THREE ESSAYS ON MINERAL ECONOMICS AND ECONOMIC GEOGRAPHY

by

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ABSTRACT

This dissertation presents three essays on resource economics. The first essay discusses economics of mineral supply as a by-product. Specifically, this essay estimates how much uranium might be recoverable from current phosphoric acid production in the United States and what the associated costs might be. The second and third essays deal with resource economics in the context of economic geography. The second essay studies locational determinants of manufacturing related to wind energy. Econometric technique is applied to investigate the location of wind equipment manufacturing facilities in the United States. To our knowledge, it is one of the first studies to analyze the topic in quantitative way due to sparseness of data. The third essay studies knowledge localization in innovative industry with a case study on additive manufacturing. Knowledge plays an important role in early stages of technology development. Unlike wind equipment manufacturing which has already been fully commercialized, additive manufacturing is a newly growing industry which is not fully mature yet. The empirical results improve our understanding on localization of knowledge in innovative industry. These three essays contribute to expanding our knowledge of resources economics by providing case studies.

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I have a fear that I might miss someone from the thank you list. For that I am not naming any particular person. If you are reading this acknowledgements, I am sure that you are the one to whom I am very grateful.

CHAPTER 1

INTRODUCTION

This dissertation consists of three essays that investigate different topics in resource economics. The first essay discusses the economics of mineral supply as a by-product. Specifically, this essay estimates how much uranium might be recoverable from current phosphoric acid production in the United States and what the associated costs might be. Recovery of uranium as a by-product from phosphoric acid is not unprecedented. Phosphoric acid plants used to produce uranium as a by-product until the early 1990s before the uranium prices fell. In the last decade, this topic regained attention due to higher uranium prices and expected increase in demand for uranium. Based on U.S. phosphoric acid production in 2014, 5.5 million pounds of uranium oxide (U_3O_8) could have been recovered. This is more than domestic U.S. mine production and corresponds to roughly 10% of demand from U.S. nuclear plants in the same year. Annualized costs for a hypothetical uranium recovery plant are US$44-61 per pound U_3O_8 for solvent extraction and US$33-54 per pound U_3O_8 for ion exchange. These results suggest that it is technically possible for the United States to recover significant quantities of uranium from current phosphoric acid production. For this type of uranium production to be economically viable on a large scale, however, either recovery costs should fall, or uranium prices should rise.

The second and third essays deal with resource economics in the context of economic geography. The second essay studies locational determinants of wind equipment manufacturing in the United States. A conditional logit model is applied to study new facilities opened between 1995 and 2014 using a dataset constructed from the beginning. To our knowledge, it is one of the first studies to analyze locational decisions of wind equipment manufacturing in a quantitative way due to sparseness of data. Estimated results show that existing manufacturing activity and wind resource potential are significant determinants of

location decisions. Renewable Portfolio Standards requirement is found to be insignificant as a locational determinant despite its importance in renewable energy deployment. These findings are robust after resampling and change in the number of alternatives.

The third essay studies knowledge localization in an innovative industry with a case study on additive manufacturing. Knowledge plays an important role in early stages of industry development. Unlike wind equipment manufacturing which has already been fully commercialized, additive manufacturing is a newly growing industry which is not fully mature yet. Using U.S. patents and citation data from 1990 to 2009, we find that knowledge in additive manufacturing is localized at the Metropolitan Statistical Area level which is largely affected by self-citations. Excluding self-citations, knowledge in additive manufacturing is not significantly localized compared to the control group. The logit analysis results reveal that knowledge from public research is more local than non-public research.

These three essays contribute to expanding our knowledge of resource economics by providing case studies.

CHAPTER 2

POTENTIAL URANIUM SUPPLY FROM PHOSPHORIC ACID: AN U.S. ANALYSIS COMPARING SOLVENT EXTRACTION AND ION EXCHANGE

A paper published in *Resource Policy*[1]

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Uranium fuels nuclear power. In 2015, nuclear power plants worldwide operated with over 375 GWe of total capacity corresponding to an annual uranium requirement of 174 million pounds U_3O_8 (World Nuclear Association (2015)). World nuclear capacity is projected to either increase slightly to 386 GWe (low estimate) or significantly to 632 GWe by 2035 (high estimate) and uranium requirements are expected to change correspondingly (International Atomic Energy Agency (2015)).

Conventional resources, defined as uranium resources with previous production as a main product, a co-product or a significant by-product, are estimated at 42 billion pounds U_3O_8.[6] In comparison, unconventional uranium resources are uranium resources at very low-grade or those from which uranium could be recovered as a non-significant by-product (Nuclear Energy Agency and International Atomic Energy Agency (2014)). Various authors estimate that from 16 billion to 57 billion pounds of U_3O_8 are contained in unconventional resources, almost all of which are in phosphate-rock resources but not all of which are recoverable (De Voto & Stevens (1979); Gabriel *et al.* (2013); International Atomic Energy Agency (2001); Nuclear Energy Agency and International Atomic Energy Agency (2014); Ulrich *et al.* (2014); World Nuclear Association (2015)). Considering worldwide uranium consumption in

[1]Reproduced with permission. Resources Policy, 49, 222-231. DOI:10.1016/j.resourpol.2016.06.004

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[6]Identified conventional resources

2015, this is equivalent to approximately 95 to 330 years of world supply at current rates of use if it becomes commercially feasible to recover. Gabriel *et al.* (2013) estimate around 53% of this uranium to be recoverable (9 billion from their estimated resources of 17 billion pounds).

This study estimates how much uranium might be recoverable from current phosphoric acid production in the United States and what the associated costs might be. To estimate costs, two different recovery processes are considered: solvent extraction and ion exchange. Based on U.S. phosphoric acid production in 2014, 5.5 million pounds of U_3O_8 could have been recovered, which is more than domestic U.S. production and corresponds to nearly 10% of the U.S. demand for uranium in same year. Costs of recovering uranium for a hypothetical plant are US$44-61 per pound U_3O_8 for solvent extraction and US$33-54 per pound U_3O_8 for ion exchange.

The remainder of the paper is organized as follows. The background section provides a brief history of uranium recovery from phosphoric acid and uranium in phosphate rock. The data-and-method section explains the sources of data and method of cost estimation. The results section presents the quantity and cost estimates for the two processes. The implications and concluding sections suggest implications and summarize findings of the study.

2.1 Background

2.1.1 History

Recovering uranium from phosphoric acid produced during the recovery of phosphorus from phosphate rock is not unprecedented in the United States (Table 2.1). Uranium was recovered in the United States during two periods in the second half of the 1900s. In the 1950s and early 1960s, three plants in Florida recovered uranium from phosphoric acid. Although exact production figures are not available, the overall level of production during this period was limited. The first period came to an end in early 1960s as the price of uranium fell and recovering uranium from phosphoric acid became uneconomic. The second

period began in the middle of 1970s, following a significant increase in uranium prices, and lasted until the 1990s. Eight plants were active in the United States, and 44 million pounds U_3O_8 were produced. Later in this period, uranium prices fell and phosphoric acid plants ceased to produce uranium as a by-product in the 1990s. The most recent production on a commercial scale occurred in 1999, and no production on a large scale has been reported since then.

In the last decade, producing uranium from phosphate rock has regained attention due to higher uranium prices and expected increase in demand for uranium. Recent studies of uranium in phosphate rock focus on (a) physical availability of uranium in phosphate rock (Adam & Eltayeb (2009); Ragheb & Khasawneh (2010); Schnug & Haneklaus (2014); Ulrich *et al.* (2014)), (b) recovery processes (Beltrami *et al.* (2014); Elsayed *et al.* (2013)), or (c) case-specific cost estimation by industry (Frame (2011); PhosEnergy (2013, 2015)). NUKEM, Inc. and CF Industries proposed recovering uranium from phosphoric acid at one of CF Industries operations in Florida and a feasibility study was completed in 2009 (Frame (2011) and 2015, personal communication). Most recently, a transportable demonstration plant based was tested in the United States (PhosEnergy (2013, 2015)).

2.1.2 Uranium in Phosphate Rock

Phosphate rock contains phosphate minerals that can be mined profitably, providing the phosphorus used in fertilizers. Estimated U.S. production of phosphate rock was 27.1 million tonnes in 2014. Florida and North Carolina produced 80% of total output, with the remaining 20% produced in Idaho and Utah. Reserves are estimated as 1,100 million tonnes (Jasinski (2015a)).

Table 2.1: Past Uranium Recovery from Phosphoric Acid in the U.S.

Location	Process [7]	Capacity P_2O_5 (tonnes/yr)	Capacity U_3O_8 (lbs/yr)[8]	Operating period	Cumulative Production U_3O_8 (lbs)[9]	Producer (Phosphoric acid/Uranium)
1952-1961						—
Joliet, Illinois	Precipitation	100,000	80,000	1952-1961	n/a	Blockson
Bartow, Florida	OPPA	100,000	80,000	1955-1961	n/a	IMC
Tampa, Florida	OPPA	200,000	160,000	1955-1961	n/a	US phosphoric Products (Gardinier)
1976-1999						—
Bartow, Florida	OPAP	n/a	330,000	1976-1980	228,000	W.R. Grace/ Uranium Recovery Corp.
Pierce, Florida	DEHPA-TOPO	450,000	400,000	1978-1981	722,000	Farmland/ Wyoming Minerals Corp.
Uncle Sam, Louisiana	DEHPA-TOPO	675,000	690,000	1978-1999	14,008,000	Freeport/ Freeport Minerals Co.
Donaldsonville, Louisiana	DEHPA-TOPO	360,000	420,000	1981-1998	6,268,000	Agrico/ Freeport Minerals Co.
New Wales, Florida	DEHPA-TOPO	1,000,000	800,000	1980-1992	13,176,000	IMC/ IMC
Bartow, Florida	DEHPA-TOPO	720,000	600,000	1981-1985	718,000	CF Industries/ IMC
Plant City, Florida	DEHPA-TOPO	680,000	600,000	1980-1992	8,806,000	CF Industries/ IMC
Tampa, Florida	OPPA	500,000	420,000	1979-1982	507,000	Gardinier/ Gardinier
U.S. Total					44,433,000	

Source: Walters *et al.* (2008); Pool (2014); Personal communication with Pool (2015)

[7]OPPA: Octyl-pyrophosphoric acid; OPAP: Octyl-phenylphosphoric acid; DEHPA-TOPO: Mixture of di-2-ethylhexy phosphoric acid and tri-octylphosphine oxide. For details about the processes, refer to A.1 Recovery Processes

[8]Capacities presented can be considered as initial design capacities reported by each company. At stable operating situations, actual output may increase due to process optimization and/or higher ore grade. This explains why cumulative productions are greater than expected cumulative production (annual capacity of U_3O_8 multiplied by years of operation) at some operations.

[9]Source: Personal communication with Pool (2015).

Most of the worlds phosphate rock production is from sedimentary deposits. Sedimentary phosphate rock worldwide contains 18-40% P_2O_5 by weight and 70-220ppm of uranium, roughly proportional to P_2O_5 content (World Nuclear Association (2015)).

2.1.3 Phosphoric Acid Production

Phosphate rock is mainly used in the production of wet process phosphoric acid and superphosphoric acid in the United States (Jasinski (2015a)).[10] These intermediate products are used primarily in manufacturing fertilizer. The production of phosphoric acid from phosphate rock is illustrated in Figure 2.1.

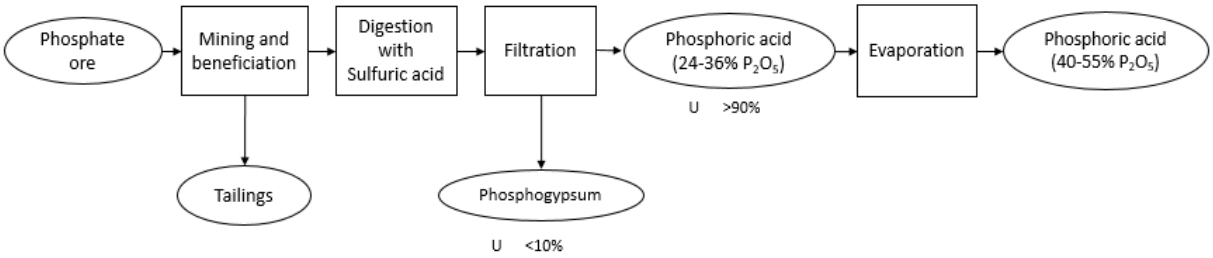

Figure 2.1: Wet Process Phosphoric Acid Flow Sheet

Source: Authors' representation, modified from International Atomic Energy Agency (2013) and De Voto & Stevens (1979)). Note: The percentages in the figure refer to the disposition of the uranium contained in the phosphate ore.

Phosphate ore mined in the United States contains sand, clay, and large pebbles. These impurities are removed by beneficiation, which usually starts with wet screening. After being mined and beneficiated, phosphate rock goes through a wet digestion process. Phosphorus in phosphate rock is insoluble in water and needs to be digested with acid, sulfuric acid in most cases. Adding sulfuric acid yields phosphoric acid and phosphogypsum. During digestion, more than 90% of the uranium in the phosphate rock is dissolved into the phosphoric acid while the rest migrates to the phosphogypsum (Gabriel *et al.* (2013); International Atomic Energy Agency (2013)). The resulting phosphoric acid is filtered, and phosphogypsum is

[10]Other uses of phosphate rock are animal feed supplements, direct application to soil as fertilizer, and elemental phosphorus production (Jasinski (2015b))

separated from the acid and stacked at a disposal site. Phosphoric acid after filtration usually has P_2O_5 in the 24-36% range by weight. Since most industrial applications require higher content of P_2O_5 in the acid, additional processes such as concentration and purification are commonly necessary. Through evaporation, the content of P_2O_5 is increased to 40-55%. For further purification, producers could choose to add processes such as flocculation, solvent extraction, crystallization and ion exchange to lower the content of impurities in the acid.

2.1.4 Uranium Recovery from Phosphoric Acid

As noted earlier, more than 90% of the uranium in the phosphate rock is dissolved into the phosphoric acid. Unless recovered, dissolved uranium stays in the phosphoric acid and ends up in the phosphate fertilizer produced from the acid. However, uranium could be recovered by adding a recovery process before evaporation. This section describes two processes for recovering uranium from phosphoric acid: solvent extraction and ion exchange.

Solvent extraction has been used in the past to recover uranium from phosphoric acid. Among the 11 previous operations in the U.S., 10 plants were based on solvent extraction (Table 2.1). Though historically proven, solvent extraction is known to have high operating costs. In contrast, ion exchange has low operating costs, but it has not been used on a commercial scale to recover uranium from phosphoric acid. In 2012, PhosEnergy Limited and Cameco operated a PhosEnergy demonstration plant in the United States. Compared to solvent extraction, ion exchange has several potential advantages (Beltrami *et al.* (2014); International Atomic Energy Agency (2013); Volkman (1989)): no contamination of the phosphoric acid with organic solvents; tolerance of higher temperature and thus eliminating the need for temperature adjustment; lower operating costs; elimination of the acid post-treatment step. For detailed steps of both recovery processes, see Appendix A.1.

2.2 Data and Method

2.2.1 Quantity estimation

To estimate recoverable quantities from current phosphoric acid production, data on acid production in 2014 and uranium concentration are collected for the active phosphoric acid plants in the United States. Uranium concentration is mainly based on the projection of uranium in U.S. phosphoric acid for year 2000 (De Voto & Stevens (1979)).

2.2.2 Cost estimation

Recovering uranium from phosphoric acid is an example of by-product production. As long as the phosphoric acid production is commercially viable on its own, only the additional costs of recovering the uranium by-product should be attributed to uranium. In other words, the costs of mining and transporting the phosphate rock, producing phosphoric acid, and other processes prior to recovering the uranium as a by-product are not relevant for considering the commercial viability of recovering by-product uranium.

Cost estimates for uranium recovery are developed for both solvent extraction and ion exchange processes. The cost estimates are based on a hypothetical plant adjacent to a phosphoric acid plant. Capital costs are based on adjusted historical (published) figures. Operating costs represent current costs. For ion exchange, we rely on published, recent cost estimates, and adjust them to conform to the scale of operation at our hypothetical plant. Assumptions on plant characteristics are summarized in Table 2.2.

Estimated costs in this study are order-of-magnitude estimates based on the level of project definition for which the probable accuracy lies between -30% and +50% (Green & Perry (2008)).[11] For fixed capital costs, historical figures for each process are first escalated to 2014 dollar values using the Chemical Engineering Plant Cost Index (CEPCI, hereafter)[12]

[11] This uncertainty range accounts for uncertainty inherent in early stages of project development. It does not explicitly account for the technical risks or degree of commercialization associated with specific process.

[12] The index is published on a monthly basis and aggregated to annual level each year. As of now, the index for year 2014 is the most recent figure on annual level.

Table 2.2: Plant Characteristics and Key Assumptions for Cost Estimation

	Solvent Extraction	Ion Exchange
Location[a]	Florida, United States	
Phosphoric acid plant capacity	870,000 tonnes P_2O_5/yr	
Uranium content[b]	145 mg U_3O_8/l	
Process[c]	Two-stage DEHPA-TOPO process	PhosEnergy
Uranium recovery rate[d]	95%	92%

[a]Florida is the largest producer of phosphoric acid in the United States. Also, most of the previous operations occurred in Florida (Table 2.1). Annual capacity of the hypothesized plant is 870,000 tonnes P_2O_5, the average production of existing phosphoric acid plants in Florida in 2014.

[b]Uranium content is based on the projections of uranium in Florida phosphoric acid for year 2000 (De Voto & Stevens (1979)). Note that uranium content actually reported by PhosEnergy (2013) is higher than this figure (165 mg U_3O_8/l). The content from De Voto & Stevens (1979) is applied in our study to make sure that comparison of two processes is based on the same profile of phosphoric acid. On average, phosphate rock in Florida contains 100 ppm uranium (Bruneton (2013)).

[c]Process for solvent extraction is assumed to be identical to the case from Botella (1989) where DEHPA/TOPO ratio is 6/1. Ion exchange recovery plant is based on the PhosEnergy process.

[d]Recovery rates are derived from recent prefeasibility studies: Personal communication with Frame (2015) for solvent extraction and PhosEnergy (2013) for ion exchange. With these recovery rates, recoverable uranium for solvent extraction and ion exchange are 734,000 pounds U_3O_8 and 711,000 pounds U_3O_8, respectively.

and then adjusted for differences in capacity:

$$Cost_{2014} = Cost_{old}(CEPCI_{2014}/CEPCI_{old}) \tag{2.1}$$

$$Cost_{new} = Cost_{2014}(Capacity_{new}/Capacity_{2014})^{0.7} \tag{2.2}$$

where Cost_{new} represents the estimated costs after time and capacity adjustment. Cost_{old} is the fixed capital cost from earlier operation and Cost_{2014} is the cost after time adjustment assuming identical capacity with the previous operations. To account for capacity, the seven-tenths rule is applied. For a chemical process plant, cost is adjusted in proportion to an exponential of the ratio of capacities of the two plants. The parameter 0.7 is often used to account for economies of scale in engineering cost estimation (Couper (2003); Green & Perry (2008)). In this step, the time-adjusted cost from the previous step Cost_{2014} is adjusted to a new Cost_{new} based on capacity.

2.3 Results

2.3.1 Quantity estimation

In 2014, eleven phosphoric acid plants were active in the United States: five in Florida, two each in Idaho and Louisiana, and one each in Wyoming and North Carolina.[13] Total capacity and estimated production are 8.2 and 7.0 million tonnes P_2O_5, respectively (Table 2.3). To estimate the recoverable quantities of uranium from phosphoric acid, the following approach is taken: First, convert the weight of P_2O_5 into phosphoric acid of which 30% by weight is P_2O_5. Second, convert the U_3O_8 content into weight ratios using the density of 30% phosphoric acid ($\approx$ 1.2 g/ml). Third, multiply the acid weight by the U_3O_8 content in weight terms and by the recovery rate. For a reference calculation, see Appendix A.2.

According to our assessment in Table 2.3, 5.5 million pounds of U_3O_8 would have been recoverable from U.S. phosphoric acid production with solvent extraction in 2014. The recoverable quantity would be 0.2 million pounds lower with ion exchange. In comparison,

[13]Phosphoric acid plants do not necessarily have to be located close to where phosphate rock is mined. In other words, not all phosphoric acid plants use phosphate rock coming from local sources. Some phosphoric acid plants bring phosphate rock from different states, or even import from different countries.

domestic production of U_3O_8 from conventional mining was 4.9 million pounds, smaller than potential production from phosphoric acid production. In 2014, U.S. nuclear plants purchased 53 million pounds of U_3O_8 equivalent (U.S. Energy Information Administration (2015)). If recovered, uranium from U.S. phosphoric acid could have met 10% of domestic demand.

Table 2.3: U.S. Phosphoric Acid Producers and Potential Recovery Quantities (Source: Authors' calculations)

Phosphoric Acid Producers	Location	Capacity (tonnes P_2O_5/yr) [14]	Acid Production in 2014 (tonnes P_2O_5)[14]	U_3O_8 (mg/l) [15]	U_3O_8 (lbs/yr) [16]
Agrium US Inc.	Conda, Idaho	350,000	299,000	140	244,000
J.R. Simplot Company	Pocatello, Idaho	408,000	349,000	140	284,000
J.R. Simplot Company	Rock Springs, Wyoming	367,000	314,000	100	183,000
The Mosaic Company	Plant City, Florida	900,000	600,000	145	506,000
The Mosaic Company	Bartow, Florida	900,000	1,000,000[17]	145	844,000
The Mosaic Company	New Wales, Florida	1,700,000	1,500,000	145	1,265,000

[14] Information on phosphoric acid plant capacity and actual production are from International Fertilizer Industry Association (International Fertilizer Industry Association (2014)), The Mosaic Company (The Mosaic Company (2015)), and Potash Corporation of Saskatchewan (Potash Corporation of Saskatchewan Inc. (2015)). Production for three operations (one Agrium US Inc. and two J.R. Simplot Company) are estimated using average capacity factor of the other plants with production data (85.5%).

[15] Uranium content is based on the projections of uranium in U.S. phosphoric acid for year 2000 (De Voto & Stevens (1979)). The content is defined as the weight of U_3O_8 in 30% phosphoric acid. Although somewhat dated, it is the most comprehensive evaluation available. It is assumed that uranium is found in phosphate rock at nearly constant concentrations. The concentration for Rock Springs, Wyoming, is adjusted after personal communication with Davidson (February, 2015). In general, sedimentary phosphate rock contains 70-220ppm uranium (World Nuclear Association (2015)).

[16] Recoverable quantities in this table are based on solvent extraction with recovery rate of 95%. Ion exchange has lower recovery rate (92%) and recoverable quantities would be 0.2 million pounds lower than solvent extraction in total.

[17] Fewer days of both planned maintenance and unplanned outage enabled high performance at Bartow, Florida. In comparison, production greater than capacity in White Springs, Florida, was possible because of partial shutdown of facilities. In the second half of 2014, one of the two chemical complexes in White Springs was closed. As a result, production capacity dropped from 1 million to 0.5 million tonnes P_2O_5 per year.

Table 2.3: Continued.

Phosphoric Acid Producers	Location	Capacity (tonnes P_2O_5/yr)	Acid Production in 2014 (tonnes P_2O_5)	U_3O_8 (mg/l)	U_3O_8 (lbs/yr)
The Mosaic Company	Tampa, Florida	900,000	700,000	145	591,000
The Mosaic Company	Uncle Sam, Louisiana	800,000	600,000	145	506,000
Potash Corporation of Saskatchewan	Aurora, North Carolina	1,200,000	1,000,000	80	465,000
Potash Corporation of Saskatchewan	Geismar, Louisiana	200,000	120,000	145	101,000
Potash Corporation of Saskatchewan	White Springs, Florida	500,000	550,000[17]	145	464,000
U.S. Total		8,225,000	7,032,000		5,453,000

The recoverable amount of uranium is affected by the concentration of uranium in the phosphoric acid, which is roughly proportional to the grade of uranium in ore. If uranium concentration decreases by 10% (or 20%), so would recoverable quantities and 4.9 million (or 4.4 million) pounds of U_3O_8 would be recoverable. In comparison, if uranium concentration increases by 10% (or 20%), recoverable uranium will rise to 6.0 million (or 6.5 million) pounds U_3O_8.

2.3.2 Cost estimation

Estimated costs for both processes are summarized in Table 2.4. For detailed cost estimates, see Appendix A.2. Total capital costs for solvent extraction are less than those for ion exchange recovery plant by US$23 million. Not knowing exactly what a companys actual cost of capital would be, three interest rates are used to adjust for the time value of money: 5%, 10%, and 15%. For the plant life, three periods of plant life are assumed: 15 years as a lower bound (Frame 2015, personal communication), 20 years as a reference, and 25 years as an upper bound. Annualized capital costs per unit of uranium are derived by

dividing annualized capital costs by projected U_3O_8 production. As a result, it is estimated that solvent extraction would cost approximately US$14 per pound U_3O_8 in capital if the interest rate is 5%, increasing to US$28 per pound U_3O_8 at an interest rate of 15% with the plant life of 20 years. For the same plant life and range of interest rates, ion exchange would cost from US$17 to US$34 per pound U_3O_8 which is greater than solvent extraction by US$3-6 per pound U_3O_8. Considering only operating costs, ion exchange clearly has a significant advantage over solvent extraction. Estimated operating costs for solvent extraction are US$32 per pound U_3O_8 while those of ion exchange are US$18 per pound. Comparing total costs per unit of U_3O_8, ion exchange also has an apparent advantage because its much lower estimated operating costs more than offset its higher capital costs. Depending on the interest rate and plant life, ion exchange would cost from US$33 to US$54 per pound U_3O_8 which is lower than solvent extraction by US$7-11 per pound U_3O_8. However, it should be noted that ion exchange is a process not completely proven at a commercial scale. Hence, there is technical risk associated with scale-up and commercialization of the technology. For example: resins are highly sensitive to degradation in concentrated acid, mechanical stresses are present on resins during the process, and iron co-extraction may result in contamination of the resins and decrease resin capacity (Beltrami *et al.* (2014)). In contrast, solvent extraction has been operated at several different commercial plants. Still, consistent uranium prices in excess of US$44 to US$61, depending on the interest rate and plant life, are needed to justify investment in new solvent-extraction plants.

Total costs per unit are influenced by the concentration of uranium in the phosphoric acid. At an interest rate of 10% and plant life of 20 years, a 10% (or 20%) decrease in uranium concentration leads to US$2-3 (or US$5-6) per pound U_3O_8 increase in total costs per unit. In comparison, 10% (or 20%) higher uranium concentration lowers total costs per unit by US$1-2 (or US$3-4) per pound U_3O_8. Figure 2.2 and Figure 2.3 present the total unit estimates compared to historical uranium prices. Figure 2.2 presents total unit cost estimates based on varying assumptions on interest rate and plant life. Figure 2.3 presents total unit cost

Table 2.4: Cost Estimation Summary

	Solvent Extraction			Ion Exchange		
Phosphoric acid plant capacity (tonnes P_2O_5/yr)	870,000			870,000		
Recoverable uranium (lbs U_3O_8/yr)	734,000			734,000		
Cost item						
Capital costs (million US$)	126 [89-190][a]			149 [105-224][a]		
Annualized capital costs (million US$)[b]	i=5%	i=10%	i=15%	i=5%	i=10%	i=15%
15 years	12	17	22	14	20	26
20 years	10	15	20	12	18	24
25 years	9	14	20	11	16	23
Annualized capital costs per unit (US$/lb U_3O_8)[c]	i=5%	i=10%	i=15%	i=5%	i=10%	i=15%
15 years	17	23	29	20	28	36
20 years	14	20	28	17	25	34
25 years	12	19	27	15	23	32
Operating costs (US$/lb U_3O_8)	32 [22-48][a]			18 [13-27][a]		
Total costs per unit (US$/lb U_3O_8)[d]	i=5%	i=10%	i=15%	i=5%	i=10%	i=15%
15 years	48	54	61	38	46	54
20 years	46	52	59	35	43	52
25 years	44	51	58	33	41	50

Source: Authors' calculation

[a]Figures in bracket represent probable uncertainty range of order-of-magnitude estimates (Green & Perry (2008)).

[b]Annualized capital costs are total capital costs annualized over three different periods (15 years, 20 years, and 25 years) with three different interest rates (5%, 10%, and 15%).

[c]Per unit annualized capital costs are annualized capital costs divided by projected U_3O_8 production from each technology.

[d]Total cost per unit is the summation of annualized capital costs per unit and operating costs. Incorporating the lower bounds of the uncertainty ranges for both capital costs and operating costs, interest rate of 5%, and a 25-year plant life yields the lowest possible annualized costs: US$31/lb U_3O_8 for solvent extraction and US$23/lb U_3O_8 for ion exchange. All discussion in the text about minimum prices, however, uses the reference estimates for capital and operating costs that does not incorporate the lower bounds of uncertainty ranges, but the point estimates themselves.

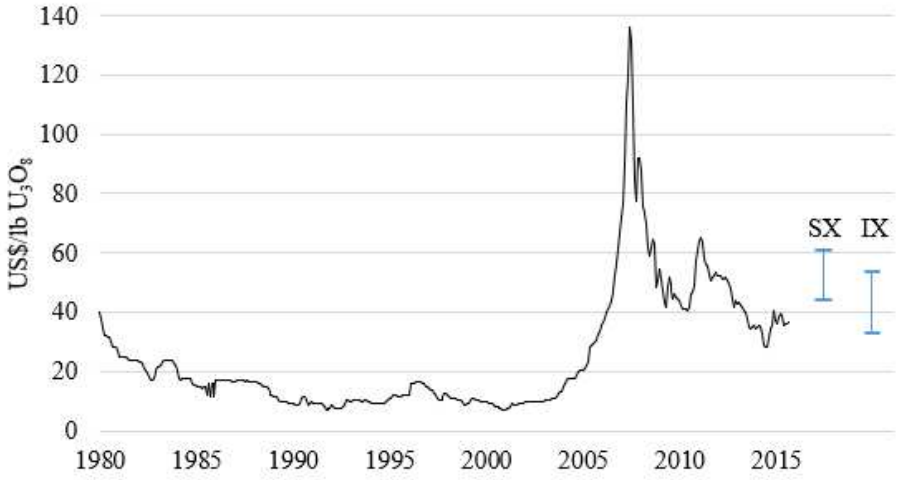

Figure 2.2: Historical Uranium Prices (nominal) and the Range of Estimated Total Costs of Recovery under different interest rates and plant lives

Source: Nuexco Restricted Prices via IMF Primary Commodity Prices (International Monetary Fund (2015)). SX and IX denote solvent extraction and ion exchange, respectively. Horizontal bars represent upper and lower bounds of cost estimates and vertical lines connecting the bars represent possible variation.

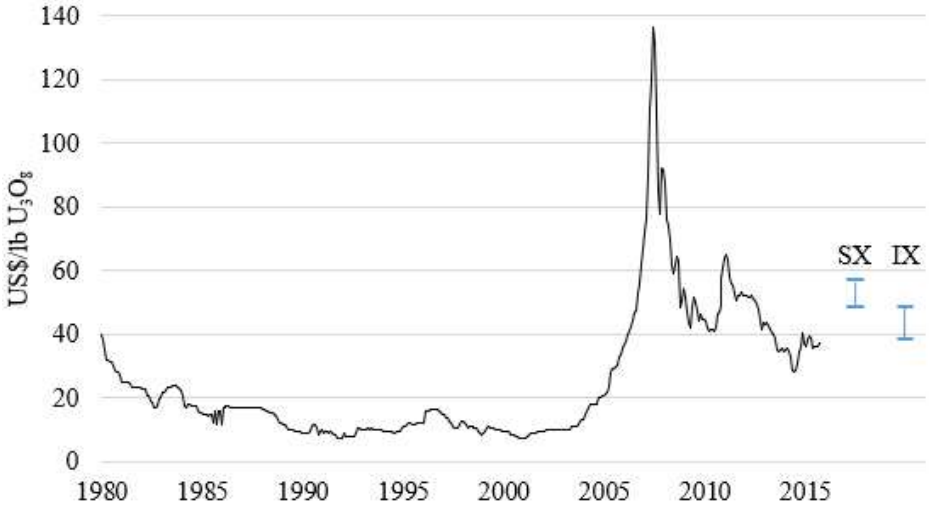

Figure 2.3: Historical Uranium Prices (nominal) and the Range of Estimated Total Costs of Recovery in a reference case (10% interest rate and 20 years of plant lite) reflecting quantity sensitivity

Source: Nuexco Restricted Prices via IMF Primary Commodity Prices (International Monetary Fund (2015)). SX and IX denote solvent extraction and ion exchange, respectively. Horizontal bars represent upper and lower bounds of cost estimates and vertical lines connecting the bars represent possible variation.

estimates at an interest rate of 10% and plant life of 20 years and possible variations reflecting the quantity (concentration) sensitivity described in the previous paragraph. These figures indicate that recent uranium prices are somewhat lower for ion exchange and significantly lower for solvent extraction than necessary to justify investments.

2.4 Concluding Remarks

To conclude, this study shows that it is technically feasible for the United States to recover significant quantities of uranium from phosphoric acid. If uranium prices are sustained at or above approximately US$50 per pound U_3O_8 and/or if technology advancements can further reduce costs of recovery, this source of uranium could become economically feasible on a large scale.

Three major implications stand out from this study. First, there are significant quantities of uranium potentially recoverable from the phosphate-rock/phosphoric-acid/fertilizer supply chain. In the United States, 5.5 million pounds of U_3O_8 are potentially available per year from existing phosphoric acid production. This uranium quantity is larger than U.S. production from conventional uranium mining, 4.9 million pounds U_3O_8 in 2014. Considering U.S. uranium purchases from domestic and foreign sources in 2014, 10% of demand could have been met by uranium from phosphoric acid. U.S. phosphate-rock reserves are sufficient, in physical terms, to support uranium recovery at the same rate for forty years assuming no change in phosphoric acid production and uranium content of phosphate rock. Broadening the scope to the world, other authors estimate that 28-29 million pounds of U_3O_8 are potentially available per year from phosphoric acid production (Gabriel *et al.* (2013); Ulrich *et al.* (2014)), compared to 146 million pounds U_3O_8 annual production from conventional uranium mining (World Nuclear Association (2015)).

Second, production of uranium as a by-product of phosphoric acid production will not occur without prolonged higher uranium prices, lower recovery costs, or both. At an interest rate of 10% and plant life of 20 years, uranium prices would need to be at least US$43 per pound U_3O_8 for the not-yet-fully-proven ion exchange technology or US$52 for solvent

extraction. Revived attention on recovering uranium as a by-product of phosphoric acid may work towards improving recovery technologies leading to cost reduction. Simultaneous recovery of other valuable elements could be another possibility to lower costs. In addition to uranium, phosphate rock contains other valuable elements such as rare earth elements and thorium. Researchers have tried simultaneous recovery of rare earth elements and uranium from phosphoric acid which turned out to be successful at lab scale (Bunuş *et al.* (1994); Bunuş & Dumitrescu (1992)). If it becomes possible to recover these elements with uranium at a commercial scale, recovery costs of uranium may go down as they share some of the costs. A variant of higher prices or lower costs would be for a national government to pay higher-than-market prices or to subsidize costs, or to have long-term contracts with producers for strategic reasons (for example, to diversify uranium supplies, or to purchase more uranium from domestic sources).

Third, this entire analysis of uranium availability as a by-product depends fundamentally on the viability and sustainability of phosphate rock. It is difficult to imagine recovering uranium as the main product from phosphate rock and phosphoric acid. Schneider & Linder (2014) estimate such costs to be at least three times higher than recent uranium prices,[18] implying that the only way uranium will be recovered from phosphate rock is as a by-product. There are no known substitutes for phosphorus in fertilizers, and phosphate rock is the only known source of phosphorus capable of supplying large quantities of the element. Since the main use of phosphate rock is to produce phosphoric acid used in fertilizer production, phosphate rock production is greatly dependent on agriculture. World fertilizer consumption is projected to increase from 166 million tonnes in 2005/2007 to 263 million tonnes in 2050 (Alexandratos & Bruinsma (2012)). As a result, demand for phosphate rock is likely to increase accordingly. Despite the non-renewable nature of phosphate rock, there is no consensus on peak phosphorus. In addition, there is a tendency for mineral reserves to be added

[18]The estimates from Schneider & Linder (2014) range from 3 times to 21 times of current uranium price, which is assumed as US$40 per pound U_3O_8. Another set of estimates on uranium recovery costs as a primary product from Gabriel *et al.* (2013) ranges between 13 and 61 times current price.

over the lifetime of a mine (Crowson (1982)) and there is no indication that the phosphorus production will peak, at least for several decades (Van Kauwenbergh (2010); Van Vuuren *et al.* (2010)). Consequently, uranium as a by-product is likely to be physically available for the foreseeable future.

CHAPTER 3

LOCATION DECISIONS OF WIND EQUIPMENT MANUFACTURING FACILITIES

Haeyeon Kim,[19] Roderick G. Eggert,[20]

Over the last decade wind energy has shown significant growth as a source of electricity generation in the United States. During this period, the domestic wind-equipment manufacturing industry has grown as well to meet the increased demand for wind power. As of 2016, the United States has the capability to manufacture approximately 11.7 GW of wind turbine nacelles, 8 GW of blades, and 7 GW of towers each year (Wiser & Bolinger (2017)).

States with wind-equipment manufacturing are likely to see greater economic development from the deployment of wind energy (Ejdemo & Söderholm (2015); Lantz & Tegen (2008); Reategui & Hendrickson (2011); Slattery *et al.* (2011)). For instance, Slattery *et al.* (2011) used an input-output based Jobs and Economic Development Impacts model to estimate economic impacts from wind energy projects in Texas. As part of sensitivity analysis, one scenario assumes 25% of the wind turbines are manufactured in-state. With in-state manufacturing, the economic output measured in dollar terms from the construction period is estimated to increase by nearly 140% compared to the base case where there is no in-state manufacturing.

Given the possible benefits of domestic wind equipment manufacturing, studies have found the determinants of location decisions in a qualitative manner. Factors such as mature supply chain, proximity to end markets, proximity to existing manufacturers, available wind resources, transportation infrastructure, and state and local incentives are found to contribute to location decisions (James & Goodrich (2013); Lantz *et al.* (2010); Wiser &

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Bolinger (2017)). To our knowledge, there has been no econometric study on location of domestic wind equipment manufacturing due to challenges originating from sparse data.

Industrial location has long been a topic of interest in economics. Isard (1948) studied historical change in the location of iron and steel industry since the early nineteenth century. With coal, iron ore deposits, and markets as a set of major determinants, relative importance of these three factors is analyzed. Hekman (1978) analyzed change in the location of iron and steel production in the twentieth century using supply and demand equations. Mueller & Morgan (1962) studied location decisions of manufacturers by interviewing manufacturers in Michigan. They distinguish between types of locational decisions new firms, relocation of existing firms, and expansion of existing firms and examine determinants for each type of location decision.

More recently, Coughlin *et al.* (1991) studied location decisions of foreign direct investments in the United States between 1981 and 1983 using state characteristics as variables. A later version of this study analyzed locational determinants of new foreign-owned manufacturing facilities in the United States during the period of 1989-1994 at a county level (Coughlin & Segev (2000)). Friedman *et al.* (1992) examined manufacturing locations of foreign multinational corporations in the United States from 1977 to 1988 at a state level. Woodward (1992) analyzed locational determinants of Japanese manufacturing in the United States from 1980 to 1989 at a county level. These studies used variables such as market demand, labor market, transportation, and state policies, but the results are mixed.

Some studies focus on certain determinants such as agglomeration economies (Alamá-Sabater *et al.* (2011); Guimaraes *et al.* (2000); Head *et al.* (1995); Lee *et al.* (2011)), environmental regulation (Bartik (1988); Levinson (1996); McConnell & Schwab (1990)), state development policy (Lee (2008)), energy prices (Kahn & Mansur (2013)), and transportation (Holl (2004)).

This paper analyzes wind equipment manufacturing locations in the United States using county-level data constructed from open and reliable sources. The data consists of 53 wind

equipment manufacturing facilities opened during the period of 1995-2014.

This essay is of interest for a number of reasons. First, it is one of the first studies analyzing wind equipment manufacturing location with an econometric technique. By using the conditional logit model, we can understand location decisions more precisely. Second, we use counties as our geographic unit of observation. Counties within a state have differences as well as similarities. By using county-level data, we expect to capture the variation between counties. Third, we focus the scope of industry to the major categories of wind equipment such as turbines, blades, towers, and nacelles. A broader definition of wind equipment entails subcomponents such as bolts, plastics, and steel. These parts are not specific to the wind industry and thus, their locational determinants could be different from those of major wind equipment. Understanding the spatial behavior based on the econometric model with county-industry level data will help us understand the preferences of manufacturers better.

In this study we use a conditional logit model to find determinants of wind equipment manufacturing location. The results suggest that wind resource potential and existing manufacturing activity are significant determinants of location choices.

The rest of the paper is organized as follows. Section 3.1 describes the model and section 3.2 discusses data used in the analysis. The results are presented in section 3.3 and section 3.4 provides concluding remarks and further research.

3.1 Model

Since the number of facilities opening in our data is small, what we observe is whether a location is selected or not, not how many times a location is selected. In this situation, the conditional logit model is the most appropriate model to apply.

Conditional logit model was developed by McFadden (1973) and has been used in location decisions frequently. According to this model, profit for a manufacturer choosing location j is assumed as a function of observable characteristics as

$$\pi_j = \beta' X_j + e_j$$

$$\pi_j \geq \pi_k \qquad \forall k, k \neq j$$

where β is a vector of parameters, X_j is a vector of variables observed at location j, and e_j is an error term. Location j is selected over other locations if the profit from choosing location j (π_j) is at least as great as that of choosing location k (π_k) for all alternative locations. Assuming the error terms are identically and independently distributed and follow a Weibull distribution, the probability of location j being selected is given by

$$P_j = \frac{exp\, \pi_j}{\sum_k exp\, \pi_k}$$

Estimation of this model in our study has a problem in that the number of alternatives is too large compared to choices we observe. Since our geographic unit of observation is counties, there are more than 3,000 alternatives in the United States. In comparison, we have only 53 observed actual choices. Fortunately, McFadden (1978) showed that the model can be estimated from a subset of alternatives. For each selected site j, we randomly select 9 alternative sites from the choice set of counties in 48 contiguous states. The conditional logit model is then estimated by maximum likelihood.

3.2 Data

This study focuses on wind equipment manufacturing facilities in the United States opened between 1995 and 2014. The data on wind equipment manufacturing facilities is compiled from various sources (Baranowski *et al.* (2016); David (2009); Wiser & Bolinger (2009, 2010, 2011, 2012, 2013, 2014, 2015)). The data contains information on facilities that manufacture wind equipment at a city level. We match cities to their counties since the number of general manufacturing establishment, one of our variables of interest, is available at county level. We focus the study on major categories of wind equipment such as turbines, blades, towers, and nacelles. During the observation period, 53 major wind equipment manufacturing facilities opened in 26 states (Figure 3.1). Arkansas, Colorado, Illinois, Iowa, and Texas are the states with more than one facility opening.

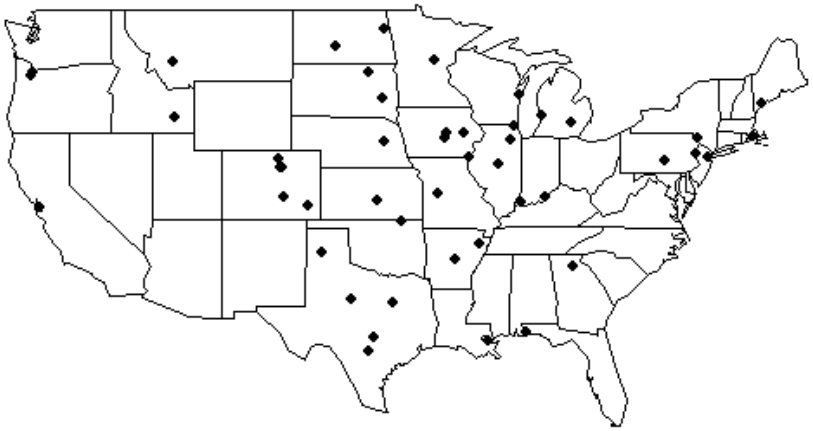

Figure 3.1: Location of Wind Equipment Manufacturing Facilities opening

Data source: Baranowski *et al.* (2016); David (2009); Wiser & Bolinger (2009, 2010, 2011, 2012, 2013, 2014, 2015)

The location of wind equipment manufacturing presumably reflects general characteristics of manufacturing, as well as factors specific to wind. Regarding general manufacturing characteristics, numerous reasons could explain why certain counties exhibit high degrees of manufacturing activity: agglomeration economies (Arauzo-Carod & Viladecans-Marsal (2009); Guimaraes *et al.* (2000); Head *et al.* (1995); Lee *et al.* (2011)), local energy prices and regulation (Kahn & Mansur (2013)), and transportation infrastructure (Holl (2004)). As a measure of general manufacturing activity, we use manufacturing establishments counts. We use this variable in a broader context than in other studies. Previous studies have included not only manufacturing establishment counts but also other variables such as energy prices and labor-related variables. The caveat of that approach is that the number of manufacturing establishment could be already reflective of the other variables. Alamá-Sabater *et al.* (2011) found that the establishment counts are determined by human capital, agglomeration economies, and industrial availability. Kahn & Mansur (2013) found that electricity prices and environmental regulation determine the manufacturing establishment counts depending on the characteristics of the industry. Holl (2004) found that population, labor character-

istics, industry share, inter-regional demand accessibility as well as road infrastructure are determinants of the establishment counts. Therefore, including the number of manufacturing establishments and its likely determinants as separate variables could make it difficult to clearly distinguish the effect of the variables. For this reason, we do not separately use variables such as energy price and labor, the influence of which could be already reflected in the degree of existing manufacturing activity. The data on manufacturing establishments comes from the Bureau of Labor Statistics. This contains information from the *Quarterly Census of Employment and Wages* and provides the number of manufacturing establishments by county annually. We merge this data with the list of wind equipment manufacturing facilities so that we have a dataset consisting of all counties in 48 contiguous states with or without wind equipment manufacturing facility openings. With this variable, we expect to measure the attractiveness of a county to manufacturers including agglomeration economies.

As for characteristics specific to the wind industry, wind resource is a potential determinant for wind equipment manufacturing. It is likely that a county with abundant wind resources has a higher potential of using wind power compared to other counties with less wind resources. Wind equipment manufacturing facilities could choose to locate near this region to exploit abundant wind resources. Wind resource potential is measured by the land area with a gross capacity factor greater than 30% based on available wind technology in 2008. The calculated area reflects wind energy potential that could be available from the development for the area.[21] The unit of observation for wind resource potential is a land area with an average size of 360km^2 with detailed location information in latitude and longitude. First, we aggregate this information to county-level and calculate wind energy potential by county. Then, since wind resource is continuous and county borders are conceptual boundaries, we incorporate the resource of neighbor counties weighted by the inverse of the distance between counties.

[21]Source: National Renewable Energy Laboratory. Available at https://maps.nrel.gov/wind-prospector

Third, transportation infrastructure has been shown to affect location decisions of manufacturing facilities (Coughlin & Segev (2000); Coughlin *et al.* (1991); Holl (2004); Levinson (1996)). This could be even more influential for wind equipment manufacturing than for manufacturing in general. The average hub height and rotor diameter of wind turbines installed in 2016 was 83 meters and 108 meters, respectively (Wiser & Bolinger (2017)). To deliver this tall and heavy equipment, an established way of transportation is crucial. To account for this aspect, we construct a variable measuring the distance to the nearest interstate highway for each county. This variable is expected to have a negative sign because of the way it is defined: The greater the proximity is, the less likely that a location is selected.

While wind resource provides a basic scheme of availability, it does not guarantee the deployment of wind energy. In this regard, the fourth variable we consider is Renewable Portfolio Standards (RPS). RPS is a state level policy which mandate utilities in a state a supply certain percentage of electricity from renewable sources. Roughly 50% of wind capacity built in the United States from 2000 to 2016 is related to utilities with RPS obligations (Wiser & Bolinger (2017)). RPS requirements can promote a state to actually develop wind energy. We consider RPS as a policy variable which could contribute to wind equipment manufacturing by promoting wind power development. It could be also interpreted as a proxy for market demand. State level RPS is taken from the RPS Compliance Summary Data by Lawrence Berkeley National Laboratory. This data summarizes RPS requirements in MWh by year at state level. As a variable, we define RPS in a broader scope. It is possible that manufacturing activity and deployment of manufactured equipment take place in different states. That is, a state could be considered as a good candidate for wind equipment manufacturing because it is surrounded by states with RPS. For this reason, we create a broader RPS variable which includes adjacent states RPS requirements.

Location decisions are made a few years before a plant opening, and we do not have detailed information on the actual timing of the location decisions. For this reason, we assume the decisions are made based on five-year bins starting in 1995. Variables affected by

this assumption are manufacturing activity and RPS. A decision to open a facility reflects manufacturing activity in the past and RPS requirements in the future. For instance, it is assumed that a facility opened in 2003 is reflective of manufacturing activity in 2000 and RPS requirement for 2005.

3.3 Results

Since nine alternative locations are randomly selected for each selected location, it is possible that results may be biased. We resample and rerun the analysis 500 times to account for this possible biasedness. Table 3.1 presents the summary of empirical results of the conditional logit model which estimates the location decision of wind equipment manufacturers in the United States. It reports the results in terms of mean from the repeated analysis and the percentage of the coefficients being statistically significant at 10% level. Coefficients from conditional logit model are not straightforward to interpret. For this reason, using average probability elasticity has been a common practice in previous empirical studies (Head *et al.* (1995); Lee *et al.* (2011)). In a profit function specified in the log of variables, the elasticity of the probability of a manufacturer choosing location j (E_j) is calculated by differentiating equation (2) with respect to X_j.

$$E_j = \frac{\partial P_j}{\partial X_j} \frac{X_j}{P_j} = \beta(1 - P_j)$$

Average probability elasticity indicates by how much location choice probabilities are affected from the change in variables. It can be calculated by summing E_j over all locations as

$$E = \sum_{j=1}^{J} E_j = \beta \frac{J-1}{J}$$

where J is the number of alternatives. Calculated average probability elasticities are presented in Table 3.1 as well.

Result (1) provides one of the results from 500 replications. Coefficients for wind resource potential and manufacturing activity are positive and significant in all replications implying

Table 3.1: Conditional Logit Estimates, 1995-2014

	(1) All counties		(2)Windy counties	
	Coefficient	Elasticity	Coefficient	Elasticity
Manufacturing activity	1.048	0.932	1.045	0.929
	(0.122)		(0.126)	
Wind resource potential	2.365	2.102	1.405	1.249
	(0.320)		(0.290)	
RPS	0.087	0.085	0.109	0.097
	(0.057)		(0.055)	
Transportation	-0.080	-0.071	-0.038	-0.033
	(0.077)		(0.066)	
Log-likelihood	-71.54		-75.66	
Number of choices	53		53	
Number of alternatives	9		9	

that the location choices of wind equipment manufacturing in the United States are affected by both wind resource potential and existing manufacturing activity. In terms of elasticities, the elasticity of wind resource potential (E=2.102) implies that an average county with 10% more wind resources has a higher probability of being selected by 21%. In the same way, a 10% increase in manufacturing establishments leads to a 9% increase in the probability of a county being chosen by wind equipment manufacturers. These two variables are significant in all the replications. Transportation turns out to be significant only in few replications even though it has expected negative sign. Contrary to general expectation, RPS turns out to be insignificant in determining wind equipment manufacturing location. Of the 500 replications, RPS requirement is significant in only eleven samples. Distribution of estimated coefficients are presented in Figure B.1.

Wind resource potential is exogenous to location and a highly significant determinant. In result (2), we categorize all counties into four groups based on wind resource potential and limit the choice set to counties that are reasonably windy by excluding the first quartile. After ruling out scant wind counties, wind resource potential is still positive and significant. The sign and significance of the other variables hold up well after restricting choice set to

windy counties.

Before 2006, domestic wind equipment manufacturing facility openings were intermittent. Facility openings are steadily observed each year starting in 2006 (Figure 3.2). Table 3.2 reports the results for the period after 2005. This analysis for sub-period is conducted to account for possible change in determinants. Result (3) provides the results for all counties for the period of 2006-2014. As seen from the results for the entire period in Result (1), coefficients for wind resource potential and manufacturing activity are positive and significant with elasticities of 2.228 and 0.896, respectively. Transportation and RPS coefficients have expected signs, but still the percentage of the coefficients being significant is low. Result (4) for windy counties in sub-period is similar to that of all periods in terms of coefficient signs and the significance. Estimated coefficients and their significance are similar implying that determinants of location decision have not changed over time.

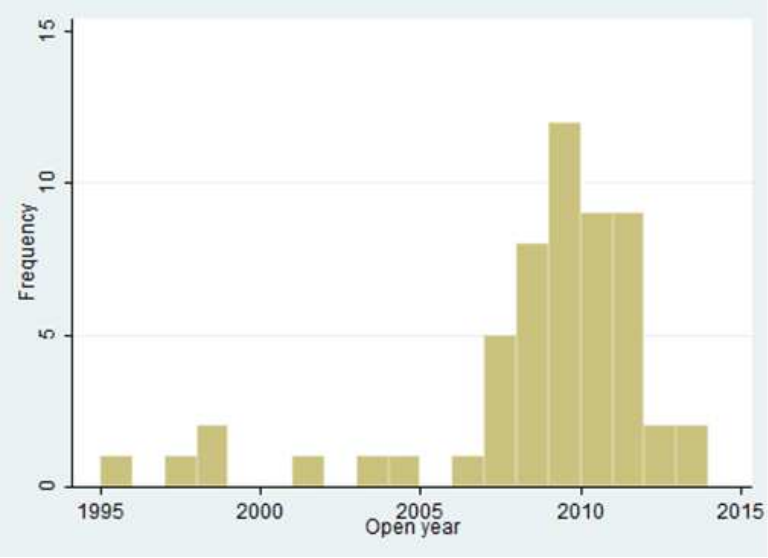

Figure 3.2: Number of Wind Equipment Manufacturing Facility Openings by Year

Source: Baranowski *et al.* (2016); David (2009); Wiser & Bolinger 2009-2015

For each selected site j, we randomly select 9 alternative sites from the choice set of counties in the contiguous states. This is based on the assumption that the model could be

Table 3.2: Conditional Logit Estimates, 2006-2014

	(3) All counties		(4)Windy counties	
	Coefficient	Elasticity	Coefficient	Elasticity
Manufacturing activity	1.007	0.896	1.003	0.892
	(0.133)		(0.129)	
Wind resource potential	2.507	2.228	1.558	1.386
	(0.335)		(0.328)	
RPS	0.178	0.158	0.216	0.192
	(0.067)		(0.069)	
Transportation	-0.146	-0.129	-0.100	-0.089
	(0.078)		(0.084)	
Log-likelihood	-61.78		-66.1	
Number of choices	46		46	
Number of alternatives	9		9	

estimated from a sample of alternatives from the full choice set and the number of alternatives in sample does not affect consistency of estimators (McFadden (1978)). To investigate whether the results are robust to the number of alternatives, we run the model with different sizes of alternatives in samples. The results of estimation for all counties during the entire period with different sample sizes are presented in Table 3.3. The first result with 9 alternatives is equivalent to the result (1) from Table 3.1. It shows that the magnitude and significance of estimates for each coefficient is robust to the sample size justifying our approach to a subset of choices.

Table 3.3: Robustness Check with Different Number of Alternatives

	Elasticities			
Manufacturing activity	0.93	0.94	0.93	0.92
Wind resource potential	2.1	2.15	2.14	2.13
RPS	0.08	0.08	0.08	0.09
Transportation	-0.07	-0.05	-0.04	-0.03
Log-likelihood	-71.54	-93.4	-106.73	-117.4
Number of choices	53	53	53	53
Number of alternatives	9	15	20	25

3.4 Concluding Remarks

This paper focuses on the location decisions of wind equipment manufacturing facilities in the United States from 1995 to 2014. Using conditional logit model, we estimate the effects of wind resource potential, existing manufacturing establishment, transportation, and RPS.

We find that counties with abundant wind resources and active manufacturing activity attract wind equipment manufacturing. A county with 10% more wind resources has a higher probability of being selected by 21% and a 10% increase in the number of manufacturing establishments raises the probability of selection by 9%. Contrary to our expectation, other variables of interest - transportation and RPS - turn out to be insignificant as determinants of location choices. RPS may have been an effective state policy in wind power development (Wiser & Bolinger (2017)), but we have not found statistically significant effects of this variable as a direct determinant of related manufacturing location decision. Excluding counties with less wind resources from the choice set reduces the elasticity of wind resource potential to 12%, but high significance is maintained. These findings are consistent for shorter period and different number of alternatives in the choice set.

Comparing the importance of wind resources potential and manufacturing activity, wind resource has higher elasticity. However, one should be noted that wind resource is given by the nature and there is little room to change this. Hence, if a county is to hold a wind equipment manufacturing facility, it is recommended that the county strengthens its general manufacturing activity.

Still, there is enough room for further study. Investigating more complete set of determinants would be an interesting next step. There are state and local level policies directly related to promoting clean energy manufacturing. While important, these are not included in our current study due to lack of ways to quantify them. Another possible next step would be to run a simulation on which counties would be selected in the future. With an expectation on continued growth of wind industry, further research on the manufacturing location is warranted.

CHAPTER 4

KNOWLEDGE LOCALIZATION IN INNOVATIVE INDUSTRY: EVIDENCE FROM ADDITIVE MANUFACTURING

Haeyeon Kim,[22] Roderick G. Eggert,[23]

Since the early recognition as a key determinant of the locational pattern of industries by Marshall (1920), knowledge has been considered as one of the keys of innovation and economic growth (Romer (1990)). Despite its conceptual importance, knowledge used to be considered as not suitable for empirical studies due to difficulty in measurement (Krugman (1993)). More recently, attempts have been made to utilize knowledge in empirical studies using measures such as patents and R&D. For instance, Ellison *et al.* (2010) used both patents and R&D as measures of knowledge in their empirical study. They found the three Marshallian factors - goods, people, and idea - have a strong effect on agglomeration of industries in the U.S. manufacturing sector. They also indicated that ideas might be more important than goods and people in highly innovative sectors.

In this chapter, we analyze the geographic localization of knowledge in innovative industry with a case on additive manufacturing. Additive manufacturing is a growing industry and regarded as a high technology sector. High technology sector is characterized by the importance of non-routine functions in contrast to standardized conventional mass production (Anselin *et al.* (1997)). Not being standardized and settled yet, there is more room for innovative activity to contribute to the process in high technology sector.

Knowledge has characteristics as a public good: It is non-excludable and non-rival in consumption. With perfect knowledge spillovers, the results of a successful R&D will not be limited to the innovators even if they bear most of, it not all, the costs of innovation. This

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could possibly lead to a free-rider problem that works against the efforts of the innovators. In this case, innovators may be discouraged from doing their best providing lower than optimal level of the socially desired outcome. To mitigate this market failure, government may intervene the market by providing funding for R&D or assign property rights to innovations.

Tacit knowledge is a main source of knowledge spillover which may lead to market failures (Kaiser (2002)). In geographic context, we are likely to observe geographic localization if knowledge is tacit. For instance, knowledge is likely to be localized if it is shared more closely and tacitly by engineers and scientists within a region (Almeida & Kogut (1999)). Geographic distances would be less important if knowledge is well codified and transferred through an open system such as patents and licenses.

Whether knowledge is localized or widely spread is an interesting topic since understanding the diffusion of knowledge could provide an important implication for science and technology policy. If knowledge is localized, there exists an incentive for firms in the same industry to locate closer to capture the locally created knowledge. From the perspective of entrants, it would be advantageous to locate near the existing innovative regions. In this regard, a favored way of promoting innovation from the local governments perspective would be to fully exploit the localness of innovative activity such as establishment of research park. To spread economic benefits from the knowledge to a national level, the government may support R&D consortia to promote collaboration between various entities.

Studies have found evidence of knowledge localization. Jaffe *et al.* (1993) is one of the early attempts to investigate geographic localization of knowledge in a quantitative way. Using U.S. patents from two originating years (1975 and 1980) and citations, they investigate knowledge localization at three different geographic levels: Metropolitan Statistical Area, state, and country. They construct control sample based on the need for comparing geographic match of citations based on citation link (case-control method). They find significant evidence of knowledge localization at all geographic levels. Details about control sample will be explained later in our paper. Almeida & Kogut (1997, 1999) study geographic

localization of innovation in semiconductor industry. They use U.S. patents filed in 1980 and 1985 and apply the case-control method to assess localization of patent citations.[24] They find that knowledge in semiconductor industry is localized. In the earlier study (Almeida & Kogut (1997)), they compare the geographic localization of innovation in small and large firms and find an evidence that the degree of knowledge localization is stronger for small firms. The later study (Almeida & Kogut (1999)) focuses on the mobility of engineers in regional networks. Using logit model, they find that the localization of knowledge is affected by the regional labor networks. Fischer *et al.* (2009) study geographic localization of knowledge in high technology industries in Europe. They use patent citation data of two cohorts of originating patents (1990 and 1995) at two geographic levels: regional and country. Using the case-control method, they find significant evidence of knowledge localization at both times and both geographic levels. Peri (2005) studies determinants of knowledge flows and their effect on innovation. In this study, knowledge flow is estimated using a gravity-like equation. Patents and citations are identified at 147 European and North American subnational regions. Regions in the U.S. are defined at state level. He finds that 20% of the knowledge created in the region flows out of it; knowledge from the most innovative regions travels further; and localization varies by technological field.

With the increasingly global nature of telecommunications, one might expect that localization of knowledge to have lessened over time. Nevertheless, findings on the evolution of the degree of localization are mixed. Keller (2002) used R&D spending and total factor productivity on manufacturing industries in selected OECD countries between 1970 and 1995. Splitting the entire period into two periods, he finds that the benefits of R&D spending are localized and the degree of localization is smaller for the later period. This implies that there has been a trend towards the globalization of technology. In contrast, Sonn & Storper (2008) find that inventors cite local patents increasingly over time. They use U.S. patents data from 1975 to 1997 and citations with the time lags no more than seven years. Calcu-

[24]They identify 18 main regions of semiconductor activity in the U.S. using the information on semiconductor plants. Examples of these regions are California Silicon Valley and New York New Jersey Pennsylvania.

lating net local citation percentage, they find that the degree of localization has grown over the years at various geographic levels: Metropolitan Statistical Area, state, and country. They argue that this could be explained by the increasing role of tacit knowledge on the technological frontier; increasing organizational flexibility; technological uncertainty and the need for timelier innovation arising from shorter product lifecycles.

Among various measures, patent citation is one of the most widely used to investigate the localization of knowledge. A patent is a property right to exclude others from making use of the invention. By providing legal rights to inventors, patents make the knowledge contained in the invention excludable. Thus, patents are expected to attenuate market failure arising from the public good nature of knowledge. Patents and patent citations are widely used in empirical studies of innovation for several reasons. First, patent data is openly available and discrete. Second, significant inventions are patented, in general. Third, patent citations are exact. Inventors should cite related previous patents and it is the role of patent examiners[25] to add to (or remove from) the list of previous work if there are missing (or unnecessarily cited) inventions. In consequence, patent citations are considered to document the flow of knowledge between the originating and the citing agents.

There are three major findings of this work. First, there is evidence of knowledge localization. Second, there is limited evidence of knowledge spillover evidenced by results excluding self-citations. Third, spillovers from public research is more localized.

Major contribution of this paper is in providing empirical evidence of the knowledge localization of additive manufacturing. Despite being a rapidly growing industry with numerous benefits and potential, there has been little systematic study on the knowledge aspects of additive manufacturing. We analyze this topic by using the most comprehensive patent data, to our knowledge.

[25]Some researchers argue that citations by patent examiners undermine the role of patent citations as a measure of knowledge localization. Examiner citations are not directly reflective of knowledge flow (Fischer *et al.* (2009)); and may add bias (Peri (2005)). However, no systematic difference is found between examiner citations and inventor citations in terms of localization (Alcacer & Gittelman (2006)).

The rest of the paper is organized as follows. Section 4.1 gives a brief background on additive manufacturing. Section 4.2 elaborates empirical strategy and data. Our empirical strategy uses the case-control method introduced by Jaffe *et al.* (1993) to identify whether localization exists; we then apply a logit model to investigate the determinants of knowledge localization. Section 4.3 provides the results. Section 4.4 discusses the findings and provides policy implications.

4.1 Background

Additive manufacturing, commonly called as 3D printing, is a class of processes which builds up objects layer by layer compared to traditional subtractive processes. Additive manufacturing is not a brand-new method of manufacturing. It was first introduced in the 1960s and initially commercialized in the late 1980s based on a technology called stereolithography. However, it was not until the 1990s that interest in additive manufacturing grew significantly.

More recently, additive manufacturing industry is growing at a rapid pace. In 2017, additive manufacturing industry expanded by $1.25 billion and reached the industry size of $7.3 billion. There were 135 companies producing and selling industrial additive manufacturing systems around the world, up from 97 companies in the previous year (Wohlers Associates, Inc. (2018)). Being a growing industry, there is enough room for innovative activity to contribute to the process in high technology sector.

Additive manufacturing offers numerous benefits compared to conventional subtractive manufacturing (U.S. Department of Energy (2015)). First, additive manufacturing allows more complex and innovative designs. It enables realization of designs closer to ideal that would have been impossible with conventional manufacturing. Second, additive manufacturing can reduce the consumption of materials and energy by building up only the necessary parts, not cutting away and throwing away nonessential parts. For instance, additively manufacturing an aircraft bracket reduces the weight by 65% and can contribute to save energy by 66% compared to conventional manufacturing. Third, additive manufacturing can simplify production process by consolidating many simple parts to fewer composite parts. In a similar

context, additive manufacturing can contribute to increased efficiency in supply chain. Flexible design and simplified production process can make disaggregated supply chain simple. Third, additive manufacturing can bring end-products faster to market by reducing the time for prototyping. For further discussion on the benefits of additive manufacturing, see U.S. Department of Energy (2015).

Recognizing these benefits, Advanced Manufacturing Office collaborates with the national laboratory to advance additive manufacturing with following objectives: (1) Widen the range of materials and processes outperforming conventional manufacturing; (2) Develop rapid qualification process to reduce certification cost; and (3) Develop next-generation additive manufacturing systems with consistently improved properties.

In this study, we investigate localization of innovative activity in additive manufacturing by analyzing U.S. patents filed between 1990 and 2009 and associated citations. Patents before 1990 are excluded from our study since there was very low innovative activity in terms of patent filing. Since we examine localization with patent citations, young patents (filed after 2009) are not included in analysis for there has not been enough time to observe citations.

4.2 Empirical Strategy

4.2.1 Data

Patents on additive manufacturing are identified by a subclass for additive manufacturing by the Cooperative Patent Classification between the U.S. Patent and Trademark Office and the European Patent Office. This subclass is defined as technologies involving the use or application of processes or apparatus that produce three-dimensionally shaped structures by selectively depositing successive layers of material one upon another (United States Patent and Trademark Office (2017)). It covers multi-faceted aspects of additive manufacturing: Processes and methods; machines and systems; handling or treating of materials; data processing; materials used in additive manufacturing; and products made by additive manufacturing. Our study is based on this subclass which is, to our knowledge, the most

comprehensive collection of patent information on additive manufacturing.

In this study, we use patents and citations data from the U.S. Patents and Trademark Office. Each patent contains detailed information about the invention, technological field of the invention, related previous work in the form of citation, and names and locations of the inventors and assignees. We define the location of each patent based on the residence of the primary inventor whose name comes first among the inventors. By using inventor location, not the location of the assignee, we are able to pinpoint the actual location of innovation. The location of inventors is reported at city level. Using this information, we assign a county to which the city belongs and then find a corresponding Metropolitan Statistical Area (MSA, hereafter). All analysis will be conducted with patents of which the primary inventors location is identified at the MSA level in the United States.

Our sample consists of 3,872 patents applied between 1990 and 2009 (Figure 4.1).[26] During this period, there has been substantial increase in the number of patents along with the growth in the additive manufacturing industry. Since we are interested in the citation of patents as well as patents themselves, nearly 60% of the patents that have never been cited are removed from the sample. Even after removing patents without any citations received, the distribution of citations per patent is highly skewed (Figure 4.2). The mean of citations per patent is 34, but the median is 13. 25% of the patents received less than 5 citations. Studies have shown that the number of citations received are reflective of the quality of the innovation and the impact on the future of technology (Albert *et al.* (1991); Hall *et al.* (2005); Moser *et al.* (2015); Trajtenberg (1990)). For this reason, we analyze only valuable patents of the received citations that are greater than or equal to 10. As a result, our final dataset includes 891 patents filed between 1990 and 2009 that generate 50,430 citations.

To account for possible temporal variation, we divide the entire period into four five-year sub-periods. Table 4.1 shows descriptive statistics for the important patents and citations

[26] A patent has two associated dates: application date and grant date. The processing time of a patent varies by case and is affected by unexpected factors e.g., abrupt increase in patent application resulting in sudden increase in processing time. Also, application date better represents the actual timing of invention. Throughout this study, we use application date as a basis of date.

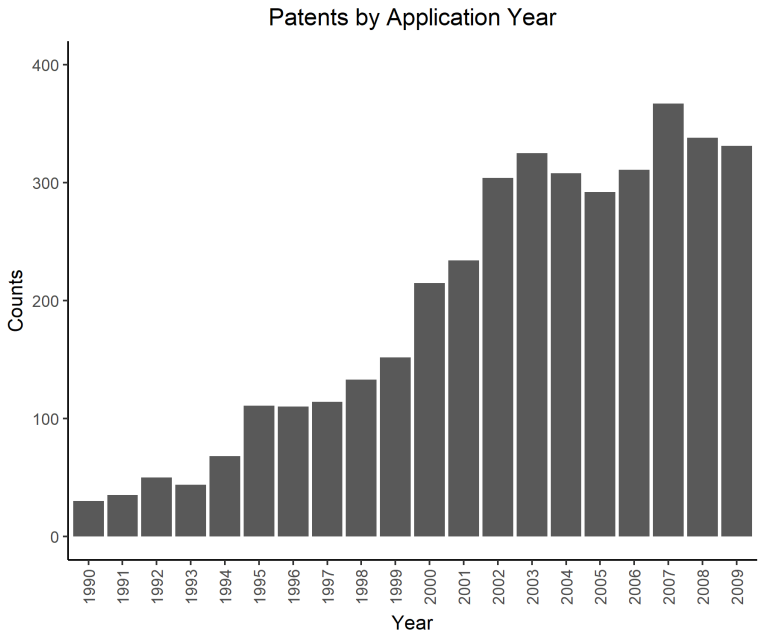

Figure 4.1: Number of Patents in Additive Manufacturing by Year

Source: U.S. Patents and Trademark Office

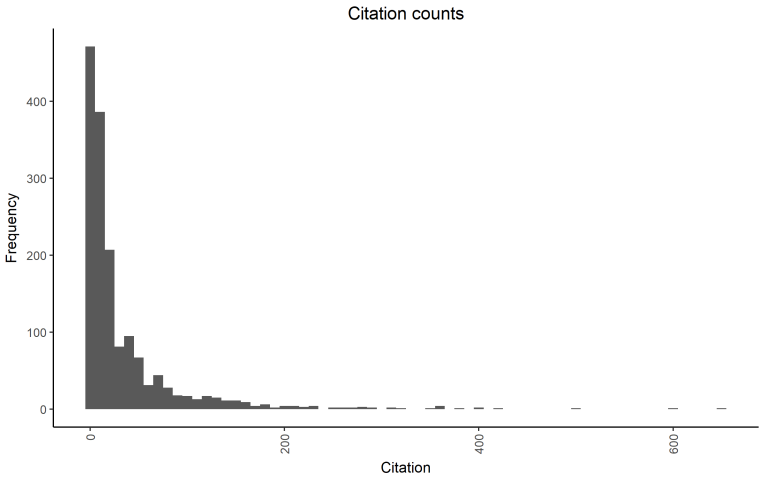

Figure 4.2: Citations Per Patent

Source: U.S. Patents and Trademark Office

received by 2017. The earliest period (1990-1994) contains 117 patents that received a total of 10,276 citations. Nearly 5.5% of these citations are self-citations[27] and excluding these reduces the number of citations to 9,707. On average, a patent on additive manufacturing from this period received 87.8 citations including self-citations and 83.0 citations excluding self-citations. In comparison, later periods contain more patents, fewer citations per patent, and a higher degree of self-citation. Lower citations per patent for later periods can be explained by the shorter time span after the patent application. That is, a patent from 1994 has twenty-three years of time until 2017 during which it could have been cited while a patent from 2009 has only eight years.

Table 4.1: Summary Statistics

	1990-1994	1995-1999	2000-2004	2005-2009
All citations	10,276	16,449	15,574	8,131
Number of patents	117	226	334	214
Citations on average	87.8	72.8	46.6	38.0
% self-citation	5.5	6.2	23.0	32.1
Self-citation Excluded				
Citations	9,707	15,421	11,991	5,520
Number of patents	117	226	329	213
Citations on average	83.0	68.2	36.4	25.9

4.2.2 Case-Control Method

Geographic matching probabilities are defined by the probabilities of citing patents located in the same region as the originating patents. Figure 4.3 illustrates how these probabilities are calculated. Suppose there is an originating patent cited by five different patents.

[27] Self-citation is defined as a citation of which the assignee of the cited patent is the same as the that of the citing patent. Self-citations capture knowledge flows and localization well, but they do not reflect knowledge spillover. For this reason, studies focusing on knowledge spillover have sometimes excluded self-citations from analysis. Not representing knowledge spillover, self-citations are still considered as important. Self-citations may be reflective of cumulative nature of innovation, increasing returns of knowledge accumulation, and strength in corporate technological policy and thus, have larger effect on market value than citations by others (Albert *et al.* (1991); Hall *et al.* (2005); Hall & MacGarvie (2010)). The scope of our research is knowledge localization, which is broader than knowledge spillover, we include self-citations as well.

Among the five citing patents, three patents are from the same MSA as the originating patent (Location 1) and the other two patents are from different location (Location 2 and 3). In this case, 60% of the citations are from the same MSA.

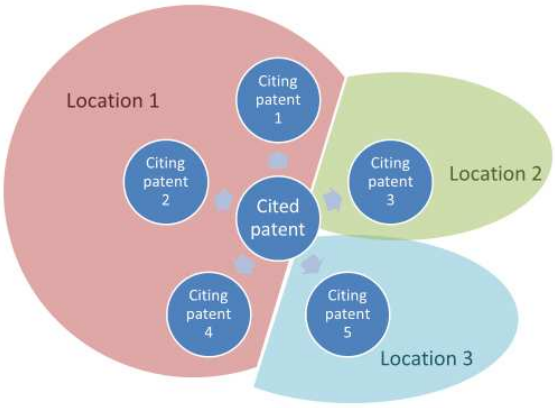

Figure 4.3: Geographic Matching of Patent Citations

To control for underlying citation tendency, we use case-control method. This method was developed by Jaffe *et al.* (1993) and has been used as a good way of investigating localization (Almeida & Kogut (1997, 1999); Fischer *et al.* (2009)). For each citing patent, a control patent is selected such that the patent is 1) from the same patent subclass other than additive manufacturing, 2) with same application year, and 3) closest patent grant date. Let P and P_c represent the geographic matching probability of the citations for the sample and the control, respectively. Assuming binomial distributions, null hypothesis (H_0) and alternative hypothesis (H_a) are:

$$H_0 : P = P_c$$

$$H_a : P > P_c$$

with the t-statistic

$$t = \frac{P - P_c}{[\frac{P(1-P)}{n} + \frac{P_c(1-P_c)}{n}]^{0.5}}$$

Rejecting the null hypothesis implies that knowledge on additive manufacturing is significantly localized compared to the control group.

4.2.3 Logit Analysis

The case-control method is a simple and efficient way of finding evidence of geographic localization of knowledge. However, it is not suitable for investigating underlying factors affecting localization. To analyze the determinants of knowledge localization, we use a logit model. Our dependent variable is geographic match for each originating citing patent pair. Ordinary Least Squares cannot account for this binary dependent variable since it assumes linear and continuous dependent variable. For this reason, we employ a logit model to accommodate the dichotomous dependent variable. Results from the logit model are estimated by maximum likelihood estimation.

The variables used in the logit model are presented in Table 4.2. The dependent variable is the geographic match for each citation and coded as 1 if the citing and originating patent are from the same MSA and 0, otherwise. As independent variables, we include dummy variable for public research,[28] dummy variable for self-citation percentage for each patent, and dummy variables for existence and location of additional assignee.

We include a dummy variable for public research patents since knowledge localization might appear differently for different types of assignees. For instance, innovation from universities, national labs, and government tend to be focused on understanding basics while private firm innovation is more focused on commercialization (Perry IV *et al.* (2011)). Universities play an important role in innovation directly as a performers of basic research and indirectly as a creator of human capital in the form of highly skilled labor (Anselin *et al.* (1997)). One might expect to see basic innovations to diffuse more, but empirical evidence is mixed. By using a survey of R&D laboratories by U.S. manufacturing firms, Adams (2002) found that university spillovers and learning the knowledge from universities are significantly

[28]Public research refers to research from universities and national laboratories following conventional terminology. This does not necessarily distinguish how public or private a university is.

more localized than industrial spillovers and learning about industry. Hicks *et al.* (2001) also found that citations to university patents are more localized in information and health technologies. In contrast, Almeida & Kogut (1999) and Jaffe *et al.* (1993) found no significant evidence that innovations from universities are different from other organizations innovation in terms of localization. To account for possible temporal change in the characteristics of public research, we also include interactions of the public research and period dummies.

We include self-citation percentage as a variable characterizing the originating innovation. It represents how much of an assignees innovation is built on its own previous innovation. A patent with high self-citation percentage is taken as a successful claim of the innovation (Jaffe *et al.* (1993)). In this regard, it is expected that citations to those patents with high self-citation rate are likely to be more confined to narrow field of technology. The sign for this variable suggests the existence agglomeration of the industry or further, co-agglomeration of industries. If positive, there is an evidence that citations are from the neighbors in the same region even after excluding self-citations.

Dummy variables for the existence of another assignee and locational match with the other assignee are included as well. If an originating patent has more than two assignees (Dummy variable for assignee = 1), it is expected that the knowledge would be less localized. Dummy variable for another assignees region is an attempt to take a deeper look into this issue. If an originating has more than two assignees and the second assignee is from different region, the knowledge is likely to be less localized.

As control variables, we include the number of lag years and a dummy variable for the geographic match of originating control patent pair as in previous studies (Almeida & Kogut (1999); Jaffe *et al.* (1993)). Also, dummy variables for technological fields are included as control variables to account for the variations across technology field (Fischer *et al.* (2009); Lerner & Seru (2017); Noailly & Shestalova (2017); Peri (2005)).

Table 4.2: Description of Variables

Variables	Description	Expected sign
Dependent Variable		
Geographic match	Dummy variable for geographic match. 1 if originating patent and citing patent are from the same MSA; 0, otherwise	
Independent Variables		
Public research	Dummy variable for patents of which the assignee is either university or national laboratory	-
Period	Dummy variables for five-year periods. Dummy variable for the last period is not constructed since it is set as a point of comparison.	+/-
Self-citation ratio	Percentage of self-citation from total citations a patent received	+
Another assignee	Dummy variable for having another assignee. 1 if there is more than one assignee to patent; 0, otherwise	-
Another assignees region	Dummy variable for the location of another assignee. 1 if another assignee and the primary assignee are from the same MSA; 0, otherwise	+
Control Variables		
Number of lag years	Citation lag between the originating patent and citing patent in years	-
Control patent	Dummy variable for geographic match of control patent. 1 if originating patent and control patent are from the same MSA; 0, otherwise	+
Technological field	Dummy variables for broad technological field of the patent based on Cooperative Patent Classification: (B) Performing Operations and Transporting; (C) Chemistry and Metallurgy; (D) Textiles and Paper; (E) Fixed Constructions; (F) Mechanical Engineering; (G) Physics; (H) Electricity. Dummy variable for (A) Human Necessities is not constructed since this field is set as a point of comparison.	+/-

4.3 Results

4.3.1 Case-Control Analysis

Table 4.3 presents the results for case-control analysis. Let us first focus on the results for all citations including self-citations. For the patents from the 1990-1994, 7.8% of the citations come from the same MSA. It means that of the 10,276 citations (Table 4.1), 802 citations are from the within MSA citations. This is significantly higher than the matching percentage for the control group (5.0%), i.e., knowledge in additive manufacturing evidenced by patent citations is significantly localized after controlling for technological subclass and time. For the patents from the 2000s, more than 20% of the citations to additive manufacturing patents are from the same MSA. Compared to the matching percentage of the control group in the same period (6.5-6.7%), this is significantly higher matching percentage.

Excluding self-citations reduces the matching percentage significantly. Citations to patents from the 1990s are not significantly more localized than citations to control patents. Rather, citations to additive manufacturing patents from the 2000s are significantly less localized than citations to control patents. This implies that the higher matching percentage including self-citations is driven by self-citations.

Table 4.3: Geographic Match Results

	1990-1994	1995-1999	2000-2004	2005-2009
All citations				
Sample	7.8	7.2	20.6	23.4
Control	5.0	4.3	6.5	6.7
t-statistic	8.4***	11.3***	37.0***	30.6***
Self-citation Excluded				
Sample	5.4	4.2	4.1	4.4
Control	5.1	4.2	5.7	5.7
t-statistic	1.1	-0.0	−5.9***	−3.2***

Note: *** indicates significance at 1% level

The results in Table 4.3 does not reflect the difference in time space of patent citations since it covers all the citations until 2017. To keep a consistent time range for patents, we limit the citations to be within the 10 years of the application of originating patents and present the results in Table 4.4. Limiting the time range does not change the general voice of results including self-citations: citations to additive manufacturing are more localized than citations to control group. Excluding self-citations, citations to patents from the 1990-1994 are significantly more localized than citations to control patents. For patents from the 2000s, citations to additive manufacturing patents are significantly less localized than citations to control patents. During the entire period of observation, the degree of localization decreased from 9.8% in the early 1990s to 4.4% in the late 2000s. This is consistent with the findings from Keller (2002) that knowledge has become less localized over time. It can be explained by development in telecommunications despite possible explanations for increasing localization such as the importance of tacit knowledge on the technological frontier and technological uncertainty.

Table 4.4: Geographic Match Results (Citations until 10 years after each patent)

	1990-1994	1995-1999	2000-2004	2005-2009
All citations				
Sample	13.0	8.6	25.4	23.6
Control	5.2	4.2	7.4	6.7
t-statistic	11.2***	11.3***	37.2***	30.7***
Self-citation Excluded				
Sample	9.8	3.7	4.7	4.4
Control	5.2	3.9	6.2	5.7
t-statistic	6.9***	-0.6	−4.1***	−3.2***
Note:			*** indicates significance at 1% level	

4.3.2 Logit Analysis

Table 4.5 reports the results from the estimation of logit model by maximum likelihood. Coefficients from logit model do not directly deliver meaningful interpretation in magnitude.

Instead, we focus on the sign of the estimate coefficients.

Table 4.5: Logit Analysis Results

	Dependent variable: Geographic match			
	(1)	(2)	(3)	(4)
Public research	0.423***	0.407***	-0.318	-0.292
	(0.053)	(0.055)	(0.208)	(0.209)
Public research * Period 1			1.269***	1.243***
			(0.228)	(0.229)
Public research * Period 2			0.375*	0.348
			(0.226)	(0.227)
Public research * Period 3			0.566**	0.555**
			(0.243)	(0.244)
Self-citation	-0.383**	-0.584***	-0.575***	-0.581***
	(0.162)	(0.168)	(0.175)	(0.175)
Another assignee	0.385***	0.396***	0.555***	0.064
	(0.124)	(0.128)	(0.132)	(0.290)
Another assignees location				0.633***
				(0.321)
Lag years	-0.036***	-0.034***	-0.046***	-0.046***
	(0.005)	(0.005)	(0.005)	(0.005)
Control match	0.700***	0.673***	0.644***	0.642***
	(0.082)	(0.083)	(0.084)	(0.084)
Constant	-2.837***	-3.051***	-2.944***	-2.958***
	(0.054)	(0.068)	(0.089)	(0.089)
Technology field	N	Y	Y	Y
Time period	N	N	Y	Y
Observations	42,215	42,215	42,215	42,215
Log Likelihood	-7,666	-7,562	-7,503	-7,501
Akaike Inf. Crit.	15,345	15,149	15,045	15,043
Note:			* p<0.1; **p<0.05; ***p<0.01	

The results with the most basic set of variables without technology field are shown in column 1. Citations to public research patents are more likely to be from the same MSA. This is consistent to the finding that public research spillovers are more localized (Adams (2002); Hicks *et al.* (2001)). Self-citation has negative sign. Patents with high fraction of self-citation are likely to be less cited from the same region other than itself. It implies that firms in the same region do not necessarily rely on the innovative activity of their neighbors.

This could be because of a simple reason that the cost of accessing intra-organizational knowledge is lower. Or it may originate from so-called Not Invented Here Syndrome which explains a phenomenon where R&D people putting less value or even ignoring innovations external from their organization (Agrawal *et al.* (2010)). Having additional assignee shows positive sign. This suggests that having additional assignee contributes to localization of knowledge.

Column 2 - 4 add technology field dummies. Detailed estimates for technological field are provided in Table C.1. It is found that the degree of geographic match varies by technological field. Compared to the field of Human Necessities, knowledge in Performing Operations and Transporting, Textiles and Paper, Fixed Constructions, and Electricity is more localized.

Columns 3 and 4 add dummy variables for time periods and their cross terms with public research. None of the period variables turn out significant and thus, are not presented in the table. Public research variable for periods 1-3 show positive signs implying that there is a positive effect of public research patent on geographic match of citation.

Column 4 takes a further look at the additional assignee variable by using a dummy variable for the locational match of the additional assignee. Comparing columns 3 and 4, it is evident that having additional assignee raises the probability of localization (column 3) and it is determined by additional assignees located in the same MSA as the primary assignee (column 4).

Estimated results for control variables are as follows. The number of lag years and the geographic match of control group are consistent across different specifications and have expected signs. Number of lag years turn out negative. It implies that the longer the lag years between the originating and citing patent are, the less likely those two patents are from the same MSA. During the early period after innovation, knowledge is considered as naturally excludable, accessible by a small community involved in the innovation. As time passes, the knowledge spreads out and could possibly become a routine science (Zucker *et al.* (1998)). The geographic match for control patent is positive and significant. It should

be noted that control patents are designed to reflect possible temporal and technological variation in citation and thus, function as a baseline of knowledge localization. If a control patent similar to a citing patent in terms of technology field, application year, and grant date is from the same MSA as the originating patent, then the citing patent is also likely to be from the same region. The implication is that underlying knowledge localization affects the localization of knowledge in additive manufacturing.

4.4 Concluding Remarks

This paper investigates the knowledge localization innovative industry with a case study on additive manufacturing. We try to answer the following research questions: Is the knowledge on additive manufacturing localized? And what factors contribute to geographic localization of knowledge? To address these questions, we use two different approaches. First, we use the case-control method by Jaffe *et al.* (1993). Second, we employ a logit model to find the determinants of the localization of knowledge.

The results from the case-control method show that the knowledge on additive manufacturing is significantly localized at MSA level. Excluding self-citations, however, wipes out the significance and even finds an evidence that knowledge in additive manufacturing is less localized than the base line for later periods. These results are not consistent with previous studies where the evidence of knowledge localization in innovative industry is found at regional level even after excluding self-citations (Almeida & Kogut (1997, 1999); Fischer *et al.* (2009)). A possible explanation is additive manufacturing is a combination of various technologies. Patents from a technological field may not have similar degree of knowledge localization as in other technological fields. We confirmed this technological field effect in the logit analysis.

The analysis also provides some evidence of decreasing knowledge localization excluding self-citations and within 10 years of citation window (Table 4.4). The degree of localization decreases from 9.8% in the early 1990s to 4.4% in the late 2000s. This is consistent with the findings from Keller (2002) that knowledge has become less localized over time. It can be

explained by development in telecommunications despite possible explanations for increasing localization such as the importance of tacit knowledge on the technological frontier and technological uncertainty.

The logit analysis results reveal that knowledge from public research is more local consistent with the findings from Adams (2002) and Hicks *et al.* (2001). This implies that the benefits of innovation and possible economic growth coming from public research are likely to be clustered. As a result, firms may choose to physically locate their R&D center close to public research as found in Abramovsky & Simpson (2011).

The results have important policy implications. Since evidence of localization is found (results including self-citations), especially for public research, a preferred way of promoting innovation in additive manufacturing industry would be to fully reflect the localness of current development. For instance, establishing collaborative research center close to universities and national laboratories would be a good way of utilizing localized innovative activity from the perspective of local government. From the perspective of federal government, lower level of knowledge localization for more recent periods suggests high level of knowledge spillovers. Knowledge spillovers are related to a market failure in which innovators are discouraged from providing socially optimal level of knowledge to the market because of free-rider problem. Our findings support policies that provide funding for R&D in additive manufacturing to maintain and promote continued efforts on innovations. Also, R&D consortia would help promoting collaboration between various regions to achieve widespread national economic benefits.

The findings from this paper should be interpreted with a few limitations. It should be noted that measuring knowledge localization with patent citations can underestimate the contribution of public research (Roach & Cohen (2013)). Basic research is less likely to become a patent than applied research. Reasonably assuming public research tends to be basic (Perry IV *et al.* (2011)), it is possible that the knowledge originating from the public research is not detected by patent citations even if the piece of knowledge was deployed by

later patents.

As noted earlier, self-citations are clearly not spillovers. However, it is reflective of the cumulative nature of innovation and possibly the increasing returns of knowledge accumulation (Hall *et al.* (2005)). In fact, firms have a path dependency on their own previous innovations.[29] Self-citations are shown to contribute to the market value of innovations more than nonself-citations do (Albert *et al.* (1991); Hall *et al.* (2005); Hall & MacGarvie (2010)). Therefore, the importance of self-citations should not be neglected since they still count valid for knowledge localization and possibly, localization of benefits.

Future work may shed more attention on categorization of assignees. In this study, we group all observed assignees into two categories: public research (universities and national laboratories) and the others. By doing so, we might have failed to fully consider possible heterogeneity in innovating organizations. Sonn & Storper (2008) divides patent assignees into five groups: universities, innovative companies, other companies, federal government, and individuals. Aghion *et al.* (2013) argues that institutional ownership of the assignee affects a firms ability to innovate. Using citation-weighted patents per R&D expenditure as a measure of productivity, they find that the productivity of firms innovation is positively affected by the proportion of stock owned by financial institutions such as bank, mutual fund, or insurance company. Almeida & Kogut (1997) found that firm size matters in the knowledge transfer. There may even be possible variation within the category universities. In a study about university patenting in life sciences, Owen-Smith & Powell (2003) further distinguishes universities: medical school, private, and active biotechnology region. Such considerations would help us better understand geographic localization of knowledge in innovative industries.

[29] This holds true even for the innovations that are considered as not good. Aghion *et al.* (2016) finds that firms with earlier innovation on technologies with high carbon emission will tend to pursue innovation in similar regard since the stock of dirty innovation is greater than that of clean and socially desired innovation.

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APPENDIX A

SUPPLEMENTARY INFORMATION FOR CHAPTER 2

A.1 Recovery Processes

A.1.1 Solvent Extraction

This section is based largely on Astley & Stana (2012), De Voto & Stevens (1979), Gupta & Singh (2003), and International Atomic Energy Agency (2013). Solvent extraction has been used in the past to recover uranium from phosphoric acid. Solvent extraction consists of the following steps: acid pre-treatment, primary solvent extraction, acid post-treatment, secondary solvent extraction and uranium refining (Figure A.1).

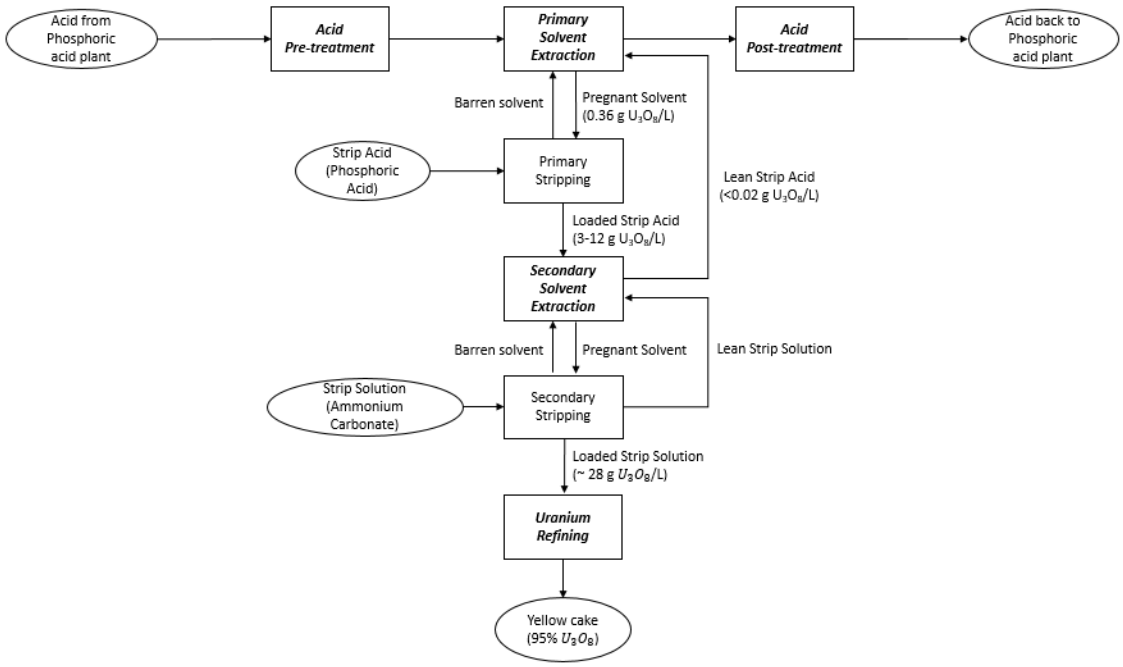

Figure A.1: Solvent Extraction Flow Sheet

Source: Authors' representation, modified from International Atomic Energy Agency (2013) and Astley & Stana (2012).

Acid Pre-treatment. This step entails temperature adjustment, uranium valence adjustment and clarification. Phosphoric acid flowing from the acid plant is about 150 °F. For the

solvent extraction, the temperature needs to be lowered to 100-125 °F. Cooling the acid is necessary to lower the risk of fire from the kerosene (which functions as a diluent in solvent), decrease the solubility of the solvent in the acid, and enhance the efficiency of extraction. Oxidizing or reducing the uranium ions is an important pre-treatment to enhance the extraction efficiency in the next stages. To which state the uranium ion should be adjusted depends on the extractant.

Primary solvent extraction. In this step, the pre-treated phosphoric acid is contacted with solvent. The solvent is a mixture of extractant and diluent, which is kerosene in most cases. Three extractants have been used in commercial scale utilization. The mixture of di-2-ethylhexy phosphoric acid and tri-octylphosphine oxide (DEHPA-TOPO) was the most common extractant (Table 2.1). DEHPA-TOPO extracts uranium in a hexavalent ion (U^{6+}) and can be used for the both primary and secondary extraction cycles. Octylphenylphosphoric acid (OPAP) and octyl-pyrophosphoric acid (OPPA), separately, were also used as extractants at a few recovery plants, in which uranium was extracted as a tetravalent ion (U^{4+}). Compared to DEHPA-TOPO, they are less stable. After 3-6 cycles of contact, 90-98% of the uranium is removed from the acid. During primary stripping, uranium is stripped from the solvent by contacting the loaded solvent with phosphoric acid. The strip acid containing uranium is then passed to the next step, secondary solvent extraction.

Acid post-treatment. It is important that the organics in the acid are removed or minimized before being returned to the phosphoric acid for fertilizer production (McGinley (1980)). Solvent lost to the phosphoric acid stream adds significant cost to the recovery process and may cause equipment damage in downstream processing. With flotation cells, the concentration of the residual solvent is lowered from 100-500 ppm to less than 50 ppm.

Secondary solvent extraction. The uranium in the strip acid is oxidized to U^{6+} using oxidants. Regardless of which extractant is used in primary solvent extraction, DEHPA-TOPO is used in secondary extraction in from three to six mixer-settlers. The loaded acid is then stripped from the DEHPA-TOPO with ammonium carbonate ($(NH_4)_2CO_3$) solution,

and uranium is stripped from the solvent almost completely (secondary stripping).

Uranium refining. Uranium is precipitated from the ammonium carbonate solution, settled in a clarifier and sent to a dryer and calciner (optional). The uranium product after calcination is more than 95% by weight U_3O_8.

A.1.2 Ion Exchange

The process based on ion exchange consists of: acid pre-treatment, primary elution, secondary elution, and precipitation (Figure A.2). The detailed explanation of each stage is based largely on Beltrami *et al.* (2014), Bristow *et al.* (2012), and Volkman (1989).

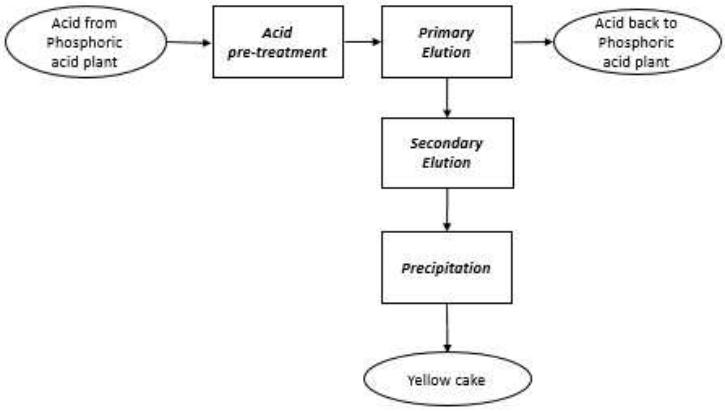

Figure A.2: Ion Exchange Flow Sheet

Source: Authors' representation.

Acid pre-treatment. Prior to the main process, suspended solids are settled to prevent possible issues with the solids in later stages. Also, the acid is reduced with the help of iron powder.

Primary elution. Pre-treated phosphoric acid is loaded on the ion-exchanger, and uranium ions are adsorbed to the anions in the exchanger. Then, phosphoric acid is displaced from the ion exchange column, and the resin bed is scrubbed with water and ammonia. Loaded uranium is eluted with aqueous ammonium carbonate solution, and uranium ammonium carbonate is formed.

Secondary elution. Uranyl carbonate eluate from primary elution is further concentrated and purified in a second ion exchange and eluted with a salt/bicarbonate mixture.

Precipitation. Yellow cake is precipitated with hydrogen peroxide.

A.2 Quantity and Cost Estimation

A.2.1 Quantity estimation

To estimate the recoverable quantities of uranium from phosphoric acid, the following approach is taken: First, convert the weight of P_2O_5 into phosphoric acid of which 30% by weight is P_2O_5. Second, convert the U_3O_8 content into weight ratios using the density of 30% phosphoric acid. Third, multiply the acid weight by the U_3O_8 content in weight terms and by the recovery rate. An example calculation is provided below.

Total weight of phosphoric acid produced by Agrium US Inc. in 2014, assuming 30% of the P_2O_5 is recoverable by weight, is

$$300,000\,tonnes\,P_2O_5 \times \frac{100\,tonnes\,phosphoric\,acid}{30\,tonnes\,P_2O_5} = 1,000,000\,tonnes\,phosphoric\,acid$$

Uranium content converted into weight terms[30] is

$$\frac{140mg\,U_3O_8}{1l\,phosphoric\,acid} \times \frac{1l\,phosphoric\,acid}{1.2kg\,phosphoric\,acid} = \frac{116.7mg\,U_3O_8}{1kg\,phosphoric\,acid} = 116.7\,ppm\,U_3O_8$$

Applying uranium recovery rate of 95%, the quantity of uranium recoverable would be

$$1,000,000\,tonnes\,phosphoric\,acid \times 116.7ppm\,U_3O_8 \times 95\% \times 110.8\,tonnes\,U_3O_8 = 244,000\,lbs\,U_3O_8$$

A.2.2 Cost estimation for solvent extraction

Capital costs. Capital costs consist of fixed capital, offsite capital, start-up costs and contingency. Total capital costs amount to US$126 million for a hypothetical solvent extraction recovery plant. Table A.1 provides the breakdown of capital costs. The costs are

[30] The second term of the conversion comes from the density of 30% phosphoric acid solution at 25°C (≈1.2 g/ml).

order-of-magnitude estimates based on the level of project definition for which the probable accuracy lies between -30% and +50% (Green & Perry (2008)).

Table A.1: Summary of Capital Costs for Solvent Extraction

	Estimated Costs[a]		
Cost Item	Base Case	Low	High
Total Capital costs	126	89	190
Fixed capital investment[b]	88	62	133
Offisite capital[c]	18	12	27
Start-up cost[d]	3	2	4
Contingency[e]	18	12	27

[a]Rounded to the nearest Million US$ in 2014 terms. Base Case estimates are point estimates which does not consider uncertainty related with the level of project definition. The estimates in columns Low and High account for probable accuracy of order-of-magnitude estimates between -30% (low) and +50% (high) following Green & Perry (2008).

[b]Costs related with manufacturing equipment, piping, buildings, structures, site preparation, engineering costs, and construction costs. It is escalated and capacity-adjusted from earlier operation.

[c]All structures, equipment, and services that do not enter into the manufacture of a product but are important to the functioning of the plant; 20% of fixed capital investment.

[d]Costs directly related to bringing new facility on-stream; 3% of fixed capital investment.

[e]For provision for unforeseen events that are likely to occur at site; 20% of fixed capital investment.

Fixed capital investment. Fixed capital investment includes the costs related to manufacturing equipment, piping, buildings, structures, site preparation, engineering costs and construction costs. For a phosphoric acid plant with annual capacity of 750,000 tonnes P_2O_5 in 1985, fixed capital investment was US$45 million (Botella (1989)). After escalation to 2014 dollars and adjustment for plant capacity as shown below, the fixed capital investment is estimated at US$88 million.

Step 1: Escalating to 2014 dollars using Chemical Engineering Plant Cost Index (CEPCI)

In this step, a dollar amount in 1985 is escalated to monetary value in 2014. Cost_{2014} is new fixed capital cost escalated from the cost in the past (Cost_{old}) assuming the two plants have identical capacity.

$$Cost_{2014} = Cost_{old}\frac{CEPCI_{2014}}{CEPCI_{old}} = US\$45\,million\frac{576.1}{325.3} = US\$80\,million$$

Step 2: Capacity adjustment using seven-tenth factor estimates rule

For a chemical process plant, cost is adjusted in proportion to an exponential of the ratio of capacities of the two plants. The parameter 0.7 is often used to account for economies of scale in engineering cost estimation (Couper (2003); Green & Perry (2008)). To apply this rule, the processes for the new plant and the earlier operation are assumed to be identical (Remer & Chai (1993)) and the capacity of the hypothesized unit is within the capacity range for which the scaling exponent is valid (Green & Perry (2008)). In this step, the time-adjusted cost from the previous step Cost_{2014} is adjusted to a new cost Cost_{new} based on capacity. Capacity_{new} is the capacity for the new plant and Capacity_{2014} is the capacity equal to the capacity from earlier operation.

$$Cost_{new} = Cost_{2014}(\frac{Capacity_{new}}{Capacity_{2014}})^{0.7} = US\$80\,million(\frac{870,000}{750,000})^{0.7} = US\$88\,million$$

Offsite capital. Offsite capital includes all structures, equipment, and services that do not enter into the manufacture of a product but are important to the functioning of the plant such as electricity and water, and transportation. It is usually calculated as a percentage of fixed capital investment and different percentages are applied for different situations. Offsite costs range from 10% to 100% of fixed capital investment. In general, offsite costs are between 20% and 50% of fixed capital investment. If a site has a developed and available infrastructure (brownfield sites), this ratio would be lower. If the site needs to start from nowhere (greenfield site), offsite capital should be greater than the base estimate. Assuming the uranium recovery plant being built next to a phosphoric acid plant, it is expected that the newly built uranium recovery plant could benefit from the already built phosphoric acid plant. Thus, offsite capital is estimated as 20% of fixed capital investment.

Start-up cost. Start-up cost entails capital costs that are directly related to bringing new facility on-line. Start-up costs are estimated as 3% of fixed capital investment (Green & Perry (2008)).

Contingency. Contingency is for provision for unforeseen events that are likely to occur. For preliminary estimates, 15-20% of the fixed capital investment is typical to account for contingency (Green & Perry (2008)). The upper bound (20%) is applied in this study to account for uncertainties associated with limited data.

Operating costs. Operating costs consist of chemicals, utilities, labor, general and administrative (G&A) and consumables. A description of the methodology for each cost item is provided below. The notes in Table A.2 provide the references for the data used along with the estimated costs per pound U_3O_8 produced. Total operating costs for solvent extraction are estimated at US$32 per pound U_3O_8. With the probable accuracy, operating costs could vary within the range of US$22-48 per pound U_3O_8.

Chemicals and Utilities. Consumption rates of chemicals and utilities (per pound U_3O_8 produced) are assumed to be identical with the case from Botella (1989). Current (2015) price quotations from suppliers are used whenever possible. If not, prices from the earlier case are escalated using price indexes indicated in Table A.2. Estimated operating costs for chemicals and utilities are US$10.1 and US$6.6 per pound U_3O_8, respectively.

Labor, G&A, and Consumables These cost items per pound U_3O_8 produced are assumed to be identical with Botella (1989). Costs for labor and consumables are escalated to 2014 terms using price indexes noted in Table A.2. General and administrative costs are calculated as 3% of total operating costs (Green & Perry (2008)). Operating costs for labor, G&A, and consumables are estimated at US$8.8, US$1.1 and US$5.3 per pound U_3O_8, respectively.

A.2.3 Cost estimation for ion exchange

Cost estimates for ion exchange are based on pre-feasibility studies for PhosEnergy demonstration plants (PhosEnergy (2013); PhosEnergy (2015); personal communication with

Table A.2: Operating Costs for Solvent Extraction

Cost Item	Unit cost (US$/lb U_3O_8)	Notes
Total Operating costs	31.7	
Chemicals	10.1	
H_2O_2	0.14	35%, technical grade. Indicative chemical prices from ICIS (2015)
Flocculant	1.23	Index adjusted. Producer Price Index for Industrial chemicals (1989=114.8, 2014=288.9), Bureau of Labor Statistics (2015)
Activated coal	2.11	Index adjusted. Producer Price Index for Industrial chemicals (1989=114.8, 2014=288.9), Bureau of Labor Statistics (2015)
Activated clay	0.45	Activated Bentonite Clay for oil refining FOB price, Personal communication with Hangzheng Chemical Co., Ltd. (May 2015)
NaOH	0.67	Sodium hydroxide solution 50%, Industrial grade, Personal communication with Tianjin Chengyuan Chemical Co., Ltd. (May 2015)
DEHPA	1.80	DEHPA price, Personal communication with SNF FloMin Inc., (May 2015)
TOPO	0.26	Personal communication with Frame (May 2015)
Kerosene	2.07	Refiner Petroleum Product Wholesale/Resale Price for Kerosene (U.S. Energy Information Administration (2014b))
Iron scrap	0.85	Index adjusted. Producer Price Index for Iron scrap (1989=173.7, 2014=543.1), Bureau of Labor Statistics (2015)
CO_2	0.27	Personal communication with Frame (May 2015)
NH_3	0.30	US Gulf, spot c.f.c. Tampa. Indicative chemical prices from ICIS (2015)
Utilities	6.6	
Process water (m^3)	0.55	Water rates (gallonage rate) for City of Bartow, Florida (2015)
Steam (kg)	1.62	Steam price for high pressure steam (U.S. Department of Energy (2003))
Electricity (kWh)	4.38	Average Retail Price of Electricity to Ultimate Customers by End-Use Sector, Florida (U.S. Energy Information Administration (2014a))
Labor	8.8	Index adjusted. Average hourly earnings of production and non-supervisory employees in chemical industry used as proxy for index (1990=12.85, 2014=21.49), Bureau of Labor Statistics (2015)
General & Administrative	1.1	3% of total operating costs (Green & Perry (2008))
Consumables	5.3	Index adjusted. Consumer Price Index for All Urban Consumers, All Items (1989=109.6, 2014=201.9), Bureau of Labor Statistics (2015)

Davidson 2015). Two demonstration plants operated at two different sites at two different scales of operations: one at 907,000 tonnes P_2O_5 per year and the other at 440,000 tonnes P_2O_5 per year. The recoverable amounts of U_3O_8 were 880,000 pounds and 400,000 pounds, respectively. Since costs are associated with the size of the plant, the demonstration plant that has similar capacity with the hypothesized plant is selected for cost estimation. Since detailed results are not publicly available, cost estimation for ion exchange is not as detailed as in solvent extraction.

Capital costs. Total capital costs for a demonstration plant with annual capacity of 907,000 tonnes P_2O_5 is US$156 million in 2012. After adjusting dollar year and capacity, capital costs for ion exchange are estimated at US$149 million.

$$Cost_{2014} = Cost_{2012}\frac{CEPCI_{2014}}{CEPCI_{2012}} = US\$156\,million\frac{584.6}{576.1} = US\$154\,million$$

$$Cost_{new} = Cost_{2014}(\frac{Capacity_{new}}{Capacity_{2014}})^{0.7} = US\$154\,million(\frac{870,000}{907,000})^{0.7} = US\$149\,million$$

As in cost estimation for solvent extraction, the capital costs are order-of-magnitude estimates due to the level of project definition and thus, the probable accuracy lies between -30% and +50% (Green & Perry (2008)). Thus, costs might vary within the range of US$105 million and US$224 million.

Operating costs. Total operating costs are estimated to be less than US$18 per pound U_3O_8 for the larger capacity plant and between US$20 and US$21 per pound U_3O_8 for the smaller plant (PhosEnergy (2013, 2015)). Due to similarity of the capacities, the hypothesized plant is assumed to have operating costs closer to those of the demonstration plant with larger capacity, which is US$18 per pound U_3O_8. With the probable accuracy range, operating costs might vary within the range of US$13-27 per pound U_3O_8.

APPENDIX B

SUPPLEMENTARY INFORMATION FOR CHAPTER 3

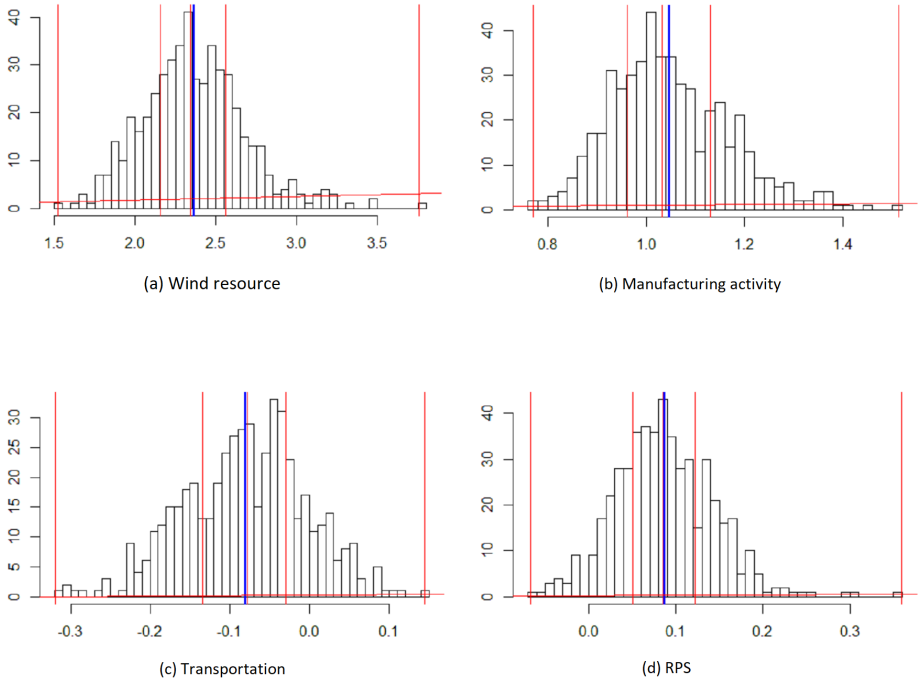

Figure B.1: Distribution of Estimated Coefficients

APPENDIX C

SUPPLEMENTARY INFORMATION FOR CHAPTER 4

Table C.1: Logit Analysis Results (continued from Table 4.5)

	Dependent variable: Geographic match			
	(1)	(2)	(3)	(4)
Performing Operations and Transporting		0.364***	0.278***	0.294***
		(0.066)	(0.069)	(0.069)
Chemistry and Metallurgy		0.279***	0.164*	0.174*
		(0.089)	(0.091)	(0.091)
Textiles and Paper		0.705***	0.939***	1.084***
		(0.163)	(0.169)	(0.180)
Fixed Constructions		2.314***	2.287***	2.301***
		(0.156)	(0.157)	(0.157)
Mechanical Engineering		-0.326*	-0.292*	-0.279
		(0.174)	(0.175)	(0.175)
Physics		0.025	-0.063	-0.052
		(0.078)	(0.081)	(0.081)
Electricity		0.351***	0.393***	0.403***
		(0.082)	(0.085)	(0.085)
Technology field	N	Y	Y	Y
Time period	N	N	Y	Y
Observations	42,215	42,215	42,215	42,215
Log Likelihood	-7,666	-7,562	-7,503	-7,501
Akaike Inf. Crit.	15,345	15,149	15,045	15,043
Note:		* p<0.1; **p<0.05; ***p<0.01		