aims to identify the huge restructure during this period and estimate how much the technology has changed on productivity. Does the technology make our society better-off or worse-off? How will the corporations be affected with rapid digital technologies revolution? What is the effect on the work labors who are replaced by the robots? These are the concerns that this research tries to identify. The main research question is to seek the effect of this kind of technological shocks.

The paper is organized as follows. Section 2 describes the industry background. Section 3 describes the data and some relating issues. Section 4 develops a theoretical framework to find how our experiment is designed to identify such effects and to analyze the effects of technological shocks. Section 5 presents evidence on the effect of technological shocks across sectors and some interesting findings in association with the analysis. Section 6 concludes.

2 Literature Review and Industry Background

The paper is also related to a small but growing literature on the artificial intelligence used in firms where human beings are easier to be replaced by these kind of new technology. At first, this new kind of technology is first found on the science fiction or on research prediction (Rifkin, 1996). But now, it is invented and applied in our society ranging from manufacturing factories to households. The replacement will even expand because the contemporary computer science can actually understand and mimic human beings (Vardi, 2015). Lin et al (2012) raised the issues concerning on the impact of robotics on a growing chorus on international level, which means that custom-designed computer vision systems are being applied to specific manufacturing tasks for a broad range of industrial applications. Moreover, Stuart Elliot (2016) found that the robots could replace 80% of the current work and may eliminate tens of millions of jobs in the manufacturing, agricultural and service industries in the future. This prediction hides the fact that huge chaos may happen in our economics nowadays. There are more and more studies concerning the artificial intelligence.

Manufacturing industry in the United States of America is the largest industry in the world during the year of 2000 to 2010 (Levinson, 2013). The introduction of artificial intelligence is transforming the whole industry during this period. The production and shipment of goods in manufacturing industry in the United States is a large and important part of the economy in general.

Usually, manufacturing jobs loss was at an average rate of 0.5 percent per year from 1980 to 1999. But this rate suddenly rose to 3.1 percent per year from 2000 to 2011, almost six times faster than the prior two decades (Atkinson et al, 2012). According to Hicks et al (2015), 13 percent of manufacturing job losses are accounted to trade and the rest are because of robots and other factors. Decker et al. (2013) found that the decline exists within detailed industry, firm size and firm age categories. Specifically, the rates of job destruction are greater than the rate of job creation over the past 30 years with notable further declines in the Great Recession.

In this brief, we identify and explain this gap by the introduction of artificial intelligence. In order to evaluate the technological effects on firms and employment, we focus on a period from

2000 to 2010, which contains the largest impact of artificial intelligence in manufacturing industry in U.S. history. This situation is what we tried to explore in this paper.

However, the job lost is not proportional applied to all the sectors from the data of U.S. Bureau of Economic Analysis. Actually, the low-value-added sectors (textiles, furniture, and wood sectors) are most vulnerable while the food, petroleum, beverages and chemicals sectors have less effect.

Industry	2000	2010	Changes
Oil and gas extraction	144879	289670	99.94%
Mining, except oil and gas	54258	114750	111.49%
Wood products	93161	70261	-24.58%
Nonmetallic mineral products	95841	90787	-5.27%
Primary metals	154726	234132	51.32%
Fabricated metal products	266786	295006	10.58%
Machinery	291805	316064	8.31%
Computer and electronic products	527883	368702	-30.15%
Electrical equipment, appliances, and components	122572	108328	-11.62%
Motor vehicles, bodies and trailers, and parts	482142	422670	-12.33%
Other transportation equipment	162215	248092	52.94%
Furniture and related products	74899	57571	-23.14%
Miscellaneous manufacturing	116363	154316	32.62%
Food and beverage and tobacco products	552124	804260	45.67%
Textile mills and textile product mills	85284	49872	-41.52%
Apparel and leather and allied products	67809	18603	-72.57%
Paper products	163590	168730	3.14%
Petroleum and coal products	230706	601691	160.80%
Chemical products	452737	714857	57.90%
Plastics and rubber products	177026	185079	4.55%

Table 1: Output Classified by Industry (Millions of Dollars)

Manufacturing jobs are lost a greater percentage since 2000 than it did, especially during the Great Depression (Aktinson, 2012). However, although the recession has the most severe impact in the manufacturing industry, the recovery rate is the fastest after the recession. It nearly regained those jobs in the subsequent 30 months. (Atkinson et al, 2012) The firm startup rate is high even in the recession. (Decker et al, 2013)

In sum, labor and productivity output are the major change during the research period. But national manufacturing production, after the adjustment of inflation rate, remains on a steady and long-term growth path (Hicks et al, 2015). Despite the continued growth and long-term health of manufacturing, significant revolution remains within the industry. So the selecting industry and research period we choose are both representative, and cover technological shocks.

3 Data and Descriptive Evidence

3.1 The Sample

In this paper, the data our research presented are in the firm level, explicitly collected one by one to shed light on the issues concerning new technology in manufacturing industry in the United States of America. The data are concentrated on the manufacturing industry from 2000 to 2010 in the United States of America because the huge transformation of artificial intelligence was introduced during this period. This research tries to collect the data on the annual report of the all corporations in manufacturing industry from the U.S. Securities and Exchange Commission. All the data used in this paper are annual rather than quarter because the technological shocks are usually in lower frequency, which implies that the annual data may fits better in the model. Since all the data are verified by both the auditing firms and government, they are reliable under Comparability Principle. The corporations' individual records contain the performance each corporation plays each year.

Throughout, we analyze data on the main operating performance on the firm and focus on the American employees on the firms during the research period from January 1st, 2000 until December 31st, 2010. The fiscal year ended date is ranging from January 1st till December 31st and is decided by the company. The usual fiscal year ended date is June 30th or December 31st. To contain the whole firm individual data in our sample, we do not limit the exact day or month with the assumption that a few months (less than 12 months) will not have time difference compared to 10 years revolution. This means that we consider that one report collected from one company with the fiscal year ended with January 1st, 2000 is at the same time period with the report collected from another company with the fiscal year ended with December 31st, 2000. Besides, the corporations are usually international firms and contain employees all over the world. To compare the effects of employment in the United States of America, we only count the workers that were available for work in the land of United States of America in the data set. The final sample contains 12,057 firms across 19 manufacturing sectors and 53 areas (50 states, Washington D.C., Virgin Islands and Puerto Rico). As part of our experimental design, the technological change happens within the research period.

There are a lot of ways to derived sectors. Here we follow the way of Hall (1965) to divide the manufacturing industry into 19 sectors - Food & kindred product, Textiles & apparel, Chemicals excl. drugs, Drugs & Medicine inst., Petroleum ref. & ext., Rubber & misc. plast., Stone, clay & glass, Primary metals, Fabricated metals, Engines, fan & const., Office, comp. eq., Other mach., not elec., Elec. equip. & supplies, Motor veh. & trans. Communication equip, Aircraft & aerospace, Prof. & sci. equip., Lumber, wood & paper, Misc. consumer goods and Conglomerates.

For the geographical dispersion, although Washington D.C. is not a state in the United States of America, it is the capital of the country. So it is an important area due to the political reason and the business environment may contain some difference. In this paper we take it as a separate "State". For the similar reasons, both Virgin Islands and Puerto Rico are the islands on the ocean. Since we cannot count them into any state, we also separate them. So, we have a total of 53 locations across the United States of America.

3.2 Data on Technological Shocks

The main types of technology that can replace human labors are robots, automation, and software (Roman, 2013). To define this technology, we use the data from second class account title subsidiary of “Machinery, Equipment and Software” under the account of “Property, Plant and Equipment” from the Consolidated Statement of Financial Position (Balance Sheet from Annual Report).

The term “Property, Plant and Equipment” refers to non-current tangible assets which are used in the process to generate revenues (Horngren et al, 2013). Under this fixed asset account, account of “Machinery, Equipment and Software” are mainly long-lived intangible assets for the purpose of production with or without physical existence. Robots and automation in the factory are in the form of machinery, equipment or the software in the computer. So, the account of “Machinery, Equipment and Software” can exactly define the three main types of technology that this research focuses on.

The scholars usually used the data of Research and Development cost (R&D cost) or patent data to capture technological shocks. R&D cost is spent with the intention to develop innovative goods or services as the type of operating expense (Horngren et al, 2013). However, to be clear, R&D cost is counted as expense in the Income Statement rather than the assets in the balance sheet by the accounting policy adopted all over the world. The policy makers generally agree that it is impossible to predict whether or not such a R&D project can be successful. The value under the R&D cost are the value that cannot guarantee the future benefits. More importantly, once the R&D project could provide some evidence to generate future benefits, it will be written under the account of “Patent” or “Machinery, Equipment and Software” on the balance sheet. Therefore, it is inaccurate to count the value under R&D cost as the development of technology.

The account of “Patent” is also not accurate to count as technological changes. Patent has a problem in application for the simple reason that the patents do not have broad applicability which further can be assigned to no industry use. Particularly another trouble is the fact that even the new patent is applicable, the process of application takes time, as its pattern of adoption, creating the possibility of one patent invested in one year and may have the effect of the technological shocks a few years later. Given that patent is typically verified at the time of invention, the assignment of Patent as technological shocks is presumably subject to error. Compared with patent, all the investment under the account of “Machinery, Equipment and Software” performed by a company is assigned to the industry in which the company can assure the application and is the actual amount of technology that one company adopted at that accounting year.

Apart from the advantages, I must mention two problems with the data used in this paper under the “Machinery, Equipment and Software” account. Firstly, to assure the accuracy of the data, the data used in this paper are the companies who disclosure the information in the U.S. Securities and Exchange Commission. In virtually all such cases, we suppress either the majority of small companies or some large companies that do not verify in the U.S. Securities and Exchange Commission. Secondly, the “Machinery, Equipment and Software” data are collected from the company. There may exist distinction in the data between industry of innovative and industry of use. This implies one situation that the new investment is not the new technology. Ideally, I would like to interpret the change number from the “Machinery, Equipment and Software” account as "technological innovations". My sense is that we can at least safely assume that new investment in “Machinery, Equipment and Software” contain a higher fraction of manufacture innovations, at least the new investment is innovative compared with the old machinery, equipment and software in the individual corporation level.

3.3 Data Collection

The U.S. Securities and Exchange Commission (SEC) is an exchange agency supported by United States federal government, following the Securities Exchange Act of 1934. According to the law, all of the listed companies must disclosure their operations in the accounting time period in the form of Statements of Financial Position, Income Statement and Cash Flow Statements and so on. The website (https://www.sec.gov/) is an open platform for the public especially the investors to buy or sell their shares in the stock market based on the financial data.

To have the specified sample in the SEC website, I collected the data in six steps: 1) Assorting of SIC Code by manufacturing industries, 2) Typing the SIC Code and the location in the Company Fillings, 3) Getting the CIK number and the company name, 4) Searching the data of one specified company by its CIK number, 5) Spotting that company's annual report in 2000 and 2010, and 6) Copying the figures under the different accounts.

3.3.1 Assorting of SIC Code by Manufacturing Industries

The SIC Code means the Standard Industrial Classification Code, indicating which type of the companies engaged. In the SIC Code list, not only the manufacturing industries are available, but also the agricultural industries and services industries are shown. After finding all the codes in manufacturing industries, an assortment is needed to match the 19 sectors in our research.

3.3.2 Typing the SIC Code and the Location in the Company Fillings

The Company Fillings are the quick search agency on the SEC website to have the company data. In the fillings, you can find all the listed company's name via the information you provide. Here I screen both the sectors and states.

3.3.3 Getting the CIK number and the Company's Name

Additionally, after the screening process, the CIK number and the Company's Name are shown. The CIK number means the Central Index Key (CIK) number. It is used on the website computer systems to distinguish one corporation and used for the public to identify its own information in the SEC's files. Therefore, I have a total of 12,057 companies and their CIK numbers.

3.3.4 Searching the Data of One Specified Company by its CIK Number

In succession of 12,057 CIK numbers, I come to "CIK Fast Search" on the website. Putting one CIK number in the search engine, it will show all the disclosure information including annual reports, quarter reports and registration statement under Securities Act of 1933. All documents are from this specific company in detail.

3.3.5 Spotting that Company's Annual Report in 2000 and 2010

Usually, there are hundreds of documents in the result page. To have the company's annual report in 2000 and 2010 quickly, another filter is used. Information on the annual report are classified in 10-K in SEC website and it is possible to selected the effective date of one file. After filling the type and the date in the filter, the annual report is shown.

3.3.6 Copying the Figures under the Different Accounts

Because the research tries to find a way to address the effect of artificial intelligence in the firm level and to add the empirical studies, in order to address and evaluate this issue on our society in response to this kind of technology revolution, the data I collected concentrate on production and sales part under different accounts. To analyze the data, I type the amount of the accounts into another excel sheet one by one.

Finishing the data collection in the fiscal year 2010, I turn to step 5 and change the filter information to have the data in the fiscal year 2000 and then follow step 6 to collect the data. Consequently, we have all the data we needed for one firm. Furthermore, I turn back to step 4 to put another CIK number in the "CIK Fast Search" to have another company's document. After 12,057 times to type different CIK numbers in step 4 and 24,114 times to change the filter information in step 5, I have the whole sample of the data.

3.4 Summary of the Data

From the sample dispersion table, huge transformation happened in manufacturing sectors, which fits what we observe in macroeconomics data. To have a more detail information on this dispersion, we count the Gone Rate in different sectors, which implies that the companies went bankruptcy or being mergers and acquisition during our research period. The Gone rate in the whole sample is 63.15%, the highest probability to be bankruptcy is focused on Lumber, Textiles and non-electricity machine sectors. They are all low-value-added industry, which follows the macroeconomics data we found in Section 2.

Industry	2000	2010	Changes
Food kindred prod.	3653736360	35627474.97	-99.02%
Textiles apparel	13332409.57	24323845.22	82.44%
Chemicals exci. drugs	7894303.835	37355921.48	373.20%
Drugs med. inst.	66758190.52	191094648.4	186.25%
Petroleum ref. ext.	78153321.16	211873101.1	171.10%
Rubber misc. plast.	24978950.78	38073252.06	52.42%
Stone, clay glass	23053696.42	2330754.974	-89.89%
Primary metals	4166468.612	17348255.74	316.38%
Fabricated metals	20983254.98	20417286.1	-2.70%
Engines,fan const.	18574549.72	965861.566	-94.80%
Office, comp. eq.	116089113	219445787.1	89.03%
Other mach., not elec.	5021560.406	7320408.738	45.78%
Elec. equip. supplies	31698357.28	60734829.81	91.60%
Motor veh. trans. Communication equip	164640089.6	127757952.2	-22.40%
Aircraft aerospace	19789257.79	32510061.59	64.28%
Prof. sci. equip.	61737943.1	113414736.7	83.70%
Lumber, wood paper	1439641811	34729561.35	-97.59%
Misc. consumer goods	59233092.07	73396679.66	23.91%
Conglomerates	6739865.945	10736750.13	59.30%

Table 2: Company Output Classified by Industry (Thousands of Dollars)

As shown in the Table 3, during the period of 2000 and 2010, 2,515 companies were not started to disclosure their information in U.S. Securities and Exchange Commission in total. This parts account for 20.68% in our whole sample. Since we do not have the information of these companies in 2000, we exclude the companies started later than 2000 to have a more time consistent data in company level. This reduced our sample to 9,542 observations.

Industry	Number of Company in 2000	Number of Company Remained in 2010	Gone Rate
Food kindred prod.	357	57	70.59%
Textiles apparel	396	27	79.55%
Chemicals exci. drugs	714	175	60.36%
Drugs med. inst.	1260	502	44.68%
Petroleum ref. ext.	1669	397	63.69%
Rubber misc. plast.	353	66	64.87%
Stone, clay glass	104	19	67.31%
Primary metals	625	206	58.08%
Fabricated metals	464	74	70.04%
Engines,fan const.	114	24	68.42%
Office, comp. eq.	1712	265	63.61%
Other mach., not elec.	99	1	83.84%
Elec. equip. supplies	523	62	66.73%
Motor veh. trans. Communication equip	688	143	65.26%
Aircraft aerospace	132	24	60.61%
Prof. sci. equip.	1322	241	60.29%
Lumber, wood paper	790	82	80.63%
Misc. consumer goods	589	112	67.57%
Conglomerates	146	38	59.59%

Table 3: Gone Rate Classified by Industry

Around 80.26% of the companies which disclosure their information in U.S. Securities and Exchange Commission on 2000 do not have the information in the year of 2010. It can potentially be ascribed to two reasons— bankruptcy or mergers and acquisitions. We called this ratio "Gone Rate". To begin to provide descriptive evidence on these mechanisms, we first note that the "Gone Rate" is different from the failure ratio. The Failure Rate are accounted for the firms that went bankruptcy but the Gone Rate also includes the mergers and acquisitions process. The bankruptcy is definitely a disaster for a company but through mergers and acquisitions, the shareholders of this company can even gain more profits than holding it. Moreover, the expansion of one firm can also achieved by mergers and acquisition. Although the Gone Rate may also contain the later condition which may benefit for the firms, we still consider that this high rate shows the risks. As discussing in the Section 2, the Great Recession and technological shocks can also account for that. It also fits the macroeconomics data we have in Section 2.

On the other hand, when we come to the Gone Rate after excluding the firms started later than 2000, it shows that this specific business environment affects the whole manufacturing industry, no matter in low-valued-goods or high-valued-goods. Following the theory of business dynamism (Decker, 2013), the Great Recession has the general impact across the manufacturing industry. In this way, we take the major Gone Rate accounting to the specific business environment damaging to the manufacturing firms in the United States.

However, the gone rate in the top 500 output companies is only 0.6% while the general gone rate is 63.15%. The increasing scale of the firms can actually increase the chance to survive heavily. This rose some interesting topic on whether the large cluster of corporation can resist depression.

4 Empirical Methods

Using data collected for the research, an ordinary least squares (OLS) can be designed, transforming from the Cobb-Douglas production function. Based on our research questions, we can develop a regression equation to address the relationship between production output and technology changes.

$$\mathrm{Y} = \mathrm{z}A^{\gamma}K^{\alpha}L^{\beta} \tag{1}$$

$$\mathrm{lnY} = \mathrm{lnz} + \gamma\mathrm{lnA} + \alpha\mathrm{lnK} + \beta\mathrm{lnL} + \varepsilon \tag{2}$$

"Y" is the production output, the number of "Sales" Account minus that of "Intermediate Input" Account. "z" refers to the development level of science and technology, which is unknown. But we can calculate "z" in the regression as the constant number and have the conjecture figure. "A" represent the technological shocks, which explain carefully in section 3.2. "K" and "L" are obvious capital and the number of workers. "Ɛ" captures unexpected shocks that can be originated in different sources. The error term is random and unobserved. Using the model above, we can have the correlation between dependent variable and explanatory variables.

To have a more accurate assumption on the relationship between production output and technology changes, we add the variables sectors and location as the control variables (T).

$$\ln Y_i = \ln z_i + \gamma \ln A_i + \alpha \ln K_i + \beta \ln L_i + \theta T_i + \varepsilon_i \tag{3}$$

	1	2	3
Technological Shocks	0.2961 (0.0300) ***	0.2612 (0.0239) ***	0.2441 (0.0233) ***
Capital	0.3015 (0.0318) ***	0.3268 (0.0240) ***	0.2969 (0.0234) ***
Number of Workers	0.2818 (0.0371) ***	0.4026 (0.0196) ***	0.4487 (0.0182) ***
Development Level (Constant)	2.5673 (0.2471) ***	1.1332 (0.1381) ***	1.4439 (0.9441)
Number of Observations	3140	3140	3140
F-test	342.39	669.33	239.71
R^2	0.7822	0.8030	0.8015

Table 4: the Regression Table

（Notes: Standard errors in parentheses. ***, **, * indicate significance at the 1, 5 and 10 percent level, respectively.）

The regression table is shown above. The first column is the general model, omitting the effect of location and sectors. The second column using the 19 sectors as control variable while the third column using the 53 locations as control variable.

At the first column, the correlation between the independent variable (technology changes) and dependent variable (production output) should be examined. Here we can see that the correlation is strong and all independent variables are significant at 1% level.

The coefficients of the technological shocks, capital and the number of workers are both positive, which means that the progress in technology, increase in capital and hire more workers will expand the production output. This result fits what we believed in the past century is that technology will boosts productivity. However, in this rule does not work anymore in the macroeconomics data nowadays. This is a new phenomenon that we cannot apply to the existing economic theory. Why some we still have some empirical evidence which shows that the negative relationship of the technological shocks to the comovement between the productivity output and employment?

It seems to blame artificial intelligence since this kind of technology can actually replace human labors. We are now more and more comfortable to work with such robots without necessarily supervision or encouragement to keeping humans motivated due to technology revolution. This kind of replacement seems to have the direct impact on the employment rate.

We hypothesize that an important reason for the negative relationship in macroeconomics data is a misapplication of technology within firms. According to Wolff (2016), the capitalism system is to be blamed. The employers, or the 0.1% top rich people controls the major part of capitals. They are the ones to control the corporation and to make every effort to maximize the profits and reduce the cost. That is why these employers use artificial intelligence to replace humans - it is cheaper to "hire" intelligent robots than hire the real persons. However, they forget one important thing which is that if the majority of people (employees) do not earn the wages, no one will buy the products which companies produce.

The dynamic effects of the accumulation of capital will generate these kind of financial crisis which seems to blame technological progress. With the introduction of artificial intelligence, the reduce cost on labor gives a potential movement to the relative reduce the demand at short and medium-term horizons. This implies that the goods that the firms produced cannot be sold and the firms will reduce the production in response to this situation. This can also explain why with the introduction of new technology the total output actually decreases. When neither new income nor a market is explored, it results the recession of this specific market.

This situation is what we need to change but not stop the development of artificial intelligence. In West's study (2015), he predicts that the government needs to transform the whole business environment, on health care, pension, disability and income supplements outside of full-time employment, following the new technology.

Back to our regression table, the general model can explain 78.22% of the variable. To capture the accurate determinant of the production output, we can revise our model by adding the control variables. The second and the third model explain the production better, 80.30% and 80.15% respectively. More interestingly, we find that without control of the coefficients of the three independent variables, the sum of the coefficients are around 1. The sum in the second model is 0.9906 while the sum in the third model is 0.9897, which means that if we double the inputs and we can have the double output more or less. This result raises some interesting questions that need further research.

In our experiment, we show in realistic how one company should react within competition in response to technological shocks, which can potentially explain the positive correlation between productivity and employment. The model predicts that technology shocks generate a positive movement between those two variables, labor employment and firm productivity. The intuition for the results is straightforward and satisfies our common sense. In equilibrium, the expansion of one corporation needs people. With the replacement of labors on production sector, the labors can adjust themselves and shift to non-production sector.

5 Assumption on the Development Level of Science and Technology (z)

There are already some studies that make this prediction. But the development level in one sector is hard to concreate. The previous studies usually recover it from the macroeconomics level. In this research, we provided a new way to assume the development level, not from macroeconomics data but from a bunch of firm data.

The development level of science and technology is obviously different across sectors. Following the production function, we can transfer the model and get the development level of science and technology in the table below.

Industry	Number of the Observation	lnz	lnz with Control Variable
Food kindred prod.	90	2.9891 (0.6627) ***	3.6675 (1.3523) ***
Textiles apparel	102	4.8122 (0.6535) ***	5.4374 (1.0759) ***
Chemicals exci. drugs	184	1.7017 (0.3764) ***	3.4827 (1.5484) **
Drugs med. inst.	294	1.6297 (0.3686) ***	2.9399 (1.7745) *
Petroleum ref. ext.	319	0.9957 (0.2763) ***	0.1971 (1.3127)
Rubber misc. plast.	111	1.8057 (0.4596) ***	-0.7611 (0.6331)
Stone, clay glass	30	2.4549 (0.7885) ***	3.1020 (1.8923)
Primary metals	60	-0.1785 (0.7792)	-3.7239 (2.1766) *
Fabricated metals	125	2.1697 (0.3937) ***	3.1925 (0.7744) ***
Engines,fan const.	19	1.8785 (0.4452) ***	3.2299 (1.0368) ***
Office, comp. eq.	659	2.2377 (0.2273) ***	2.2552 (0.8259) ***
Other mach., not elec.	30	0.7662 (1.4070)	2.7519 (1.6640)
Elec. equip. supplies	206	0.4912 (0.4500)	2.6286 (0.8617) ***
Motor veh. trans. Communication equip	170	1.3017 (0.2870) ***	0.9979 (0.7231)
Aircraft aerospace	53	2.1690 (0.6085) ***	0.0204 (0.9127)
Prof. sci. equip.	518	1.8254 (0.2185) ***	0.6771 (0.8662)
Lumber, wood paper	133	2.6098 (0.5244) ***	0.4759 (1.1659)
Misc. consumer goods	-	-	-
Conglomerates	34	5.3706 (0.7380) ***	3.7434 (1.3376) **

Whole	3137	2.5673 (0.2471) ***	1.4439 (0.9441)

Table 5: Assumption on lnz

(Notes: Standard errors in parentheses. ***, **, * indicate significance at the 1, 5 and 10 percent level, respectively.)

The third column is calculated from the general model while the fourth column is from the model with the 53 states as control variable. Compared with the two columns, the location seems less important in determining the development level. So the technological development is across country.

From the table, the development level in textiles sector are high, which fits what we know that during the research period, artificial intelligence is introduced in textiles industry and increases the productivity. On the high-value-added sector, the development level of science and technology is much lower because in these industries the new artificial intelligence were hard to replace human labors. These firms still need to keep investing and hiring the effective labors to produce more.

Despite the differences across sectors, we view the advantages on employers' side easily. If the development of technology is higher, the same inputs indicate higher outputs. To ensure that the employees can also benefit from the development of technology, the way we adopt new technology need reforms.

Employees are typically paid at fixed wage, with no incentive to renew the production process, and the new technology may even make them less important, at least on manufacturing operation. Fearing the layout, employees will resist the adoption of innovations in various way. The most famous case is by Masifield (1961), who observed that by-product coke ovens only applied in the iron and steel sector after 10 years since the innovation. More recent cases are found with similar patents by Stoneman (2002). Rogers (2003) identify this evidence with the introduction of innovations diffusion, which is the determinant of the contribution made by innovation and new technologies to economic growth and welfare with different rates of adoption throughout the relevant population. Through the process of maximize profits and minimum the cost, the corporation takes employees as a major contribution to the cost. That is why we seem to have huge progress in innovative technology nowadays but still our economics are not in an upward slope.

Mainly we can transform through wages. One study (Groves et al, 1994) found that if the employers paid more in bonuses and hired more workers on fixed-term contracts. Productivity is more efficient and effective. This implies that the increase in autonomy raised workers' incomes and investment in the enterprise. A new data set for the Safelite Glass Corporation (Lazear, 2000) propose one effective incentives of firms to rise output productivity by increasing wages. In Safelite, average productivity will rise amount to a 44% increase in output per worker. Later, Bandiera, Barankay and Rasul (2007) found that the flexible wages to count productivity is more efficient than fixed wages. So, we can conclude that wages imply some incentives on the performance of employees.

Overall, when the pool of technological changes is not universal, the introduction of innovations might still have different impacts on the sectors. However, with the more widely application of artificial intelligence, the difference will shrink. Even though the policies in different states are various, the attractiveness of technology is the same across the geography.

The results also imply the positive relationship between technology changes and output. The prediction of future is more accurate with empirical data supported. Implications for policy can be explained in future research. Finally, we can answer the major research question - how the society changes with the introduction of new technology.

6 Conclusion

This paper presents evidence from a firm level experiment designed to identify the effects of technological shocks on the firm side. We find that the introduction of advanced technology raises the output that firms generate. The analysis of the production of the firms and total employees shows the positive correlation in firm level. The control on the sectors and location seems to be of little use. The technological shocks have a universal impact on our society. Applied the data from the account of "Machinery, Equipment and Software" implies an innovative way to determine technological shocks. Since it is the new investment the corporation introduced to the operating performance, it is more accurate than the R&D costs or patents to define and capture the influence of technology.

Our findings shed some light on why firms need to hire more workers after the introduction of artificial intelligence. While such incentive schemes are obviously designed to increase the productivity, our results also suggest another subtler reason for the expansion. This stems from the endogenous performance interacting within the firm. This could be a cycle of technological investment, employees, and profit schemes.

Understanding whether and how technological shocks affect the society is important for two reasons. Firstly, the progress of artificial intelligence is expanding at a rapid speed. However, we do not have enough empirical and theoretical model to determine its movement. This is because this new kind of innovations can actually replace human beings in a wider work place at a rapid speed, which is hard to capture. Whether this artificial intelligence will benefit our society in the long term deserves further research. Secondly, the interaction between artificial intelligence and employees highlights a possible link between economic growth and society welfare - technology revolution can actually drive both of the two trends upward. Such a linkage exists whenever the employers can continue their business, and whenever employees can adjust themselves to satisfy the need of firms.

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Annexes

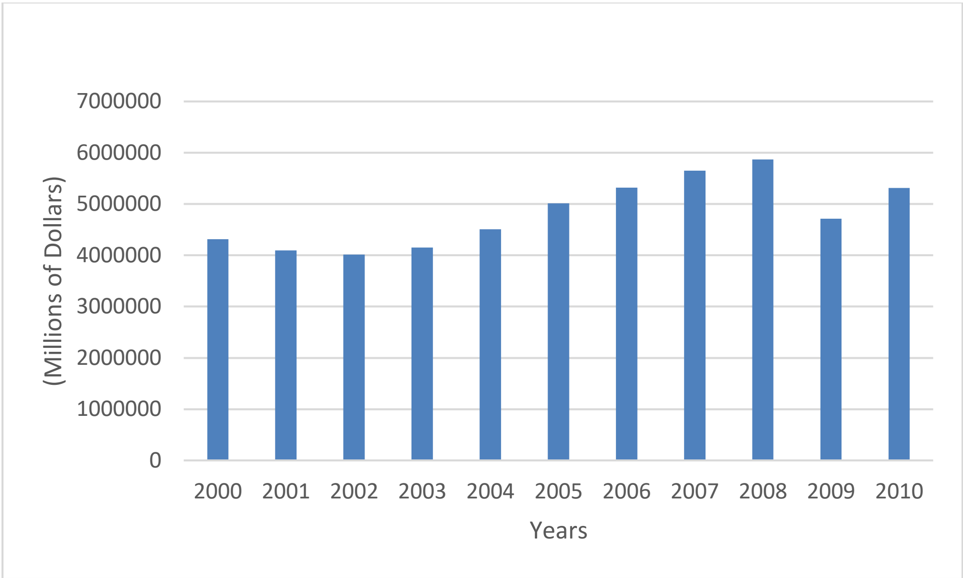
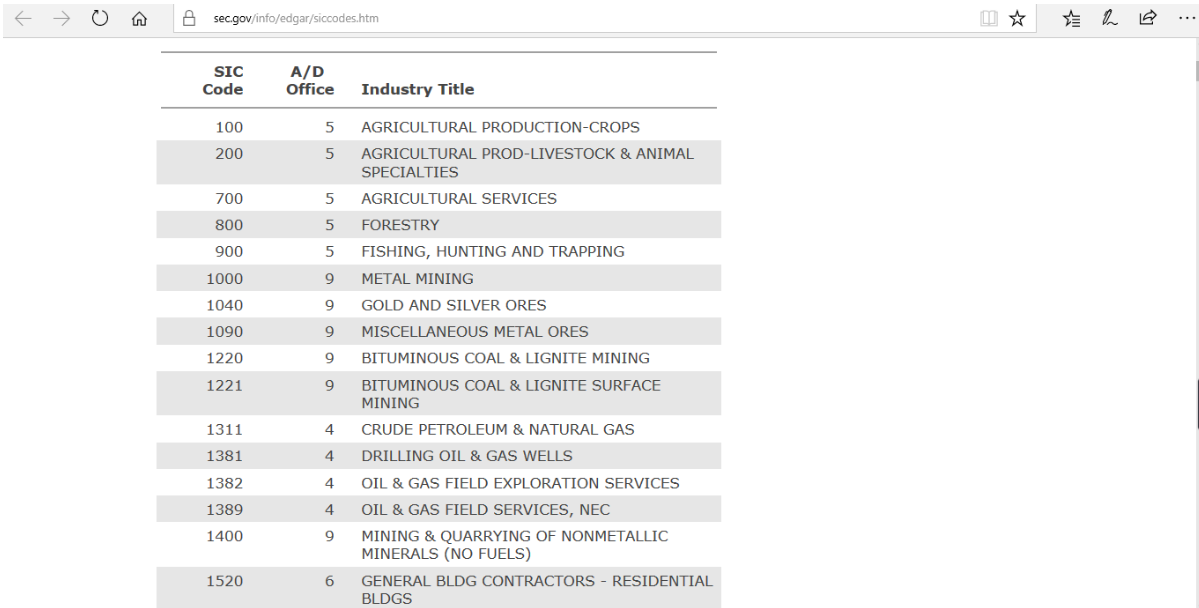


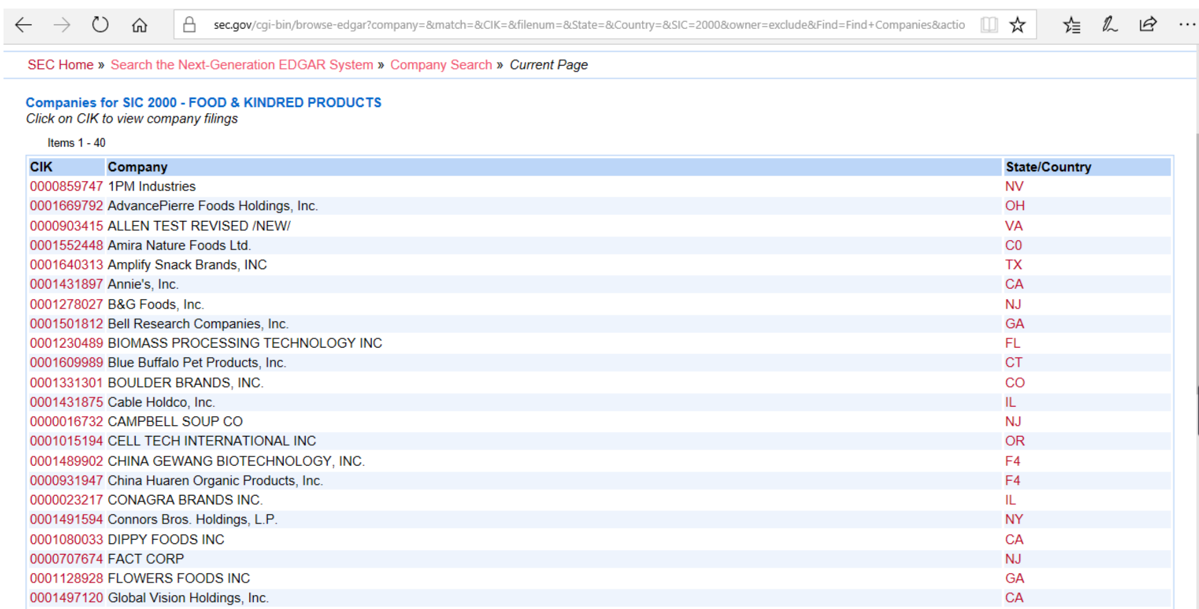
Figure 1：Production Account Gross Output from the U.S. Bureau of Economic Analysis

Figure 2：Company Fillings in the U.S. Securities and Exchange Commission (SEC) website



SIC Code	A/D Office	Industry Title
100	5	AGRICULTURAL PRODUCTION-CROPS
200	5	AGRICULTURAL PROD-LIVESTOCK & ANIMAL SPECIALTIES
700	5	AGRICULTURAL SERVICES
800	5	FORESTRY
900	5	FISHING, HUNTING AND TRAPPING
1000	9	METAL MINING
1040	9	GOLD AND SILVER ORES
1090	9	MISCELLANEOUS METAL ORES
1220	9	BITUMINOUS COAL & LIGNITE MINING
1221	9	BITUMINOUS COAL & LIGNITE SURFACE MINING
1311	4	CRUDE PETROLEUM & NATURAL GAS
1381	4	DRILLING OIL & GAS WELLS
1382	4	OIL & GAS FIELD EXPLORATION SERVICES
1389	4	OIL & GAS FIELD SERVICES, NEC
1400	9	MINING & QUARRYING OF NONMETALLIC MINERALS (NO FUELS)
1520	6	GENERAL BLDG CONTRACTORS - RESIDENTIAL BLDGS

Figure 3: Standard Industrial Classification (SIC) Code in SEC website



CIK	Company	State/Country
0000859747	1PM Industries	NV
0001669792	AdvancePierre Foods Holdings, Inc.	OH
0000903415	ALLEN TEST REVISED /NEW/	VA
0001552448	Amira Nature Foods Ltd.	C0
0001640313	Amplify Snack Brands, INC	TX
0001431897	Annie's, Inc.	CA
0001278027	B&G Foods, Inc.	NJ
0001501812	Bell Research Companies, Inc.	GA
0001230489	BIOMASS PROCESSING TECHNOLOGY INC	FL
0001609989	Blue Buffalo Pet Products, Inc.	CT
0001331301	BOULDER BRANDS, INC.	CO
0001431875	Cable Holdco, Inc.	IL
0000016732	CAMPBELL SOUP CO	NJ
0001015194	CELL TECH INTERNATIONAL INC	OR
0001489902	CHINA GEWANG BIOTECHNOLOGY, INC.	F4
0000931947	China Huaren Organic Products, Inc.	F4
0000023217	CONAGRA BRANDS INC.	IL
0001491594	Connors Bros. Holdings, L.P.	NY
0001080033	DIPPY FOODS INC	CA
0000707674	FACT CORP	NJ
0001128928	FLOWERS FOODS INC	GA
0001497120	Global Vision Holdings, Inc.	CA

Figure 4: Getting the CIK number and the company name

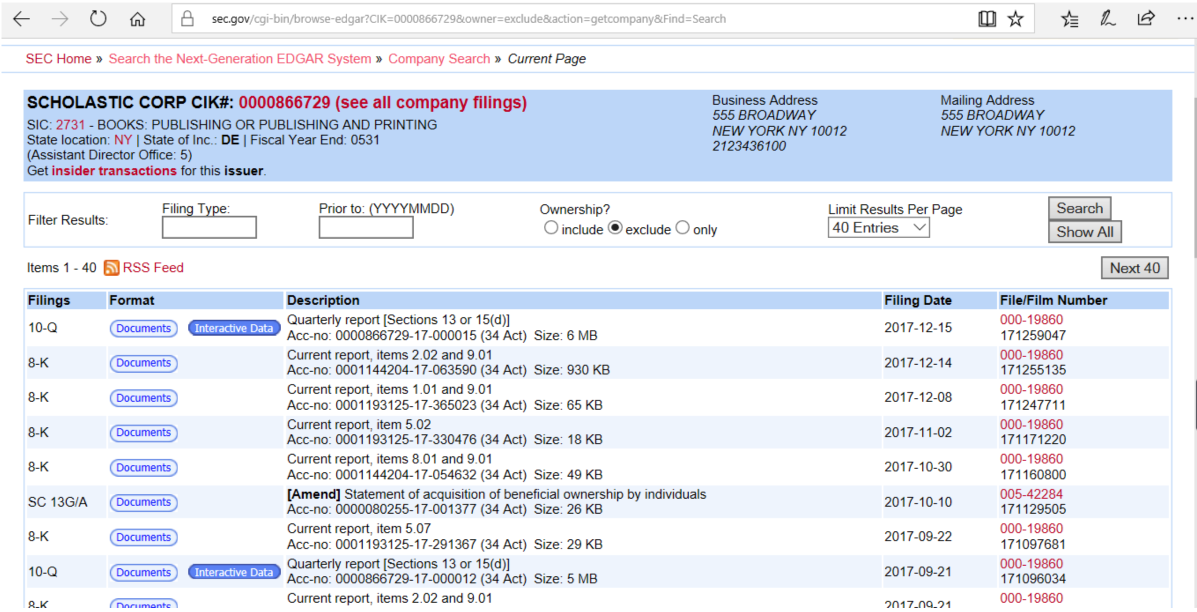


Figure 5：Searching the data of one specified company by its CIK number

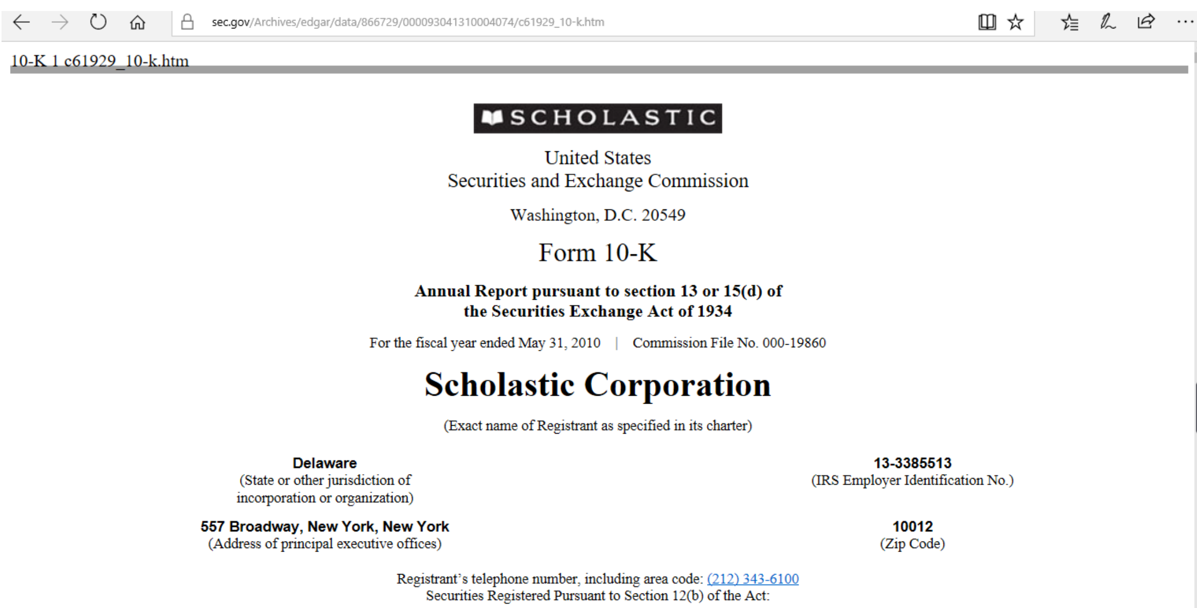
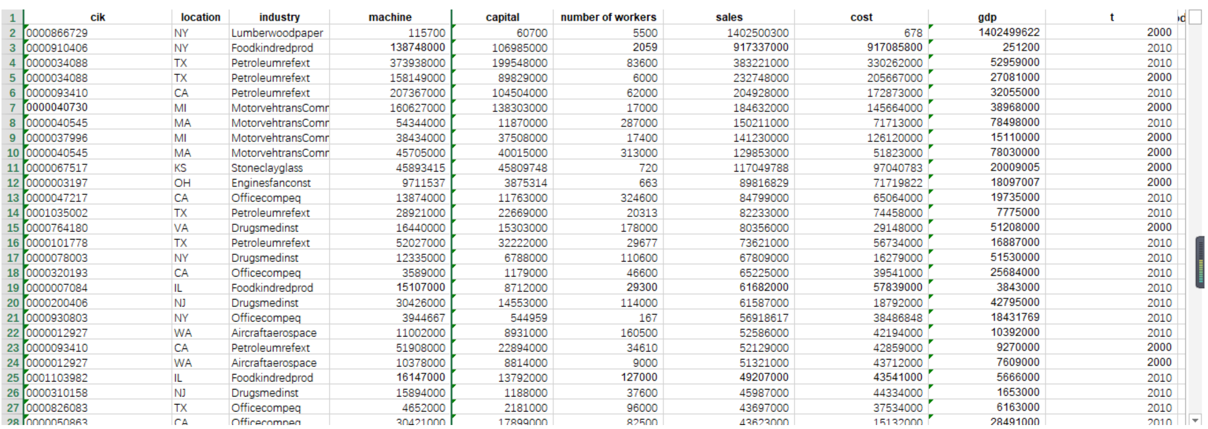


Figure 6：An example on company's annual report in 2010

Figure 7: Content of one company's annual report



1	cik	location	industry	machine	capital	number of workers	sales	cost	gdp	t
2	0000866729	NY	Lumberwoodpaper	115700	60700	5500	1402500300	678	1402499622	2000
3	0000910406	NY	Foodkindredprod	138748000	106985000	2059	917337000	917085800	251200	2010
4	0000034088	TX	Petroleumrefext	373938000	199548000	83600	383221000	330262000	52959000	2010
5	0000034088	TX	Petroleumrefext	158149000	89829000	6000	232748000	205667000	27081000	2000
6	0000093410	CA	Petroleumrefext	207367000	104504000	62000	204928000	172873000	32055000	2010
7	0000040730	MI	MotorvehtransComr	160627000	138303000	17000	184632000	145664000	38968000	2000
8	0000040545	MA	MotorvehtransComr	54344000	11870000	287000	150211000	71713000	78498000	2010
9	0000037996	MI	MotorvehtransComr	38434000	37508000	17400	141230000	126120000	15110000	2000
10	0000040545	MA	MotorvehtransComr	45705000	40015000	313000	129853000	51823000	78030000	2000
11	0000067517	KS	Stoneclayglass	45893415	45809748	720	117049788	97040783	20009005	2000
12	0000003197	OH	Enginesfanconst	9711537	3875314	663	89816829	71719822	18097007	2000
13	0000047217	CA	Officecompeq	13874000	11763000	324600	84799000	65064000	19735000	2010
14	0001035002	TX	Petroleumrefext	28921000	22669000	20313	82233000	74458000	7775000	2010
15	0000764180	VA	Drugsmedinst	16440000	15303000	178000	80356000	29148000	51208000	2000
16	0000101778	TX	Petroleumrefext	52027000	32222000	29677	73621000	56734000	16887000	2010
17	0000078003	NY	Drugsmedinst	12335000	6788000	110600	67809000	16279000	51530000	2010
18	0000320193	CA	Officecompeq	3589000	1179000	46600	65225000	39541000	25684000	2010
19	0000007084	IL	Foodkindredprod	15107000	8712000	29300	61682000	57839000	3843000	2010
20	0000200406	NJ	Drugsmedinst	30426000	14553000	114000	61587000	18792000	42795000	2010
21	0000930803	NY	Officecompeq	3944667	544959	167	56918617	38486848	18431769	2010
22	0000012927	WA	Aircraftaerospace	11002000	8931000	160500	52586000	42194000	10392000	2010
23	0000093410	CA	Petroleumrefext	51908000	22894000	34610	52129000	42859000	9270000	2000
24	0000012927	WA	Aircraftaerospace	10378000	8814000	9000	51321000	43712000	7609000	2000
25	0001103982	IL	Foodkindredprod	16147000	13792000	127000	49207000	43541000	5666000	2010
26	0000310158	NJ	Drugsmedinst	15894000	1188000	37600	45987000	44334000	1653000	2010
27	0000826083	TX	Officecompeq	4652000	2181000	96000	43697000	37534000	6163000	2010
28	0000050863	CA	Officecompeq	30421000	17899000	82500	43623000	15132000	28491000	2010

Figure 8: Excel Sheet of the Analysis Sample