DISSERTATION

INVENTING IN AN UNCERTAIN WORLD: BIOFUEL PATENTS AND THE ANTICOMMONS

Submitted by

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ABSTRACT

INVENTING IN AN UNCERTAIN WORLD: BIOFUEL PATENTS AND THE ANTICOMMONS

In 1998 Heller coined the term “anticommons” as a situation in which overlapping property rights lead to underutilization of a resource. Biofuel technologies offer a unique opportunity to explore Heller’s hypothesis as there are a dozen different pathways all leading to the same end: a marketable fuel. Ethanol is the most common biofuel on the market today, but this first-generation biofuel comes at a high environmental cost. Advanced biofuels use non-food crops and other waste materials to create a final fuel, which offers hope when considering the environmental impacts of traditional liquid fuels. The patent rights surrounding each fuel type span from a single owner to many owners and vary across technology pathways. These papers explore biofuel technologies over 60 years via granted patents and show that along all technology and ownership patterns the number of assignees on a patent negatively impact follow-on citations.

Paper 1, “The rise and fall of innovation in biofuels” was published in *Nature Biotechnology* in 2016. This paper is a patent landscape of biofuel technologies from 1960 to 2013. In this paper we show an uptick in biofuel patents in the early 2000’s, followed by a slow-down post 2008. These trends vary by location and ownership structure, which is explored further in paper 3.

Paper 2 builds on the traditional Nordhaus innovation model in which innovation outputs are a function of inputs. The model is expanded to include the potential for fragmented property rights in the form of diffuse patent ownership. The success of an innovation depends on basic research inputs, such as resources available to the researcher and existing patents for the technology in question. A hopeful inventor must consider the time and cost of negotiating rights to gain access to existing patents. And the risk of getting tied up in litigation, before deciding to move forward with a particular idea. As patent ownership becomes more diffuse private outcomes decrease relative to the social optimum and useful ideas are abandoned.

Paper 3 uses the data from paper 1 to test the hypothesis of the anticommons empirically. The model uses count of citing patents as a function of various innovation inputs, including cited patents, inventor and assignee counts, time, and other control variables. The data is divided into technological pathways to illustrate how varying amounts of patent assignees impacts follow-on inventions. In all cases the number of assignees negatively impacts the number of follow on citations, suggesting the anticommons is present.

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1 Introduction

In 1955 Quaker Oats conducted an advertising experiment, the “Klondike Big Inch”marketing ploy, in which they bought 19 acres of land in the Yukon Territory. They then drafted 21 million deeds, each worth one square inch of land. Each deed was then placed in a box of Quaker Oats, making all Quaker Oats’ consumers landowners. From a marketing perspective this plan worked very well, who doesn’t want to be a landowner? From a practicality standpoint, this program was a failure as no one could access their land (say to put a flag on it) without finding and negotiating with the thousands of other landowners whose land needed to be traversed to access a particular plot (Heller and Eisenberg (1998)). In the end, the land was reclaimed by the state for $31.00 in back taxes. Despite the fact that these deeds are no longer valid, they sell for $10-100 on Ebay for their novelty.

These papers explore the potential for a tragedy of the anticommons in the biofuels industry where rapid growth in patenting, followed by a drop off of inventing has occurred. These trends were discovered by Dr. Greg Graff, Dr. Steve Albers and myself and our results were published in *Nature Biotechnology* in 2016, titled “The Rise and Fall of innovation in biofuels”. Our paper discusses several reasons for these trends, one of which being fragmented property rights. This dissertation uses the research from our paper to further explore the tragedy of the anticommons in an attempt to tease out the differences in patenting activity along various technology pathways (Albers et al. (2016a)).

1.1 What is the Tragedy of the Anticommons?

In 1968 Hardin coined the term “tragedy of the commons” to explain the overuse of common property resources. He argued that without clear property rights a resource will be overused as no one individual has an incentive to protect the resource, implying the social benefits are greater than the private benefits of this protection (Hardin (1968)). This theory is still used in economics to explain over utilization of common property resources and public goods, such as air pollution and species extinction, and is often used as justification for privatizing common property. Mirroring the tragedy of the commons, Frank Michelman (1982) coined the term anticommons as a type of property in which “everyone always has rights respecting the objects in the regime, and no one, consequently, is ever privileged to use any of them except as particularly authorized by others.”

Given that this definition had no real world counterparts it went largely under recognized until Heller’s (1998) *Harvard Law Review* article, where he explained the anticommons as a situation in which “multiple owners each have a right to exclude others from a scarce resource and no one has an effective privilege of use” leading to underutilization of the good. In essence this is a problem of externalities as each excluder does not account for the social welfare effects her decision to exclude others causes. This is a two-fold problem; first, exclusion of one member causes negative externalities for the other members in a static case where the value of the property is then driven to zero. Second, externalities in a dynamic setting of growth imply under-use of resources today will have consequences for future generations (Parisi et al. (2003)).

Schulz et al. (2002) discuss the anticommons in the context of the commons problem, they note “that exclusion rights-the lack of which is at the origin of the well-known commons problem-give rise to anticommons situations if simultaneously granted to multiple individuals”. Before discussing the anticommons in the context of patent rights it is useful to review other examples, including the natural resource examples of this proposed tragedy.

Heller’s seminal paper spawned many follow-on papers, most of which are based in the law literature, while few model the economic concepts underlying the problem at hand. Property right fragmentation has been studied in several different settings, including: land in developing nations (Ying and Zhang (2008), Fitzpatrick (2006)), fisheries (Filipe et al. (2011)), Cyberspace (Hunter (2003)), households and planned communities (Ellickson (2006)), traditional Native American communities (Bell and Parchomovsky (2008)), river basins (Kosnik (2012)) and intellectual property rights (Heller and Eisenberg (1998); Bessen et al. (2009); Buchanan and Yoon (2000)).

1.1.1 Resource Examples of the Anticommons

Heller (1998) uses fragmented storefront property rights following the fall of communism in Eastern European cities as an example of this tragedy. He explains how many different entities (agencies and private parties) had rights over the store space, making it very difficult to negotiate lease terms for a rental space. Entrepreneurs interested in opening a store soon realized that rather than incurring high transaction costs in attempting to bargain with the various entities holding use rights, they could instead set up Kiosks on the street, which they did.

Another example of the tragedy of the anticommons is illustrated by Kosnik (2012), who shows that overlapping water regulation agencies in the U.S. leads to suboptimal use of river-basin resources. In this instance numerous regulatory agencies each control aspects of river-basin water management so that to produce any single output (such as increased in-stream reserve requirements, small scale hydroelectric power permits, or agricultural-municipal water transferrers), a producer must satisfy sometimes repetitive regulatory requirements. Producers incur costs to contact each agency and meet the overlapping requirements, resulting in a tragedy of the anticommons as river-basin resource use is shown to be suboptimal in the U.S.

1.1.2 Intellectual Property Examples of the Anticommons

In the context of intellectual property rights, Heller and Eisenberg (1998) argue that recent changes in the structure of patent offices, the creation of policies that encourage university patenting, and an increase in the patenting of public R&D has led to a tragedy of the anticommons in biomedical science innovations. Given the cumulative nature of biomedical research new inventions often build on old ones. However, if a new invention pulls from several patents and the new researcher must negotiate rights to use those patents before their invention is commercialized it may never make it to this stage. Nevertheless, without a patent system in place researchers may not have strong enough incentives to conduct R&D, as they will not be able to reap the profits from their R&D if someone can steal their idea (Aghion et al. (2008)). Murray and Mahony (2007) argue that only through "mechanisms for disclosure, opportunities for access and rewards to encourage disclosure, and access" can today's innovators build on previous generations and innovate cumulatively (Murray and Mahony (2007)).

Along these lines, the knowledge spillovers which act as positive externalities to the innovation process, are facilitated by patenting as granted patents are available to the public for free viewing. However, the possibility of being sued for patent infringement if using any of the knowledge claimed in the patent without permission implies the use of this knowledge requires negotiation and licensing costs to avoid the inherent risk. When innovation is cumulative, building off of several previous inventions (e.g. bioenergy), you may have to negotiate with several different patent holders to commercialize your invention without risking infringement (Cahoy and Glenna (2009); Murray and Mahony (2007)).

This problem is exacerbated in the case of basic research as Buchanan and Yoon (2000) explain: "to the extent that, through exclusive licensing rights, the holders of a patent on a basic research finding seek to exploit the rental value, the follow-on potential developer is inhibited from securing the value that might otherwise have been available"(pg. 11). This fragmentation of intellectual property rights can thus lead to a tragedy of the anticommons as inventors face a fog of uncertainty. Before formally modeling the anticommons it is necessary to review innovation and patent theory generally to construct a complete model.

1.2 Innovation Background

Traditionally research is divided into two categories: basic vs. applied, with different incentives and requirements for each. Many models assume universities are best suited for academic research, while private entities are better suited for applied research development (Aghion et al. (2008)), leading to models specific to each of these lines of research. However, biofuels innovation requires a blurring of the line between these two lines of research as many "basic" discoveries can be commercialized biological material used to produce fuel, requiring an innovation model that spans public and private entities. For the purposes of this paper I will briefly review two types of innovation models: 1) knowledge production functions and 2) researcher principal-agent models. This second category will include a brief discussion of both private researchers and public researcher models.

1.2.1 Knowledge Production Functions

One way to model innovation is through a knowledge production function, i.e. an equation that describes knowledge inputs and outputs as if they were being produced like any other commodity. Griliches (1990) lays the ground work for this approach and assumes new knowledge is created from research and development (which includes physical capital, other material inputs, and existing knowledge), human capital and a stochastic term: $I_i = \alpha * {RD_i}^{\beta} * {HK_i}^{\psi} * \varepsilon_i$. This basic model is depicted in Figure 1, which helps explain the drivers of this model. This model is expanded by Audretsch and Feldman to include geographic spillovers and sector specific inputs to help account for the geographic distribution of idea creation (Feldman and Audretsch (1996); Audretsch and Feldman (2002)).

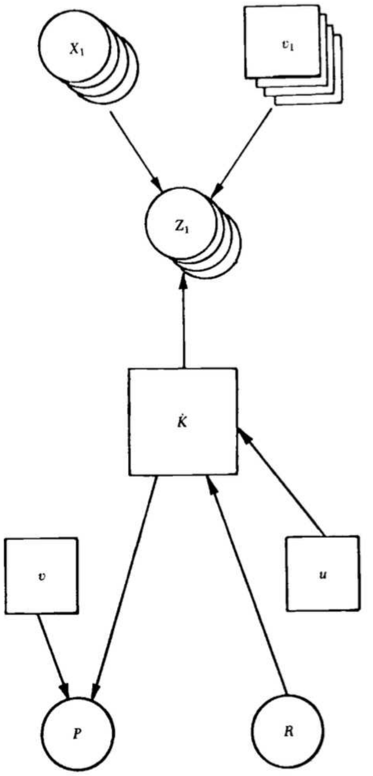

Fig. 13.3 Knowledge production function: a simplified path analysis diagram
Source: Pakes and Griliches (1984), figure 3.1.
Notes: R = research expenditures.
$\dot{K}$ = additions to economically valuable knowledge.
P = patents, a quantitative indicator of the number of inventions.
Z's = indicators of expected or realized benefits from invention.
X's = other observed variables influencing the Z's.
u, v = other unobserved influences, assumed random and mutually uncorrelated.

Figure 1: Grilliches Innovation Model

The knowledge production function approach is useful in understanding inputs and outputs of innovation, most notably patents, but says little about the incentives an individual researcher faces when choosing how to spend their time and research efforts. In this model research workers are simply an input into the function and their level of effort is not addressed. An individual researcher has a choice as to how hard to work towards any one research goal, but is constrained by their institution, which provides the researcher with research tools and access to knowledge. Often times a researchers goals are not aligned with their institution's goal of creating marketable ideas, thus institutions must put incentives in place to better align their goals with their research workers.

1.2.2 Innovation Outcomes and Patents

Patents are one of three tools inventors have to protect and potentially profit from their inventions. instead of patenting an idea, inventors can choose to hold their knowledge as a trade secret or copyright the knowledge. Patents are unique in requiring the inventor disclose enough information in their patent application for someone else to replicate it. This disclosure means the idea is now out in the public and if someone else wants to use it, they must pay you for it or do so without your knowledge. In other words, you must enforce your patent rights to get compensation for someone else using your ideas. This often requires expensive litigation and other transaction costs. However, granted patents are also a good metric of innovative achievements, a metric that does not exist with trade secrets. The institution funding your research also benefits from a granted patent as it produces profits when utilized.

Given patents are only one form of knowledge protection, they do not tell the full innovation story. But they are the most measurable metric we have. Additionally, it can be argued that biofuels, a subclass of bio-engineering, have a higher rate of patenting as compared to holding ideas as trade secrets or copyrights. Despite the limitations of patent data, this paper explores how the existing patent rights impact future patents as a proxy for innovation in the field of biofuels.

1.3 Biofuel Technologies and Policy

Demand for biofuels started in the late 1970's with the Oil Embargo and continued to increase in the following decades as concerns about national security and foreign energy dependence increased. With the looming threat of climate change and increased scientific and policy awareness surrounding the causes of climate change, demand for alternative, sustainable fuels increase further. The renewable fuels standard (RFS) in the U.S. is just one example of government policy to increase incentives to innovate in biofuels technologies. This standard is one of many around the world aimed at reducing dependence on fossil fuels and increasing national security and rural farm incomes. Following these incentives, biofuel production increased [Figure 1]. Given this steep increase in biofuel incentives and general lack of cost effective fuel conversion technologies, a plethora of R&D was invested in biofuels research, as is evident by the sharp increase in patents filled [Figure 2].

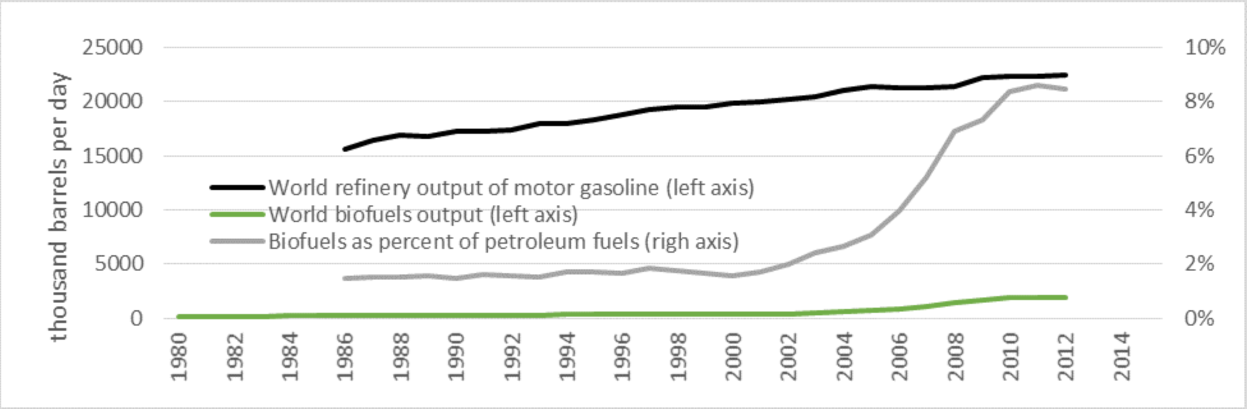

Figure 2: Patent Trends from Nature Biotechnology Article

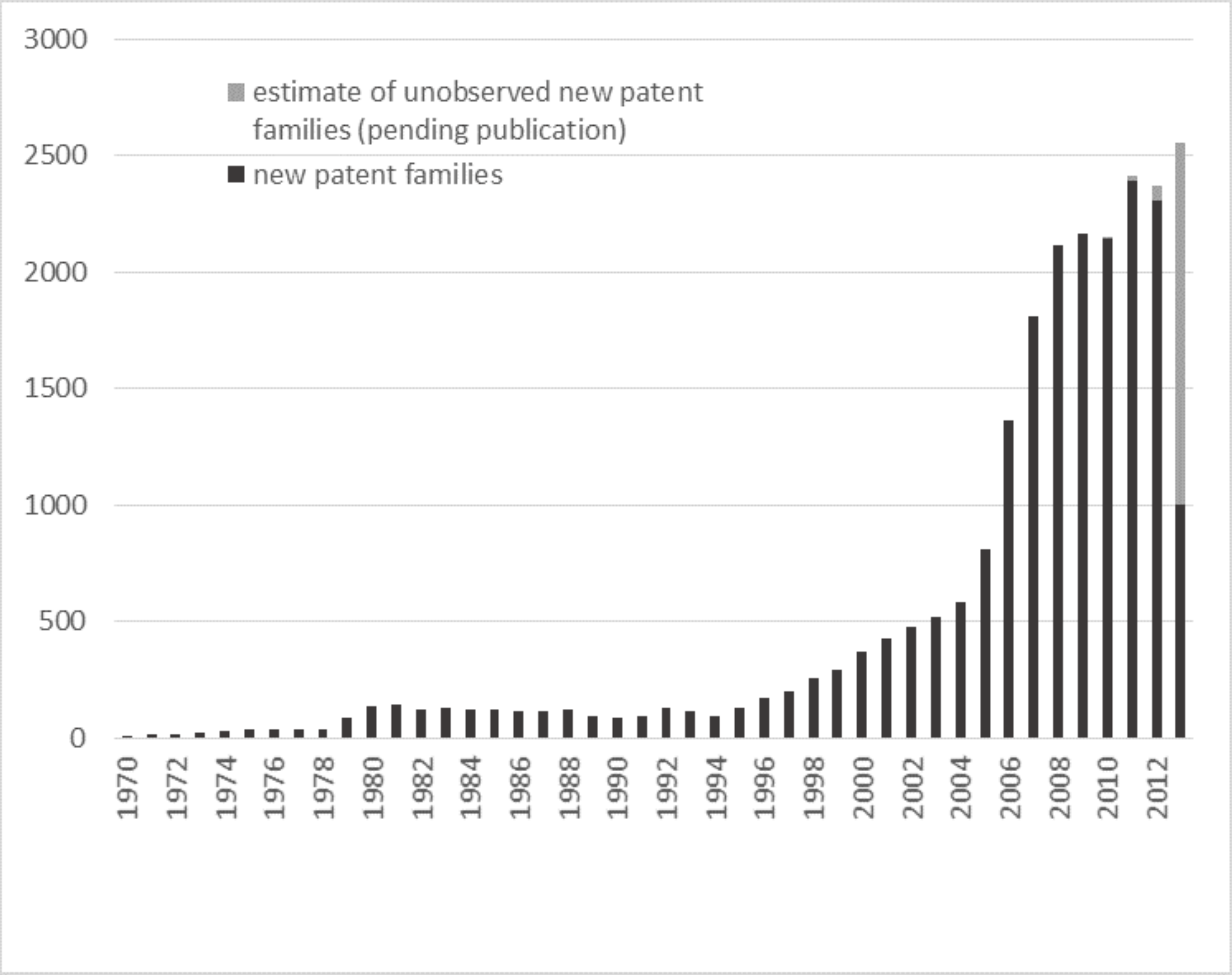

Figure 3: Patent Family trends from Nature Biotechnology Article

Given this quick increase in patenting activity, the probability of infringing an existing patent (or application) increases. This problem is exacerbated when patent applications are not publicly available prior to grant as the uncertainty surrounding the existing IPR space increases with the number of pending applications (which was the case in the U.S. prior to 1999). For example, in an April 2013 issue of *Ethanol Producers Magazine* Mccoy (2013) posits:

> You just received a letter from a technology provider, competitor or patent troll, demanding that you immediately stop production of your new ethanol processing methods and products or else face a patent infringement lawsuit. Now what do you do?

This question is one many Biofuel producers' face, thus he offers a solution: design around the existing patents. He suggests producers do so with two goals in mind: "to modify your product in a manner that avoids infringement liability altogether; and at the very least, to remove the risk of an enhanced damages award if it is later determined that your product infringes the patent". To do so requires "having competent, experienced IP counsel and ensuring they understand your product". This 'easy' solution offered by McCoy is another example of increased transaction costs and uncertainty for researchers in the biofuels industry, both of which can stifle innovation.

Despite large R&D incentives uncertainty still exists for biofuel producers and innovators as mandates, such as the RFS, are subject to change and the price of substitute products is constantly in flux [Figure 4]. Never the less, a plethora of policies are in place to help drive innovation in this industry.

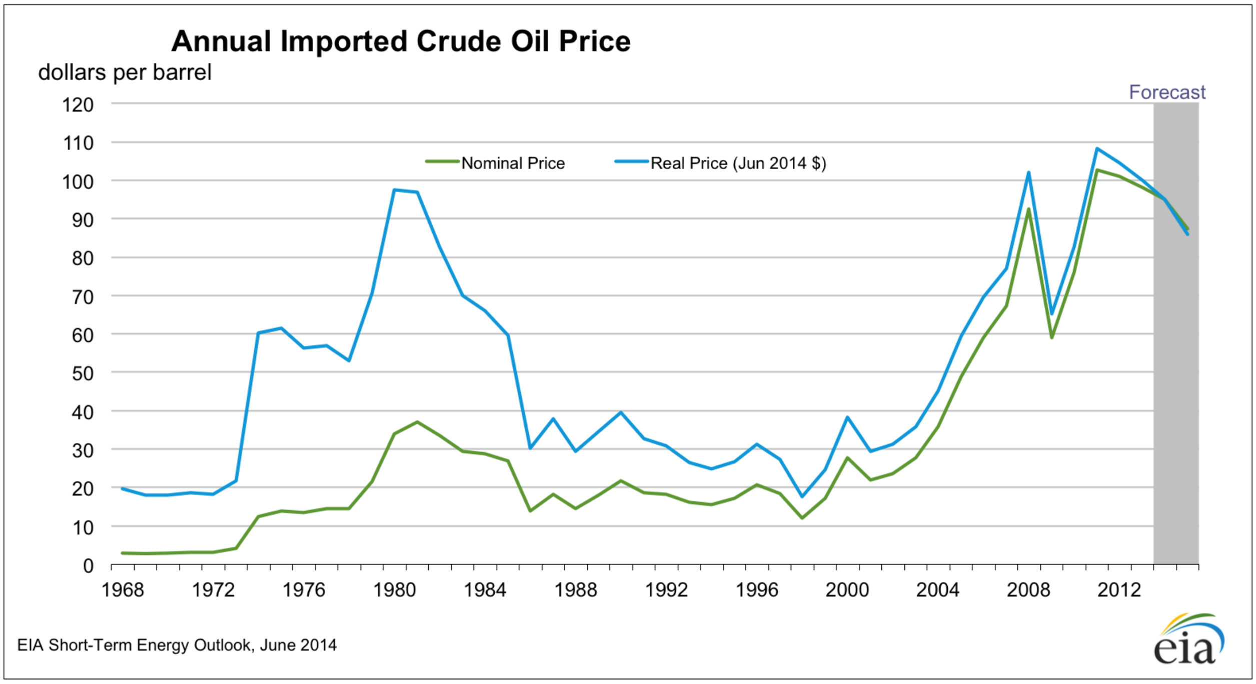

Figure 4: Crude Oil Prices

Biofuels innovation incentives can be broken into two distinct categories: supply side and demand side. On the supply side, policies that reduce the cost of R&D activities (tax credits, etc.), increase access to capital, and directly fund research play an important role. Government policies such as the U.S. 1970 Clean Air Act, 1990 Clean Air Act, and 2005 Energy Policy Act offer funds in the form of direct subsidies or tax breaks for this type of research, thus acting as a supply side driver of biofuels innovation. However, existing markets for fuel and feedstocks also play an important supply side role in biofuels innovation.

On the demand side mandates that require gasoline refiners to use ethanol blends, such as the 1990 U.S. Clean Air Act Amendments, 2005 U.S. Clean Air Act, and the 1998 Alternative Motor Fuels Act pull innovation in this sector. For instance, following the 1990 U.S. Clean Air Act Amendments demand for ethanol increased when gasoline blenders were mandated to use a refining byproduct such as MTBE or ethanol as a gasoline "oxygenator" to help decrease carbon monoxide emissions. When MTBE was discovered to be carcinogenic when leaked from gas tanks it was soon banned in many states. By 2006 25 states had banned the use of MTBE, thus further increasing demand for ethanol in gasoline blends.

Blender and distributor mandates, blend availability and cost is also important in this market. In the U.S., the 1978 Energy Tax Act was the first act to establish tax credits for ethanol blenders. The 2005 Energy Policy Act created mandates for the Renewable Fuels Standard (RFS), requiring 7.5 billion gallons of renewable production by 2012. The 2007 Energy Policy Act increased these mandates to 15 billion gallons by 2014, which included new definitions for cellulosic and imported biofuels (Wright (2014)).

Another driving factor in this industry is the large amount of collaboration and joint-ventures. These ventures include BP's pledged investment of $500 million in U.C. Berkeley for the Bioeconomy Institute, Colorado's Clean Energy Cluster, and Illinois's Energy Biosciences Institute.These collaborations were formed in part to decrease the risk of biofuels research and help diversify research efforts to help address all aspects of biofuels production and final distribution (Heisey et al. (2011)). If IP fragmentation is truly an issue in this space one can posit these joint ventures with large access to knowledge, will be more successful at innovating than individual entities.

This inventor collaboration approach allows IPR to transfer informally through personal exchange and partnerships based on trust to overcome transaction costs. This will also allow me to explore the implications of public-private partnerships within the Bioenergy space, where a large amount of private money has been dedicated to public research universities for R&D purposes (Graff and Wright). This industry can be thought of as a subset of the larger biotechnology space in which public funding has been a main driver of innovations, and has created incentives for partnerships between public and private researchers to reduce the riskiness of R&D (Mazzucato, 2013).

1.4 Dissertation outline

These three papers explore the hypothesis of the anticommons using biofuel patent data. The hypothesis posited by Heller and Eisenberg (1998) claims that overlapping property rights can lead to underuse of a resource. These papers explore this idea in terms of the innovation space or existing property rights over a particular technology pathway compared to others within the biofuels space. If the hypothesis holds, the patents with more assignees will be less cited than those with fewer assignees. This ownership space becomes more fragmented, or harder to negotiate, as the number of patent owners increases, ultimately leading to a lower number of follow-on citations for patents with a large number of owners.

Paper 1 explores the biofuels patent landscape and was published in Nature Biotechnology in 2016 (Albers et al. (2016a)). I was a lead author on this paper and use this data set for paper 3. My contributions including cleaning the data, creating valuable graphs, and helping write the paper.

Paper 2 offers a mathematical model of research effort incentives and the effect of fragmented intellectual property rights (IPR). Fragmentation can take the form of legally shared property rights or of poorly defined rights that give potential for legal conflict, and both can inhibit innovation exploration. This paper focuses on the latter as a form of market failure associated with the "anticommons" concept. The formulation is an extension of the Nordhaus (1969) model of research and development (R&D) activity planning, adding a fragmentation parameter that scales research benefits down with more fragmentation, as a reflection of the costs or barriers faced in a context of IPR fragmentation. The model allows comparison of the case of fragmentation with the case of perfectly defined IPR and shows that more fragmentation reduces research effort and both private and social research benefits. The degree of social loss is theoretically quantifiable, as is the implied benefit of countervailing public incentives such subsidies.

Paper 3 empirically explores the anticommons hypothesis in the context of biofuel patents granted between 1964 and 2014. The resource in question is innovation in the biofuels space and is measured by follow-on citations, a measure of how useful others found the existing knowledge. As ownership rights or assignee count for a particular patent increases, it becomes more complicated and expensive for inventors to use the existing knowledge (patent). In all cases explored follow-on citations decrease with the number of patent assignees. In other words, the more people who own a particular patent, the lower the rate of follow-on citations. This paper explores this hypothesis over various technology types and illustrates that some technology pathways experience larger anticommons effects than others.

2 Paper 1: “The rise and fall of innovation in biofuels”

2.1 Introduction

“The Rise and Fall of Innovation in Biofuels”published in *Nature Biotechnology* in 2016 was a joint effort with Dr. Greg Graff and Dr. Steve Albers. The paper discusses biofuel innovations, as measured by patents granted and patent applications submitted between 1960 and 2013. The first biofuel patent on record was filed in 1960, thus the start date of our dataset. This paper is a collaboration with Dr. Stevan Alberts and Dr. Gregory Graff. The paper illustrates trends in biofuel patents across the world. Among other findings, the paper discusses patent trends over time, including: public vs. private inventors and assignee(s), country of origin, biofuel feedstock type, technological pathways used, and other factors. Various political, economic, and intellectual property factors are posited to explain the trends illustrated. These factors may have driven the rise (and fall) of biofuel innovations [1] (Albers et al. (2016b)).

2.2 Data Collection and Analysis

Using Thomson Innovation’s vast patent dataset, we collected all patents with an Intellectual Patent Code (IPC) related to any part of biofuel production. This included feed stocks, processes, final fuels, and any steps required between. Dr. Steve Albers, the Biochemist in our group, created a complete list of IPCs using his extensive knowledge of the subject. The full list of IPCs used and a description of how we decided these codes were indeed for biofuel applications is explained in our supplementary materials. Once this final data set was complete and coded for the different biofuel technology steps I got to work making sense of the economic data included in these patent applications.

With the support of Dr. Graff, I tagged the data for institutional type and other author and inventor characteristics to ease data analysis. Data cleaning included determining the inventor(s)

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[1] This paper was published in *Nature Biotechnology* in 2016 and co-authored with Steve Albers and Greg Graff

and the assignee(s), who are often institution(s) of inventor employment. This data classification is necessary for determining the type and amount of resources available to each inventor. In other words, this lays the foundation for testing innovation results given the resources available to the author(s) or inventor(s) when conducting the research needed for the submitted patent application. To do so, I viewed and hand tagged each patent entry to ensure it was correct. For patents with multiple inventors or authors, I tagged each individual contribution along with their institution on record. I also tagged the data for country of origin for both assignee(s) and inventor(s).

Cleaning the data for these variables required utilizing a variety of tools in Excel and the help of Devon Phillips (a graduate research assistant at University of Minnesota, in the Department of Applied Economics) to categorize and consolidate for misspellings, and other problems. Additionally, I constructed company trees for all companies in the data set to account for acquisitions and mergers. In this particular area, several major companies have acquired more than a handful of start-up companies in this space. Although a daunting task to note these things, they offer incite to the nature of the biofuels market participants.

I was also responsible for the policy analysis and consolidation for this paper. I researched and summarized all biofuel related government programs between 1960 and 2014. This included the renewable fuels standard, oil embargoes, trade policies, refinery requirements and more. These changing policies offer insights into the nature of biofuel research and patenting activity. However, it is very hard to aggregate these trends internationally, thus paper 3 focuses only on U.S. patents.

Finally, I worked closely with Dr. Graff and Dr. Albers to conceptualization and plan of the paper. We worked together to formulate the paper outline and decide which results were most pertinent to our arguments. After deciding what to include in the paper, I drafted several different pieces, including the sections mentioned above. I also reviewed several drafts of the final paper and provided revisions where needed before submission. This paper was very much a group effort and I am very thankful to Dr. Graff and his continued support.

2.2.1 Patent Families

An important part of our final research contribution was identifying “patent families”. These were created using Thomson Innovation’s INPADOC family classifications and our specific patent numbers. If a patent was filed in more than one country, using similar, or the same wording, we grouped them as one patent family. In other words, if a patent was filed in 100 different countries, it was still considered 1 patent in our data set. This prevented double (or 100 times) counts for the same patent within the international dataset.

2.3 Results

We discovered several important things in this paper. First, there was a large uptick in patent activity between 2004 and 2008, then a drop-off after that. When looking at the worldwide data, the institution assigned included: 56% private sector, 20% public sector, 5% public and private collaboration, and the remainder were assigned to individuals with no institution assigned. When compared to Europe, the U.S. has a higher share of public assignee(s), due in part, to the strong IP policies in place to support University research. China had the largest percentage of patents assigned to universities, which can also be attributed to the IP policies in place and patent office resources.

We also found that first generation biofuels, including: ethanol, biodiesel, and biogas held flat after the large uptick experienced between 2004-2008. This is interesting when considering the hypothesis of the anticommons as these are considered more basic technologies. More advanced, or second generation biofuel technologies, such as cellulose, therochemical, and photosynthetic biosynthesis, we saw a slight uptick between 2005-2008, but these have since declined. The divergence in trends between these two technology classes offers a promising avenue to further explore the anticommons.

Lastly, we observed large variations across country of filing. Given the large variation in patent laws and filing restrictions internationally, the other two papers of my dissertation focus solely on patent applications and grants from the U.S. Patent office. This is a data set I am very comfortable with given my contribution in cleaning all of the data for inventor(s) & address(s), assignee(s) & address(s), public and/or private institutional type, and other characteristics as described in the next section.

2.4 Published Paper: "The Rise and Fall of Innovation in Biofuels: the global landscape of biofuel patenting from 1970 to 2013"

2.4.1 Abstract

After surging worldwide between 2004 and 2008, the invention of biofuel technologies slowed considerably, and in many countries went into decline. In the US, the rate has remained flat. In China, however, patent filings continue to surge ahead. Global trends point to an uncertain future for advanced biofuels.

2.4.2 Introduction

The early internal combustion engines of Nikolaus Otto, Rudolf Diesel, and Henry Ford ran on ethanol and vegetable oils. Yet, petroleum-based fuels dominated the 20th century due to plentiful supplies and low prices. Biofuels were virtually absent from the transportation energy supply in the 1970s (Figure 1) when interest was revived by the global oil crises following the 1973 Organization of Petroleum Exporting Countries (OPEC) embargo and the 1979 Iranian Revolution. Brazil led the way, introducing sugarcane ethanol to domestic fuel markets in the 1980s, but, with oil prices stably below $20 a barrel for much of the 1980s and 1990s, other countries were slow to follow suit (Figure 1.c).

Then, following the 9/11 attacks on New York and Washington D.C. in 2001, the U.S.-led occupation of Iraq in 2003, and steady growth in oil prices (Figure 5), a political confluence of environmental, national security, and agricultural interests backed efforts to develop commercially viable biofuels. Policy initiatives included replacement of Methyl Tertiary Butyl Ether (MTBE) as oxygenator in gasoline with an ethanol blend, for air quality purposes, as well as mandates for additional quantities of renewable fuels to be included on national markets. Perhaps the most notable of these was the Renewable Fuel Standard (RFS) introduced in the U.S. in 2005 and strengthened in 2007. Significant public investments were introduced for research and development (R&D) on biofuels by governments around the world. Industry and investors responded vigorously to the mix of high energy prices and policy incentives. Production of first-generation biofuels—made largely from food crops—expanded exponentially between 2004 and 2010, coming to account for over 8 percent of global motor fuel production by 2012 (Figure 5). R&D initiatives were launched by a range of entities, across a number of industries, both to increase the efficiencies of existing biofuel production technologies and to create entirely new ones, and in so doing, explored use of a diversity of different sources of feedstock, conversion pathways, and fuel molecules (summarized in Figure 11).

Following the global financial crisis and economic downturn of 2008, demand for transportation fuels weakened at the same time that hydraulic fracturing in the U.S. began adding previously inaccessible shale oil to supply. Oil prices dropped from their historic highs (Figure 5). At the same time came increasing scrutiny of the impacts of first-generation biofuels on the environment—due to requirements for land, water, and agchemicals —as well as their impact on food commodity prices —putting pressure on others within the agricultural value chain, such as livestock producers , as well as on consumers, especially those at greatest risk of food insecurity and hunger. The political alliance of environmental, national security, and agricultural interests began to unravel.

Meanwhile, second-generation or advanced biofuels—those more likely to deliver on the nascent industry's environmental, energy security, and economic development promises—proved more difficult to develop or scale up as quickly as had been hoped. These include fuels produced from biomass or cellulosic feedstock that are co-products (e.g. from crops or forestry) or waste streams (e.g. from municipal waste or livestock manure) rather than direct utilization or displacement of food resources. These also include specially-cultivated, highly-efficient photosynthetic algae. The RFS had mandated significant volumes of ethanol from cellulose to be blended into

U.S. fuel supplies starting in 2010 ; yet, only in 2014 did the world's first commercial-scale cellulosic ethanol plants begin to operate. As cellulosic ethanol production targets were missed, RFS mandates were relaxed or waived. And then, oil prices fell again in 2014, and from which they are not expected to rebound fully, given shale oil production in the U.S., the lifting of trade sanctions on Iran, the economic slowdown in China, and other factors.

While prospects for private returns on investment in biofuels R&D may have been eroded in the short run, the potential advantages of advanced biofuels—whether for reducing emissions, diversifying energy supplies, or supporting rural economic development—remain important for society in the long run. Discoveries made and technologies created during the last decade will be the basis for future innovation and growth of the industry, whatever shape it is to take. Yet, the biofuel industry is still young, with multiple competing candidate technologies, and has not yet converged on a viable dominant design. Given the diversity of technologies, industries, and actors involved, it can be difficult to see what overall progress has been made following a decade of intensive R&D efforts, having not yet fulfilled its potential.

This study assembles the global landscape of patented biofuel inventions, made and filed anywhere in the world from 1970 through 2013. By using patents as a relatively consistent indicator of inventions arising as an "output" of R&D, we are able to compare systematically across all technologies and countries. The analysis address key strategic questions for the emergent industry:

- At what rate has invention in biofuels progressed over the last decade? Has it been sustained under recent developments of lower oil prices and shifting political support?

- Which countries contribute, and how much, to patented biofuel inventions? Who are the leaders globally? How has this changed over time?

- How has effort been allocated between first-generation ethanol and biodiesel technologies and more advanced biofuel technologies? Between biological or thermochemical pathways for producing advanced biofuels?

- To what extent have different types of R&D organizations, including those in the public sector and in the private sector, contributed to biofuel technologies? From what industries?

- What do current trends indicate about the rates at which innovation will continue in coming years?

2.4.3 The global landscape of biofuel inventions

The global patent landscape of technologies for the production of transportation fuels from renewable biological feedstock was constructed using specialized patent searches, using select combinations of technical keywords, International Patent Class (IPC) codes, and specialized biofuel company names. For each invention identified, all related patent applications and grants from patent offices around the world that make up that invention's "patent family" were included. The resulting patent records were reviewed, cleaned, and categorized according to type of biofuel technology. The resulting global patent landscape encompasses 21,768 inventions (INPADOC patent families), represented by 66,170 documents published by 81 patent offices, and invented by residents of 100 different countries. (See Supplementary Materials for detail on methods and dataset).

Plotting inventions by year of first filing (Figure 7) indicates five phases of innovation in this industry: (1) R&D in biofuels began slowly in the 1970s; (2) it increased after the oil crisis of 1979, but barely held above 100 inventions per year through the early-1990s; (3) then, around 1995, it started growing steadily, at almost 20 percent per year, experiencing almost linear growth for close to a decade; (4) an inflection came in 2004 after which the annual number of biofuel inventions almost quadrupled over four years, from 586 inventions in 2004, to 2119 inventions in 2008. The fastest year-on-year increase was in 2005-2006, at 68 percent. Then, (5) in the period from 2008 to 2013, following the financial crisis and drop in oil prices, growth in worldwide biofuel inventions slowed to an estimated average annual rate of just 3.9 percent.

The patent explosion in biofuels during 2004-2008 was not matched in overall patenting trends globally, which grew at a steady rate of just 3.3 percent annually during this time period. This growth does, however, correspond closely to the growth in world oil prices (Figure 1.a) and the growth in volume of production of fuel ethanol in the U.S. and globally (Figure 5).

2.4.4 Biofuel inventions by country of first filing

The global trend of biofuel inventions observed in Figure 5 belies important differences among the different nations and regions of the world. These differences become apparent when inventions are separated out by the patent office in which they were first filed (Figure 8). It is common for inventors to make their first (or "priority") patent application at the national or regional patent office where they reside. Our analysis confirms that the office of first filing is highly correlated with the country of invention (Figure 8). Several major observations stand out.

First, inventive activity in biofuels has been spread out relatively evenly around the world, rather than having been dominated by any one country or region. Japan was an early leader, almost alone responsible for the linear growth observed in aggregate global inventions between 1994 and 2002 (as seen in Figure 7). Yet, biofuel invention in Japan peaked by 2002, at which point it was still just beginning in most other countries. Filing rates turned upward in Europe in 2004 and followed in the U.S. in 2005. Filings in both Korea and China increased slowly at first, from almost nothing in 2000, then took off in 2004 (Figure 8).

In many parts of the world, biofuel inventions peaked between 2007 and 2009 and have been in decline since. The annual number first filed in Europe has declined by a third since its peak, and in Australia, New Zealand, and Canada—favored English-language patent offices—by almost half. The annual number of biofuel inventions first filed in the U.S. has held flat, with only as many new patent families filed in 2012 as had been filed five years earlier in 2008. The annual number of patent families originating with a "WO" application filed via the World Intellectual Property Organization's (WIPO) Patent Cooperation Treaty (PCT) mechanism faltered in 2009 and 2010 then recovered, and are estimated to have continued to increase since 2011, although at a slower rate.

Only in Korea and in China did new biofuel inventions continue to grow. Korea maintained double digit growth rates until 2011, but has slowed in 2012 and 2013. In China, the number of inventions registered annually more than doubled between 2008 and 2013. In 2013, the count of new biofuel inventions first filed in China was an estimated 43 percent of the world total, overshadowing the next largest office, the U.S., by a factor of three. Given the extreme shift in patenting behavior in China, and its weight in influencing global trends, further critical analysis of what has occurred within China is warranted.

2.4.5 Biofuel inventions by country of inventor

Identification of an inventor's country of residence does give a more precise picture of where inventive activity has been funded and conducted. Inventor address data was available for 79 percent of the patent families in the biofuels landscape. Since these data are incomplete, we can treat it as if it were a random sampling to report cumulative shares by country of invention in Figure 9. Again, inventive activity in biofuels appears to have been widely distributed around the world, with relatively equal shares of inventions made by residents of China, Europe, Japan, the United States, and the combination of all other countries. Two important sources of bias affect these shares, however. First, underreporting of inventor address is greatest among records from the national patent offices of middle and low-income countries, and thus inventions by residents of these countries are underrepresented. Second, in Japan, South Korea, and China, the "unit of invention" protected (or, similarly, the number of claims made) within a single patent tends to be smaller than in the U.S., Europe, or other Western countries; with the result being more patents per unit of invention, all else being equal. Therefore, inventions by residents of these countries are overrepresented.

2.4.6 Biofuel inventions by patent assignee organization

Under the patent laws of most countries, patent rights are granted first and fundamentally to the individual inventors, who can assign or transfer those rights in the patent application process, or subsequently, to another legal entity. In most cases patents are assigned to commercial companies, over inventions made by employees or contractors they have hired to conduct R&D. Under intellectual property policies and practices in most countries, public sector organizations—including government agencies and laboratories, academic institutions, and non-profit research organizations or foundations—also take title to patents on inventions, to help stimulate private investment in the further development and commercialization of those inventions and to share in the financial benefits when those inventions generate revenues.

Analysis of what kinds of organizations have taken title to biofuel inventions can indicate where biofuels R&D is being conducted within the economy, as well as the relative contributions of public and private sector funding of R&D expenditures on biofuels. Worldwide (Figure 5.a), companies have accounted for the majority (56 percent) of biofuels inventions, while public sector research organizations have accounted for 20 percent. Inventions jointly assigned to companies and public sector organizations, indicating public-private R&D collaborations, account for an additional five percent of biofuel inventions. The 19 percent assigned to individuals includes some inventions that remain in the control of those individuals in the long run, but these also includes many inventions for which the transfer of ownership to an employer or other organization was simply not completed by the time the patent documents published. Interestingly, these relative shares remained remarkably stable over time globally and within individual countries, even during the explosive growth phase of 2004-2008: in other words, neither the public sector nor the private sector took a disproportionate lead in generating the growing number of patents (see supplementary Materials for more analysis on shares by country and over time).

Global shares, again however, belie significant differences among different nations and regions. The profile of assignee is broadly similar in the U.S. and Europe (Figure 10): in both, companies account for roughly two thirds of all biofuel inventions. Public sector organizations have taken title to a larger share in the U.S. than have their counterparts in Europe. This is consistent with the stronger policies in the U.S. under the Bayh-Dole Act and Stevenson-Wilder Act since 1980, giving them the option to take title to inventions made under federal funding. European policies regarding patenting in the public sector have been more equivocal, or in some countries have actively favored the granting of title to individual researchers under the “professor’s privilege”, which may account in part for the relatively higher share of individual applicants in Europe (Figure 10).

There is greater contrast between the profiles of assignees in Japan and China (Figure 10). In Japan, companies account for fully 75 percent of inventions, a much larger share than the global average (and also more than in the U.S. or Europe). The early growth in biofuels inventions in Japan, starting in the mid-1990s, as already noted in Figure 3, was almost entirely due to private sector R&D (Figure 10). Public sector organizations in Japan accounted for a much smaller share of inventions. Before major policy changes introduced in Japan around 2000, most inventions by academics were assigned either to the individual researcher or to a corporate partner for commercial development. The steady increase of public sector patents following 2000 may reveal changes in practice following changes in policy.

In China, the private sector accounts for a much smaller share of biofuel inventions, at only 35 percent, and this includes state-owned enterprises. Conversely, the public sector in China accounts for much more, at 38 percent. Universities and institutes of the Chinese Academy of Sciences have been very aggressive in patenting biofuel inventions, starting earlier than companies and accounting for a greater number of biofuel inventions in each year, through 2010. Only with a doubling of inventions by companies in 2011 did the private sector overtake the public sector in China.

Analysis of assignee organizations also identifies the most prevalent assignees organizations listed on biofuels patents. The list of the fifty leading organizations worldwide (Figure 6) includes a broad spectrum of organizations from the public sector and academia, startup companies, as well as corporations in the chemicals, petroleum, agriculture, biotechnology, engineering, and automobile industries. The top fifty organizations also represent a range of countries, but mostly those already identified as the top sources of invention, including the US, Europe, Japan, and China.

2.4.7 Biofuel inventions by type of technology

We find that 17,951 of the total 21,768 inventions found in the landscape dataset (82 percent) fit into one of six predominant technical pathways, represented by the Roman numerals I-VI in Figure 6, defined by the feedstock, process, and the biofuel produced. The first three—I. ethanol from starches and sugars, II. biodiesel from oil crops, and III. biogas from anaerobic digestion of biomass—are already implemented at commercial scale. The other three advanced biofuels—IV. cellulosic ethanol, V. thermochemical processes (gasification and pyrolosis), and VI. algae biofuels—are still in development or early stage research. Figure 7 plots the numbers of inventions in each of these six pathways over time (See Supplementary Materials for methods).

I. Alcohols fermented from sugar and starch crops The most common pathway is the fermentation of ethanol and other alcohols from simple sugars, extracted from sugarcane or hydrolyzed from starches of grain and tuber crops, particularly maize and cassava (Figure 11). This encompasses the corn ethanol industry in the U.S., sugarcane ethanol in Brazil, and cassava ethanol in Southeast Asia. Alternative processes for producing ethanol from simple sugars are also counted in this category.

The fact that ethanol blend mandates are capped at or around 10 percent in most countries (the so-called "blend wall") might have suggested that ethanol innovation would be curtailed once mandates were met by installed production capacity.11 In fact, ethanol production worldwide peaked in 2010 and has contracted slightly in the years following (Figure 5). However, inventions involving production of ethanol by fermentation of sugar and starch crops are the most prevalent in the patent data, and continue at an aggressive rate of 10 percent per year accounting for roughly half of all biofuel inventions in recent years (Figure 12; compare to Figure 7). Continuing innovation is likely introducing process refinements, efficiency gains, and cost savings for commercial producers.

II. Biodiesel from oil crops The second biofuel production pathway creates biodiesel, but also other fatty-acid based fuels, from oils pressed from oilseed crops, such as soybean, rapeseed (canola), and palm oil, as well as from fats rendered from animal carcasses. Both vegetable oils and animal fats typically undergo a transesterification process to make the final fuel (Figure 11).

Already an established commercial technology, biodiesel production was supported in the United States by two federal programs. The biodiesel blender's tax credit, enacted in 2004, gave producers a $1.00 per gallon tax credit. The RFS2, in 2007, mandated specific volumes of biodiesel to be produced annually. Accordingly, U.S. biodiesel production volumes grew considerably in the years after 2004, but when Congress allowed the tax credit to lapse in 2010, biodiesel production dropped 42 percent in a single year, only to recover after the tax credit was reinstated in 2011.

Such policy-induced gyrations also seem to be reflected in biodiesel inventions (Figure 712). Beginning from almost nothing prior to 2000, biodiesel inventions surged from 2004 to 2008, even superseding ethanol inventions for two years. Then abruptly, in 2009 and 2010, biofuel inventions fell, in contrast to ongoing growth in ethanol inventions. Then, in 2011, whether rescued by reinstatement of the U.S. tax credit or recovery in oil prices, biodiesel inventions picked up again.

III. Biogas from anaerobic digestion of biomass The third pathway is the generation of methane, also called biogas, by anaerobic digestion of unrefined or waste biomass (Figure 6). This is also a relatively mature technology, used on farms or in waste treatment plants for decades. Inventions in biogas surged briefly in 1979 and 1980, during the oil crisis, and subsequently tracked close to ethanol inventions through the mid-1990s. But, as ethanol (fermentation) took off in 2002, biogas (digestion) continued at a more measured pace until 2006 at which point it took off, and continues to grow rapidly (Figure 12).

IV. Cellulosic ethanol Among advanced biofuel pathways is the generation of ethanol (as well as other alcohols) by fermenting simple and complex sugars from the hydrolysis of cellulose, the primary constituent of woody and fibrous biomass (Figure 6). The biological conversion of woody biomass to ethanol has largely been constrained to the experimental and pilot project scale. In the United States, production and blend mandates for cellulosic ethanol were built into the RFS (2005) and RFSII (2007). Very few patents involving fermentation of sugars from hydrolyzed cellulose are observed prior to 2005, except for a handful for hydrolytic enzymes. The surge of cellulosic ethanol inventions was short lived, and while it aggressively trailed growth in the standard ethanol pathway from 2005 to 2008, growth in cellulosic ethanol inventions went flat in 2008 and later into decline (Figure 12).

V. Thermochemical conversion of biomass: gasification and syngas Another pathway for producing advanced biofuels, which may compete directly with cellulosic ethanol in utilizing biomass feedstock, relies on heat and pressure with specialized catalysts to break down cellulose and the other long-chain molecules that make up biomass. We classify the two main forms of thermochemical degradation—pyrolysis and gasification—together for the purpose of this analysis. Both result in reactive gasses and/or liquids that can then be upgraded via a variety of processes to form a multitude of alcohols and other molecules, potential "drop-in" biofuels (Figure 6). The general technology is not new in principle and is applied in a number of industrial settings. Requirements for scale and cost have been the main challenges. Inventions involving thermochemical processes grew relatively early, in the late 1990s, and for a couple years, from 2000 to 2002, thermochemical briefly exceeded all other pathways in numbers of inventions (largely driven by Japan, see Supplementary Material Figure S15). While it has continued to grow steadily and has been the most prevalent among the advanced biofuels, it did not experience the kind of explosive growth seen for inventions in the three commercially viable pathways. More troubling, the rate of invention of thermochemical degradation has declined significantly since 2011 (Figure 12).

VI. Direct photosynthetic biosynthesis of fuel molecules: algae The final pathway involves direct biological synthesis by specialized autotrophic photosynthetic microorganisms, using only sunlight as an energy source. This has been perhaps the most ambitious pathway for producing biofuels. Most common within this category are single celled algae, grown in water within photobioreactors or raceway ponds, and producing a vegetable oil that is converted to fuel. While a handful of pioneering patents date from the 1970s, inventions in this pathway began to grow significantly in 2005 and 2006, and followed a very similar trajectory to inventions in cellulosic ethanol. Similar to the other two advanced biofuel pathways, inventions involving algae and the direct biosynthesis of biofuels have been in decline since 2010 (Figure 12).

The most striking observations from Figure 12 are that inventions in the three commercially viable production pathways—grain and sugar ethanol, biodiesel, and biogas—have significantly exceeded inventions in the three advanced biofuel pathways—cellulosic ethanol, thermochemical conversion, and algae—and, moreover, in recent years, the global numbers of inventions in the advanced biofuel pathways appear to have gone into decline. Yet, as in previous parts of this study, more disaggregate analysis shows important differences. (See supplementary materials, Figure

S15, for analysis). Inventions in all six pathways have grown rapidly in China; however, those in the commercially viable pathways have grown more rapidly. At the same time, inventions in all six pathways have been down in Europe and Japan. In the United States, the story is mixed. Critical analysis of the biofuels patent explosion in China

Were it not for the surge of biofuels patenting in China, the global rate of inventions would have turned downward after 2008. For the rest of the world taken together, biofuel inventions declined by an average of 4 percent per year from 2008 to 2013.

The primary factor driving innovation in China is undoubtedly the major policy initiatives for developing alternative energy sources adopted during this timeframe, including major investments in biofuels R&D. At the same time, the biofuels patenting trends observed here correspond with an overall surge of patenting in China starting in 2000, following major patent reforms made to bring China into compliance with the Trade Related Intellectual Property Rights (TRIPS) agreement of the World Trade Organization (WTO). Patenting by China's academic and public sector increased dramatically following a 2002 change in regulations regarding intellectual property created under government funding, the Chinese equivalent of the Bayh-Dole Act in the United States, as well as academic reforms including patent applications in professional performance evaluations. Yet, given China's recent history of weak protections of intellectual property and relative lack of institutions or professional capacity, there are reasons to question the quality or effectiveness of these patents. Very few appear to lead to actual commercial implementation.

There are several indications that this may be the case in the biofuels landscape data. 70 percent of Chinese patent families consist of just a single patent application, without a corresponding granted patent. This may be explained, however, by the fact that so many of the Chinese inventions are so new that sufficient time may not have elapsed for the examination to have been completed and a patent granted: of the (fewer) Chinese patent applications filed 2006 to 2010, we observe an annual average grant rate of 42 percent (Figure 17 in Supplementary Materials). Second, very few inventions that originate in China include a foreign filing for protection outside of China: only 3.25 percent each year on average from 2006 to 2010. In addition, Chinese patent families are characterized by a very high rate of invention from public sector institutions, which are generally further from commercial utilization.

2.4.8 Discussion and Conclusions

Innovation in biofuels technology has involved multiple countries and multiple technical pathways. Invention in biofuels rose over the first half of the last decade, and, in most parts of the world, fell over the second half. The sheer volume of patented inventions registered in the "patent explosion" of 2004-2008 dwarfs the previous foray into biofuels innovation in 1978-1981. Although, technologies now operating at commercial scale—particularly ethanol and biogas—were advanced in that earlier round of innovation (Figure 12). Japan was an early leader, starting in the late 1990s, in the recent rise in biofuels innovation. Japan was followed, in fairly equal measures, by the United States and Europe. A surprisingly wide range of countries have contributed R&D and inventions to the global landscape (Figure 4). The sheer volume and rate of inventions from China raise interesting questions about its potential role in the future of biofuels innovation.

Comparable to other early stage technologies, public sector R&D organizations have contributed a significant share to the creation and patenting of biofuel technologies, with public-private partnerships playing a smaller but not insignificant role. Private sector innovation, essential in putting new knowledge into practice at scale, is the largest source of patented inventions.

Despite the promises and policies advocating for advanced biofuels, numbers of inventions continue to be much larger for first-generation ethanol, biodiesel, and biogas technologies, particularly in China. Of the more advanced biofuel technologies, thermochemical pathways had a long lead over cellulosic fermentation and algae.

Recent economic and political conditions, with lower oil prices and shifting political support, appear again, just as in the 1980s, to be eroding investments in biofuels R&D, at least in most high income countries, including the United States, Europe, and Japan. Accounts of large energy companies withdrawing investments and smaller startup tech companies failing have characterized the biofuels industry since the global financial crisis of 2008-9. The extent to which biofuel invention can be sustained, and even the policies that help drive it, will depend more than anything on the level and volatility of oil prices and on the economic conditions in China.

2.4.9 Graphics

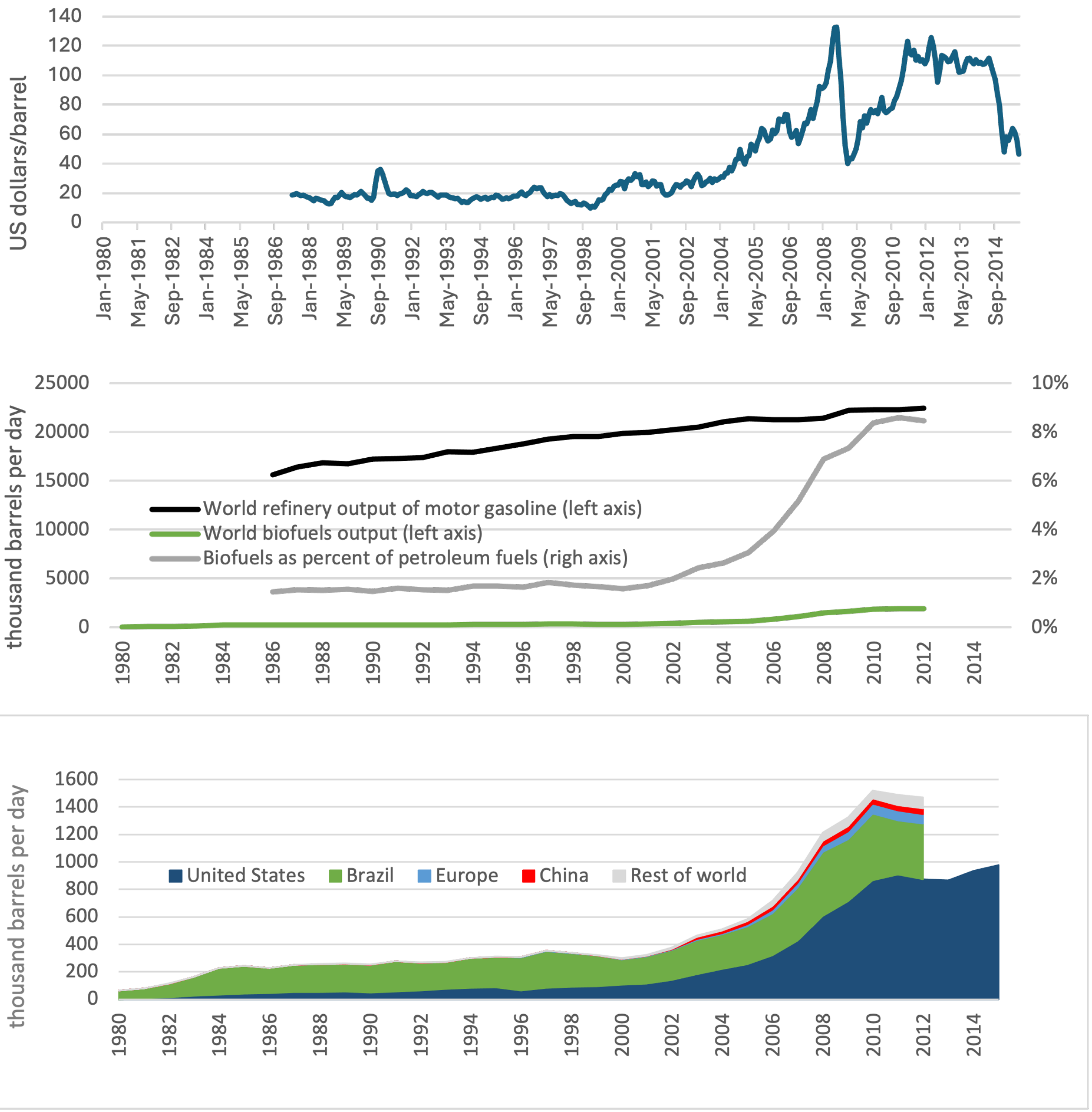

Figure 5: Patent Trends

Overall rank	Assignee organization	Country	Industry	Patent families	family rank	Patent publications	pub rank
1	DuPont/Pioneer	US	Chemicals/ Agriculture	211	3	1,432	1
2	Chinese Academy of Sciences	China	Public	293	1	491	8
3	Mitsubishi	Japan	Chemicals/ Engineering	226	2	470	11
4	Institute Francais du Petrole (IFP)	France	Petroleum	126	7	733	4
5	Novozymes	Denmark	Biotech/ Enzymes	95	14	771	3
6	Butamax	US	Biofuel	94	15	644	5
7	Shell	Great Britain/ Netherlands	Petroleum	109	11	468	12
8	Celanese	US	Chemicals	57	32	866	2
9	BP	Great Britain	Petroleum	85	22	576	6
10	Exxon	US	Petroleum	94	16	474	9
11	Chevron	US	Petroleum	86	20	435	13
12	Ebara Corp	Japan	Engineering	119	9	304	21
13	Toyota	Japan	Automobiles	127	6	282	24
14	Kior	US	Biofuels	81	24	407	14
15	Hitachi	Japan	Engineering	142	5	207	31
16	Monsanto	US	Chemicals/ Agriculture	79	25	320	20
17	Mitsui	Japan	Chemicals	114	10	206	33
18	Honeywell	US	Chemicals	72	27	304	22
19	University of California	US	Public	60	29	363	16
20	China Petroleum & Chemical	China	Petroleum/ Chemicals	120	8	178	40
21	DSM	Netherlands	Biotech/ Enzymes	50	41	382	15
22	Tsinghua University	China	Public	97	13	196	35
23	Dow	US	Chemicals/ Agriculture	53	37	328	19
24	Toshiba	Japan	Engineering	108	12	157	52
25	Sumitomo	Japan	Chemicals	89	19	179	39
26	LanzaTech	US	Engineering/ Biofuels	48	42	329	18
27	BASF	Germany	Chemicals	53	36	285	23
28	IHI Corp	Japan	Engineering	94	17	153	54
29	National Institute of Advanced Industrial Science and Technology	Japan	Public	89	18	156	53
30	Neste Oil	Finland	Petroleum	40	57	339	17
31	Nippon Steel	Japan	Engineering	86	21	151	56
32	Xyleco	US	Biotech/ Biomaterials	26	87	474	10
33	Nanjing University	China	Public	85	23	128	64
34	Mascoma	US	Biotech/ Biofuels	41	54	239	25
35	Kawasaki	Japan	Engineering	73	26	118	68
36	General Electric	US	Engineering	46	44	176	41
37	Syngenta	Switzerland/ Great Britain	Chemicals/ Agriculture	34	65	230	28
38	Bayer	Germany	Chemicals	43	48	180	38
39	Gevo	US	Biotech/ Biofuels	34	63	224	29
40	Korea Institute of Energy Research (KIER)	Korea	Public	58	31	131	63
41	Alliance for Sustainable Energy (National Renewable Energy Laboratory)	US	Public	29	71	239	26
42	Petrobras	Brazil	Petroleum	42	50	163	47
43	Kunming Science and Engineering University	China	Public	72	28	94	94
44	Verenium	US	Biotech/ Biofuels	26	86	239	27
45	Arkema	France	Chemicals	27	82	192	36
46	Dalian University	China	Public	58	30	87	100
47	ADM	US	Agriculture	29	70	172	43
48	Total	France	Petroleum	28	81	176	42
49	Agency of Industrial Science and Technology	Japan	Public	47	43	104	83
50	Tianjin University	China	Public	56	35	87	101

Figure 6: Patent Top 50 Patenting organizations worldwide in biofuel technologies

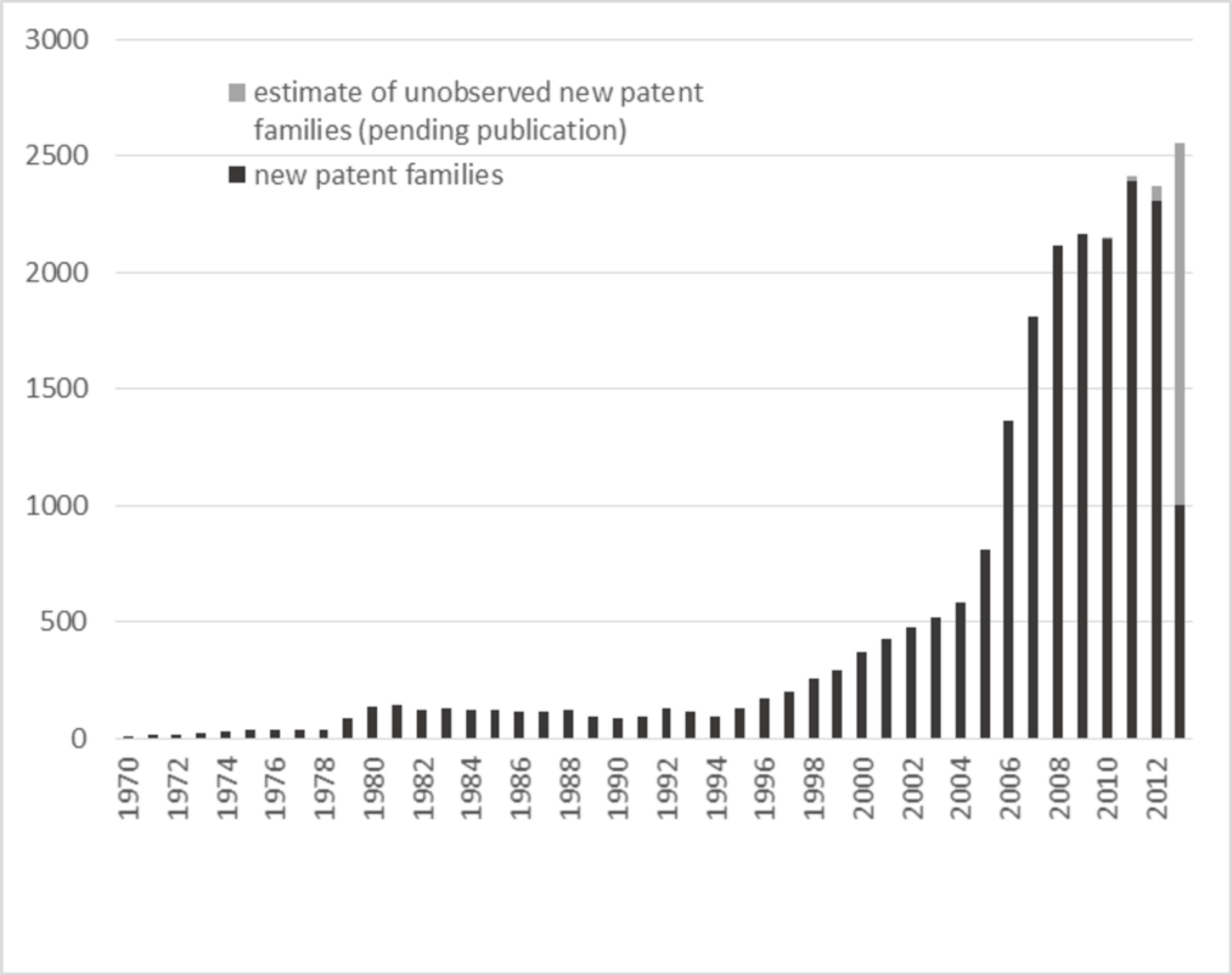

Figure 7: Patent Families

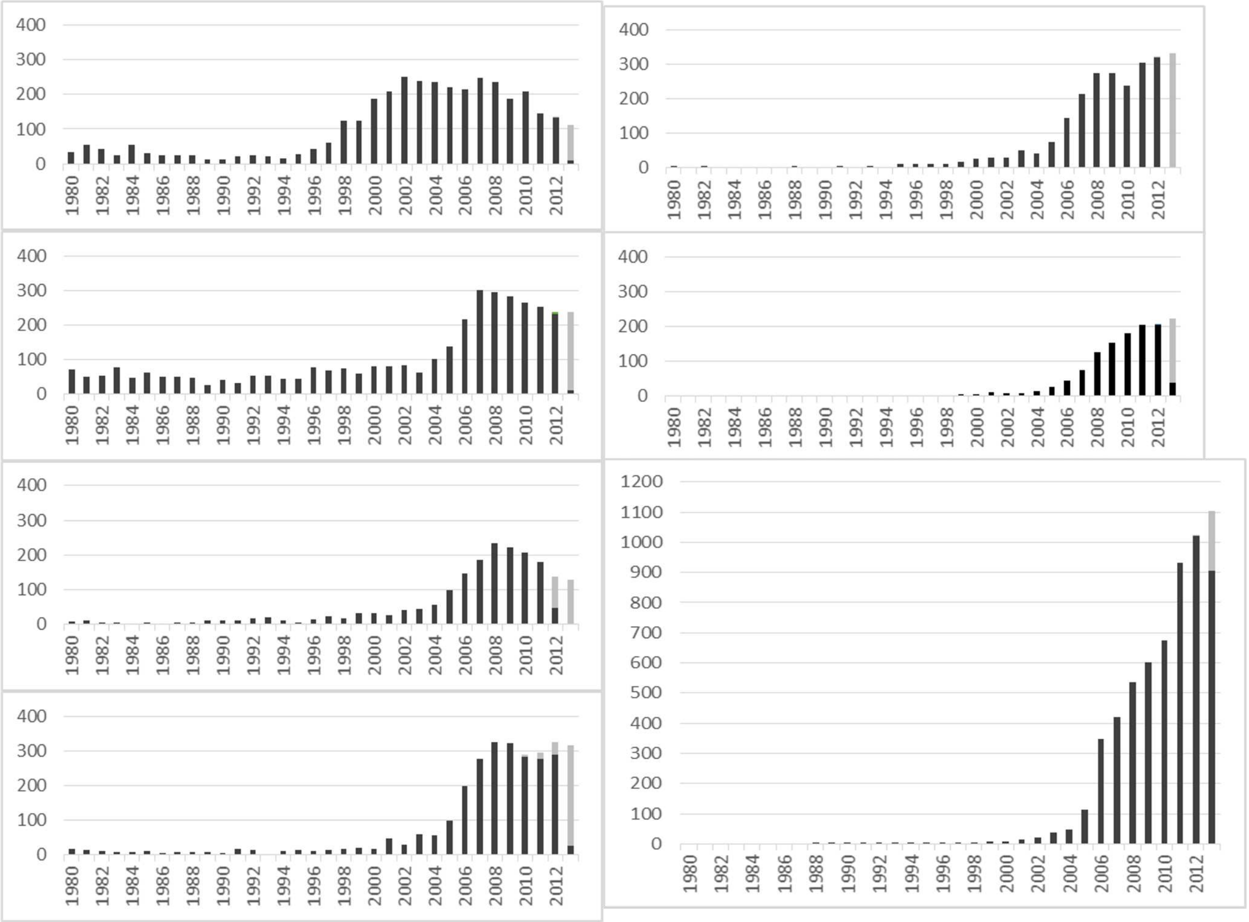

Figure 8: Patent Families by Country

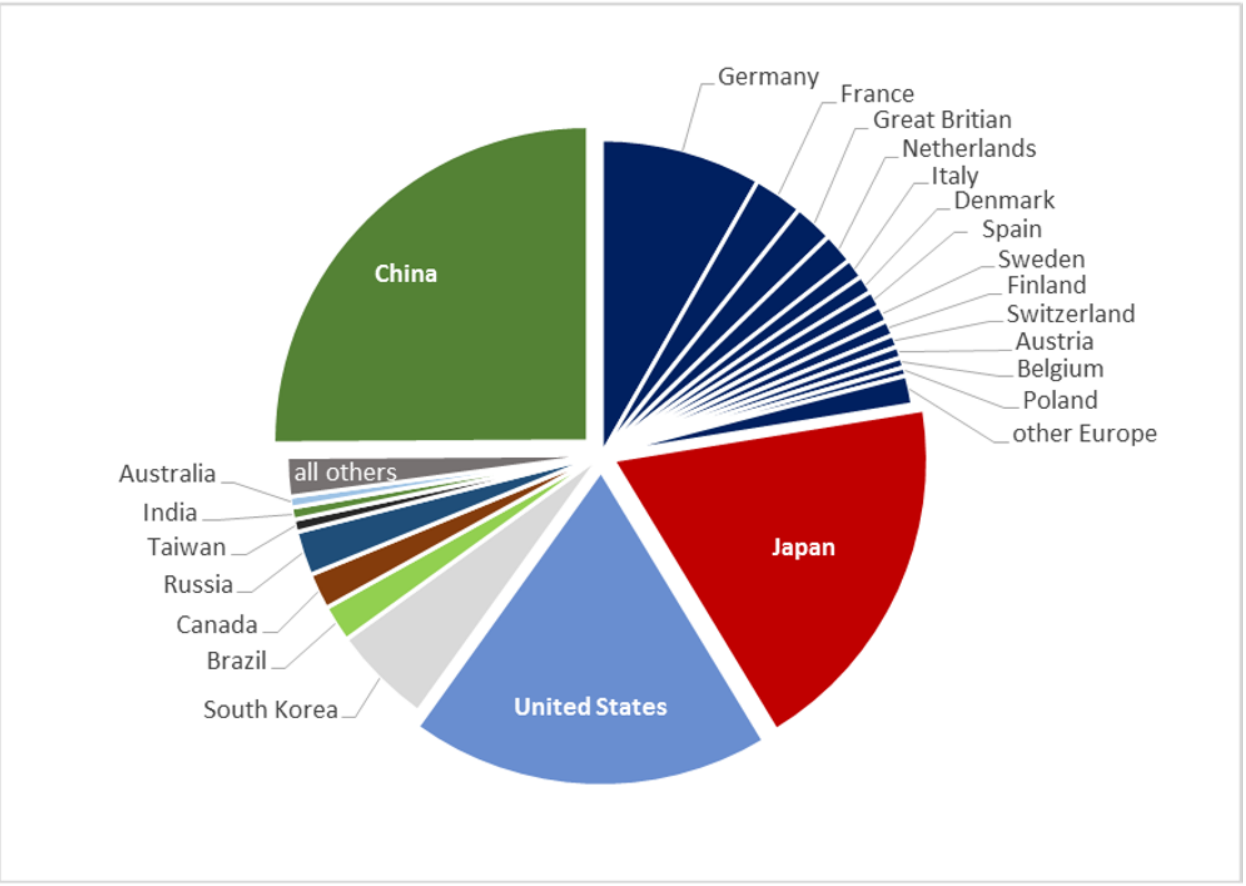

Figure 9: Share of biofuel inventions by residence of listed inventors on biofuel patent families from 1970 to 2013

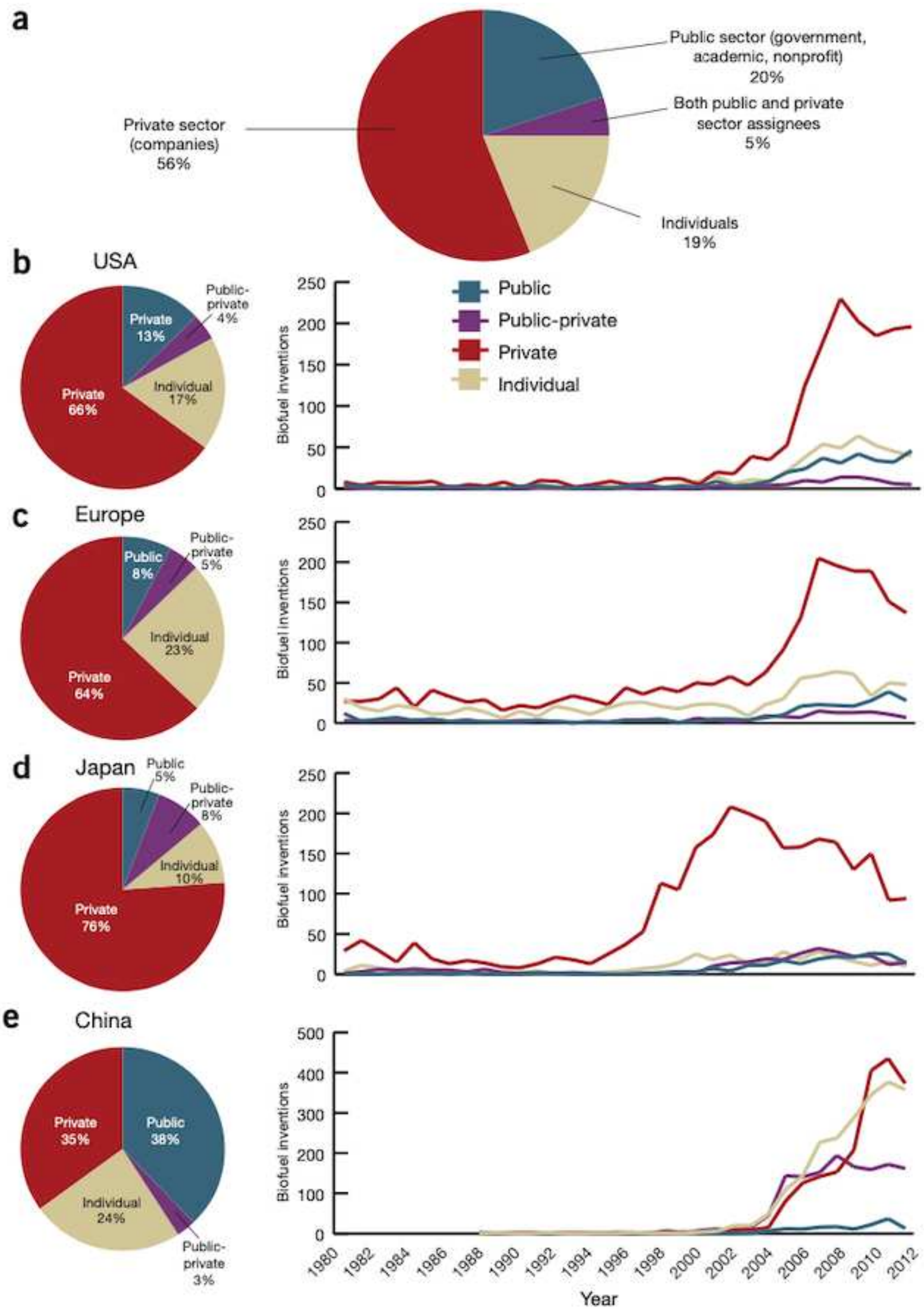

Figure 10: Patent Ownership Breakdown

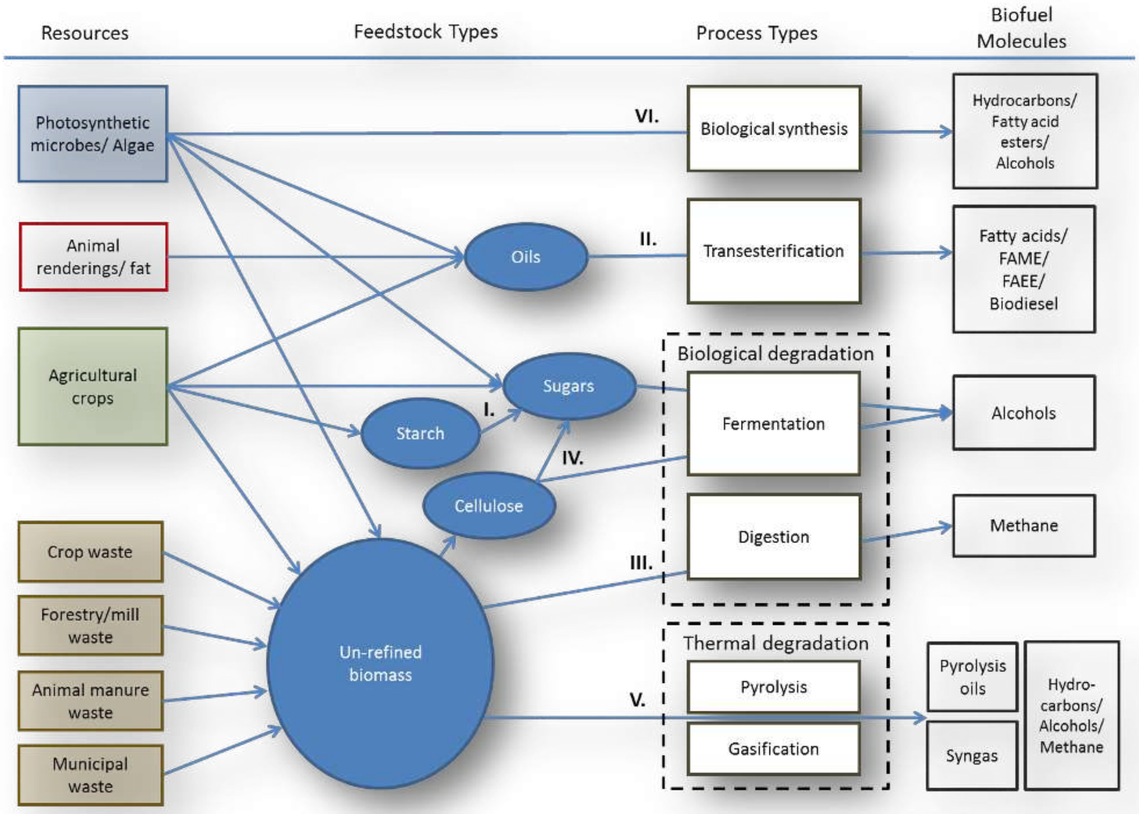

Figure 11: Biofuel Pathways

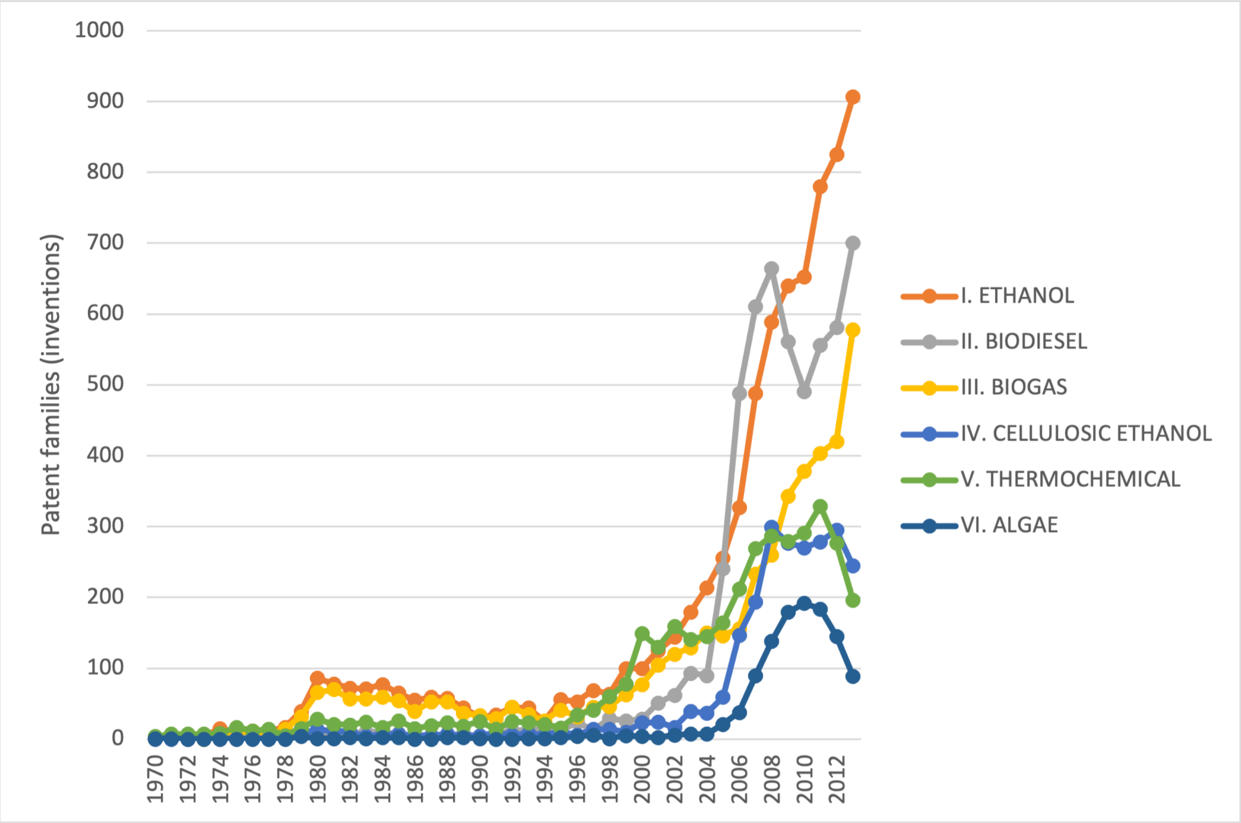

Figure 12: Patent Trends by technology type

3 Paper 2: Mathematical Model of Patent Incentives with Potentially Fragmented Patent Rights

3.1 Introduction and Motivation

This paper offers a mathematical model of research effort incentives and the effect of fragmented intellectual property rights (IPR). Fragmentation can take the form of legally shared property rights or of poorly defined rights that give potential for legal conflict, and both can inhibit innovation exploration. This paper focuses on the latter as a form of market failure associated with the "anticommons" concept. The formulation is an extension of the Nordhaus (1969) model of research and development (R&D) activity planning, adding a fragmentation parameter that scales research benefits down with more fragmentation, as a reflection of the costs or barriers faced in a context of IPR fragmentation. The model allows comparison of the case of fragmentation with the case of perfectly defined IPR and shows that more fragmentation reduces research effort and both private and social research benefits. The degree of social loss is theoretically quantifiable, as is the implied benefit of countervailing public incentives such as subsidies.

Innovation, an outcome of successful research and development (R&D), is a crucial driver of economic growth (Solow (1957)). Innovation also provides positive externalities in the form of knowledge spillovers; the extent of these spillovers varies by industry and institutional setting. The idea of the use of knowledge in society dates back to Hayek's 1945 paper in which he argues the problem is "the utilization of knowledge which is not given to anyone in its totality" (Hayek (1945)). Given this, the social value of innovations is higher than the private value observed by the inventor, implying knowledge creation has public good characteristics (Schumpeter (1943); Tirole (1988)). This is especially true in environmental and clean energy innovations as the threat of Climate Change increases and emissions have reached unsustainable levels (Jaffe et al. (2005)).

The Anticommons hypothesis with respect to intellectual property rights (IPR) has rarely been explored in recent economics literature, but it continues to gain traction. In 2018 *Science* published an article titled “The anticommons at twenty: concerns for research continue”in which they posit the anticommons effect has been at play and innovators have found ways to work around it. This includes “collective and mutually beneficial solutions to enable research to advance nevertheless”(Contreras (2018)).

The role of patents and innovation continues to appear in the news as well. In 2021 intellectual property rights surrounding vaccines were questioned. In April of 2022 a bill was introduced to help further protect U.S. patent rights. Although this bill didn’t make any headway, the question remains, are patent rights increasing innovation or hindering it?

3.1.1 Theory Models of Patent Economics and Anticommons

There are several theoretical models of the anticommons in economics literature. The first example was Cournot (1863) who coined the term “Complementary oligopoly” to describe a situation in which two independent firms hold monopolies on complementary inputs, such as iron and zinc, which are both inputs for a brass producer. Although Cournot did not call this problem the tragedy of the anticommons, it led to a similar result, namely underutilization of the two input goods and underproduction of the final product given the fragmented input good ownership. He concludes that both inputs being owned by a monopoly is welfare improving because it decreases the hold up probability and excessive rents (which can be charged when one firm “holds out”.

The first economics article to use the term anticommons is Buchanan and Yoon’s (2000) paper: “Symmetric Tragedies: Commons and Anticommons” in which they model exclusion rights leading to underutilization of a resource as contrasted against the classic tragedy of the commons where use rights lead to overutilization. They assume a linear relationship between the quantity of usage and average value product to show that with only use rights, a classic Cournot-Nash duopoly[2] problem arises in which the total rents are decreasing in the number of users. When users also have exclusion rights the Nash Equilibrium yields solutions for which the usage and total rents from the good approach zero as the number of excluders increases. They conclude, “to the

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[2] for more on this type of problem see (Mas-Colell et al. (1995))

extent that, through exclusive licensing rights, the holders of a patent on a basic research finding seek to exploit the rental value, the follow-on potential developer is inhibited from securing the value that might otherwise have been available" (Buchanan and Yoon (2000)). Although offering a useful model, it neglects to include the transaction costs of bargaining and searching for the multiple other property owners. They also limit their analysis to one period, which is restrictive when looking at inventions that take several periods to fully develop.

In their 2003 paper, Parisi et al. (2003) model the commons and anticommons problems as "the consequence of a lack of conformity between use and exclusion rights" and explore equilibrium under vertical and horizontal cases of property fragmentation. They generalize the Buchanan and Yoon (2000) model by dropping the assumption of strict complementary exclusion rights. Their "dual model of property reveals that the private incentives of users (commons case) and excludes (anticommons case) do not capture the external effects of their individual decisions" causing "dead weight losses that are monotonically increasing in complementary of use and exclusion rights"(Buchanan and Yoon (2000)). They conclude with an argument that policies are constructed to decrease these costs. Although a useful model for generalizing the anticommons and illustrating its symmetry to the commons problem, the authors do not include dynamic choices or information asymmetries in their model.

The models of the anticommons discussed up to this point have assumed non-cooperative games[3]; however, Ying and Zhang (2008) investigate enterprise licensing of fragmented property rights when cooperation is possible. Their model assumes an entrepreneur must acquire rights from several bureaucrats, each with equal bargaining power and the right to veto the project. Their model includes an approval cost, or the cost to bureaucrats to license to the entrepreneur, but it does not consider the opportunity cost of the entrepreneurs' (or researchers') time in these bargaining settings. They find that in a static model, with complete information and fixed licensing fee shares to bureaucrats, larger fragmentation will lead to an easier occurrence of the tragedy of the anticommons because the risk dominant Nash Equilibrium is for both bureaucrats to veto the project.

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[3] noncooperative games are ones in which participants do not communicate with each other, for more on the subject see Tirole (1988)

Under complete information and allowing for bribes to bureaucrats (i.e. their share of licensing fees is no longer fixed), they find bargaining can decrease the occurrence of the tragedy.

Lastly, Ying and Zhang (2008) look at this bargaining problem under incomplete information, in which case each agent assumes some probability distribution of the value of the license to the other agents. In this instance they conclude that greater fragmentation may actually decrease the occurrence of the anticommons as bureaucrats know they have less overall power in the process so they are willing to accept lower licensing fees; thus facilitating bargaining and rights acquisition by the entrepreneur (Ying and Zhang (2008)). This result counters the majority of literature surrounding the anticommons hypothesis, but they note that their results depend on the exact information structure and the payoff structure, neither of which are specified in their general model. Given the complexity and overlapping nature of intellectual property rights within the Bioenergy industry, modeling researcher and license holder payoffs and information structures may prove their results false (Cahoy and Glenna (2009)). If bargaining costs are included in their model the payoffs will decrease, surplus will decrease, and again a tragedy of the anticommons arises.

Bessen and Maskins 2009 paper titled "Sequential Innovation, Patents, and Imitation" is (to my knowledge) the first dynamic model of the anticommons within the constraints of intellectual property. Their model assumes "sequential (each successive invention builds on the preceding one) and complementary (each potential innovator takes a different research line and thereby enhances the overall probability that a particular goal is reached)"innovations. These assumptions are closely aligned with the theory of the anticommons as sequential innovations require obtaining fragmented IPR from previous inventors to move forward with one's own invention. As more innovators work on solving a particular problem the chances of a successful innovation increases. The software industry is used as example: when patent laws were strengthened firms' R&D spending actually decreased. Bessen and Maskin argue that this implies strong patent rights actually decrease R&D activities and fruitful inventions, whereas weak patents increase the potential for imitation, thus increasing competition among firms (Bessen et al. (2009)).

Their model assumes a benchmark of no patents, but high R&D startup costs serve as an entry barrier, allowing innovators to appropriate returns to their invention as a monopoly, even without patents. This also implies a first mover advantage in the innovation pipeline. This model makes several important improvements on those previously discussed: they include future profit information asymmetries and R&D cost asymmetries (with costs unknown to their competitor), and compare their results against a social planner with perfect information. However, their model is not without limitations. They make several assumptions that are counter to the discussion below of the U.S. Patent and Trademark Office (USPTO) characteristics, including: firms can capture the full social benefit of the invention, without patents firms can costlessly imitate one another, the value of an innovation is incremental (an innovation can be thought of as an improvement), a patent on an innovation is sufficiently broad to block the next innovation in the sequence, licensing to another firm increases your probability of successful innovation, but reduces payoffs, and bargaining is costless to both parties (but licensing is not). Given these strict assumptions they find that patents increase innovation in a static model, while in the sequential model patents, on average, decrease innovation (Bessen et al. (2009)).

Comino, Manenti, and Nicolo's 2011 paper, "Ex Ante licensing in sequential innovations" overcomes some of the problems discussed above as they use a three period model in which "a patent-holder and a follow-on innovator bargain over the licensing terms in a context where the former firm is unable to observe the timing of the R&D investment of the later." To do so they model a game with incomplete information and endogenous researcher types, who can negotiate licensing terms before or after committing to R& D costs. They assume the patent holder makes a take-it-or-leave-it contract offer and if the follow-on innovator rejects this offer they revert to the contract offered by the court system. Their 3-period model allows for contract negotiations between each of the 3 periods, where the information and incentives of agents vary between periods. They also include two types of inventions: good ones and bad ones, and they assume some probability of infringement for each. They find that the ability to decrease holdups, or blocking patents, through licensing is severely limited in this setting (Comino et al. (2011)).

Another flaw with the existing anticommons literature is the assumption that firms (or entrepreneurs) have full control over their invention. In reality, the degree to which a researcher controls the outcomes of their invention is constrained by the institution under which they operate. Although Zeebroeck et al. (2008) argue that “scientific anticommons show very little effects on academic researchers so far, limited to a few countries with weak or no research exemption regulations” one could argue that a model which includes both academic institutions and private firms conducting research in the same areas could have very different results than those found in their paper.

Hopeful inventors and researchers embark on a research path in an attempt to increase the knowledge base, solve an interesting question, or make monopoly profits. A researcher with new knowledge has several options as to how to protect it, if at all. One mechanism for protecting new knowledge is patents. An invention that is novel and constitutes an “inventive step” may be granted a U.S. patent, offering the researcher (who can now be deemed an inventor) 20 years of exclusive use rights over that knowledge (patent terms vary by jurisdiction). However, to apply for a patent a researcher must disclose enough information on the patent application for other researchers to replicate their work (Hall et al. (2014)). This means that their idea can be replicated easily, but the researcher can sue for infringement if replicated in a country where a valid patent over that knowledge exists. Other means of rent appropriation include secrecy and lead time as each of these can also give inventors a temporary monopoly (Schumpeter (1943)). However, this temporary monopoly can also slow the diffusion of an innovation and create a noncompetitive environment (Tirole (1988)). Additionally, even with monopoly profits the innovator cannot appropriate all the social returns from inventing, decreasing innovation incentives (Arrow (1962)).

More recent literature addressing IPR impacts on innovation outcomes includes Lee (2020) who uses an expected utility model for researcher incentives. Researchers have a choice between high and low value research lines to explore. The paper finds that as more inventors embark on the high value research project the lower final payoffs are for each researcher exploring this path. The paper includes difficulty of discovery, but not patent rights or IPR fragmentation directly. Although the anticommons effect is not mentioned, this paper includes several nuanced ideas regarding researcher effort and finds that research paths become less profitable as more people embark on the same research line.

Dawid and Hellmann (2020) use a 3 stage game to explore the relationship between a “firms’ R&D intensity and their degree of R&D cooperation”. They model firms as oligopolies in a non-cooperative 3-stage game where firms choose to join a research cluster in stage one and follow firms through the next 2 stages given their choice in stage 1. They find that desirable clusters are over invested in, leaving less desirable research paths untouched. Once the cluster decision is made each firm decides which research path to follow: high or low. Once again, we see the need for cooperation through research clusters, yet the authors fail to mention the benefits of these research clusters related to existing IPR.

Karagözoğlu et al. (2021) model optimal research incentives within the firm using a multistage game between two researchers at the same firm. The 2 employees use Nash Bargaining to find the optimal distribution of research path exploration. Their paper assumes 2 researchers compete within the same firm to create a final product. The employee with higher standing in the company has an upper hand when bargaining, thus decides the outcomes of which research path each should embark upon. This model addresses the anticommons indirectly by allowing researchers to choose their research path given existing information, but does not refer to patents or the anticommons directly.

Greve and Keiding (2023) create a probability function to compare the costs of public and private research activity. The agent chooses when to fund public research given it’s larger knowledge access. The agent only does so when the payoffs exceed the costs. They assume the underlying research path is given, so there is no choice as to what is being researched, simply if it’s in their best interest to keep that research in house or fund some level of public research.

All of the models discussed in this section relate to the anticommons hypothesis, but none address the root of the problem: how do hopeful inventors choose a path when they don’t know for certain what IPR exist along the research path they are pursuing? This theory paper hopes to fill that void using an augmented version of Nordhaus’s innovation model.

3.1.2 The U.S. Patent System and Enforcement Incentives

The value of an idea depends on how that idea is protected. For example, Hall, et. al (2014) explain “the value of a patent or secrecy depends on the financial capability of the owner to undertake legal action in case of infringement or breach of confidentiality is detected and the likelihood of success of the court case.” There is also a large amount of uncertainty surrounding the outcome of any form of knowledge protection. In the case of patents there are three sources of uncertainty, “whether a patent is granted, whether the patent is invalidated post grant (either by the patent office or a civil court), and whether infringement can be proven–that is, whether it can be shown that an infringing action falls within the valid claims of a patent” (Hall et al. (2014)).

Along these lines, “the information disclosed in a patent may be only imperfectly protected by the patent simply because infringement has to be detected and enforced through litigation” (Horstmann et al. (1985)).These outcomes vary by jurisdiction and laws in place. To simplify the analysis at hand only those U.S. patent office policies most pertinent to this study are addressed.

The U.S. patent system differs from others in several important ways. First, U.S. patents last 20 years and are subject to renewal fees. Second, before the 1999 American Inventors Protection Act patent applications were not published. This differs from other countries where “all patent applications are published within 19 months of the filling date” Nagaoka et al. (2010).

Additionally, the rules surrounding infringement of a patent grant differ from that of patent applications. Willful infringement, or intentional infringement of an existing patent also constitutes a higher fee and punishment than unknowing infringement. This gives inventors little incentive to conduct a prior art search or make themselves aware of the existing IPR space in which they are working (Hall et al. (2014)).

The debate over patents and patent breadth has escalated in the last decade as a proliferation of U.S. patents have been granted (Jaffe and Lerner (2004)). Jaffe and Lerner’s 2004 book: *Innovation and Its Discontents: How Our Broken Patent System is Endangering Innovation and Progress and What To Do About It* illustrates the problems the patent system has caused in terms of knowledge creation and sharing given the structural changes in the U.S. Patent Office (USPTO). These changes include the creation of the Court of Appeals for the Federal Circuit (CAFC) in 1982, which shifted patent cases and litigation to one national court rather than the 12 individual patent offices. They argue that this consolidated court system increased researchers' incentives to apply for patents and made it easier to obtain patents in fields such as software, business methods, and certain kinds of biotechnology that were previously thought to be non-patentable (Jaffe and Lerner (2004)).

Another seminal shift in the incentives put in place by the U.S. patent system occurred with the 1980 Bayh Dole act, which gave universities the rights to patent government funded research rather than assigning those rights to the government agency funding the project. This led to an increase in technology transfer offices among government agencies, such as the National Institutes of Health (NIH), and universities, which has increased patenting within these agencies (Mowery et al. (2001)).

Zeebroeck et al. (2008) support this as they show an increasing trend in academic patenting over the last 20 years, but find that "benefits of academic patenting on research exceed their potential negative effects". They argue this shifted researcher incentives away from publications and towards conducting R&D with commercialization potential as these projects yield patent royalties. Thursby et al. (2007) support this hypothesis further as they find that "licensing increases applied relative to basic [research] efforts". This poses a serious threat to innovators who often have incomplete information about the existing body of intellectual property rights and patent rights surrounding their research path. In biomedical research Heller and Eisenberg (1998) argue, "such a proliferation of claims presents a daunting bargaining challenge. If a firm is unable to procure a complete set of licenses they must choose between diverting resources to less promising projects with fewer licensing obstacles or proceeding to animal and clinical testing on the basis of incomplete information."

Another major shift occurred in the early 1990s when the USPTO's funding source shifted from tax revenues to the fees it collects. This created incentives for the USPTO to "process applications as quickly as possible and at the lowest possible cost. As a result, there is a widely perceived decline in the rigor with which the standards of novelty and non-obviousness are applied in reviewing patent applications" (Jaffe and Lerner (2004)). Lei and Wright (2009) argue that this shift in funding creates incentives for patent examiners to "reveal rational ignorance due to perverse incentives of patent polices". U.S. patent examiners must prove 'non-patentability', but not patentability, decreasing their incentive to deny a patent application. When the structure funding shifted the incentives for patent examiners tilted toward granting 'weak' patents to facilitate moving through a larger quantity of applications to collect more fees and increase revenues.

Taken together these shifts have led to an increase in patent activity and arguably a more fragmented pool of existing knowledge as the breadth of patent claims has increased, both of which can impede follow-on inventions. To exacerbate this issue, a researcher must take the time to conduct (or facilitate) a prior art search to identify the existing patents in their technology field if they want to decrease the risk of infringing on others' patent claims. The timing of this prior art search (if at all) can greatly change their research outcomes. For example, an innovator may conduct a prior knowledge search in phase 1 of the invention, but not update that information, thus when the invention is ready for commercialization they may find a new patent blocking the commercialization of their intended invention.

On the other hand, if a researcher finds a proliferation of patents surrounding her intended research path she may decide to take a less populated path instead, thus giving up on an invention that could have had an important impact on society. Alternatively, some have argued that researchers will strategically cite prior art, knowing that patent examiners do not have the incentives to conduct an extensive prior art search, thus not citing those patents they could not get use rights for (Oh et al. (2014)). In both instances the resources available to researchers can greatly change the outcomes of their R&D activities and could lead to the tragedy of the anticommons.

Several coping mechanisms and policy solutions to this 'patent blocking' issue have been proposed, but are often specific to a particular industry in which transaction costs from bargaining can be minimized through institutional settings. Merges (2009) argues that the existence of the "reverse doctrine serves as a judicial 'safety valve', releasing pressure that builds up when pioneers and improvers fail to agree to a license". However, this assumes both parties have the means to take the case to court and not merely give up on the invention when bargaining breaks down between the two parties. Heller and Eisenberg (1998) argue that agents have heterogeneous interests and institutional constraints, which complicates bargaining farther. For example, universities who hold upstream patents often cannot afford to bargain with others for the use of their technology; the creation and use of technology transfer offices can help mitigate this problem. This observation implies that only firms and inventors with marginal (lower value) inventions will suffer from an anticommons effect as large firms with financial means to acquire the patent rights in their way can avoid such a tragedy.

3.2 Mathematically Modeling Research Incentives with Diffuse Patent Ownership

The traditional Nordhaus model is relevant for policies offering subsidies, hence increasing returns to innovation in certain technologies. For example, specific biofuel technologies qualify for 2.5 times as many credits as traditional fuels, yet only years after the RFS was it commercially produced. Cellulosic biofuels, a product of specific biological processes, face a guaranteed market at a price higher than petroleum due to their drop-in nature and subsidies in place. Despite the possibility of commercial profits, we have not seen these fuels take off. The U.S. patent system attempts to guarantee exclusive patent rights, but when patent officers miss even the smallest overlap researchers are in danger of infringing on existing patent rights. This paper mathematically shows that IPR fragmentation leads to suboptimal equilibrium research effort and suggests how a a subsidy can offset the market failure.

3.2.1 Model Set-Up

Following Nordhaus (1969) a representative firm conducts R&D activities and production activities. The R&D is aimed at process innovations which reduce the production cost of their homogeneous output good X, with initial production: X_0. The benefits of research are calculated as the percentage cost savings $B(R)$ from the process innovation, where $B(R) = \frac{c_0 - c_1}{c_0}$, where c_0 is initial production costs and c_1 is production cost with invention i. The researcher receives revenues equal to the discounted research benefits and pays s for innovative inputs R, thus discounted total profits are:

$$V = \int_0^T B(R) X_0 e^{-rt} dt - sR \tag{1}$$

$B(R)$ is the cost reduction achieved by the new invention, where c_0 is the original cost of production and $c(R)$ is the new costs of production. X_0 is current output, r is the discount rate, T is the time horizon over which the research benefits will apply and s is the unit cost of research effort. Nordhaus defines $B(R)$ as

$$B(R) = \frac{c_0 - c(R)}{c_0} \tag{2}$$

To include fragmented property rights in this function we define $\gamma \in [0,1]$ to represent fragmentation of the IPR in the researcher's invention space. If there are no fragmented IPR, $\gamma = 1$. As the IPR becomes more fragmented, γ decreases. In instances where the entire IPR space in question is fragmented, requiring onerous negotiations and litigation, $\gamma = 0$. To include fragmented property rights and account for research overtime, we specify $B(R)$ with the functional form:

$$B(R) = \gamma(1 - e^{-\delta R}) \tag{3}$$

where $0 < \delta < 1$ introduces diminishing returns to research effort.

This function satisfies the following desirable properties:

- $B(0) = 0$, i.e. without an investment in research there are no benefits.
- $B'(R) > 0$, i.e. positive marginal benefit to research
- $B''(R) < 0$, i.e diminishing marginal returns to research
- $B \to 1$ as $R \to \infty$, i.e. research benefit has an asymptotic limit as research increases

Note that $B'(0) = \gamma > 0$, so $R = 0$ could be optimal if research costs surpass the threshold level shown below. From a social planner perspective, the patent office is responsible for ensuring no overlapping property rights, thus $\gamma = 1$, but this is not always the case. The government (patent officers in this case) may not achieve the desired level of fragmentation due to perverse incentives. If the U.S. PTO fully vetted all patents, we would have $\gamma = 1$ and the individual can freely practice in whichever research path they see fit. In reality, patent officers often miss overlapping research paths and grant patents to all researchers despite potential overlaps. In this instance the social planner and individual face the same production function, but diverge when considering the perverse incentives patent officers face. Researchers are then asked to embark on a research path without full information leading to market failure.

3.2.2 Model Results

The value function is then:

$$V = \int_0^T \gamma(1 - e^{-\delta R}) C_0 X_0 e^{-rt} dt - sR \tag{4}$$

This equation simplifies to:

$$V(R) = \gamma(1 - e^{-\delta R}) C_0 X_0 \int_0^T e^{-rt} dt - sR \tag{5}$$

Let $\varphi = (C_0 X_0)(\frac{1}{r})(1 - e^{-rT})$ The integrated value function becomes:

$$V(R) = \gamma(1 - e^{-\delta R})\varphi - sR \tag{6}$$

The social planner aims to maximize research outputs given inputs available. The first-order condition for maximization is:

$$\frac{dV}{dR} = \gamma \delta e^{-\delta R} \varphi - s = 0 \tag{7}$$

Solving the first-order condition for R^* yields:

$$e^{-\delta R^*} = \frac{s}{\gamma\delta\varphi} \tag{8}$$

$$R^* = \frac{1}{\delta}\left(\ln(\gamma\delta\varphi) - \ln(s)\right) \tag{9}$$

The second-order condition ensures that R^* is a maximum:

$$\frac{d^2V}{dR^2} = -\gamma\delta^2 e^{-\delta R}\varphi < 0 \tag{10}$$

Yielding:

$$B^* = 1 - \frac{s}{\gamma\delta\varphi} \tag{11}$$

Given these equations we see that research effort R is increasing in γ as expected:

$$\frac{\partial R}{\partial \gamma} = \frac{1}{\gamma\delta} > 0 \tag{12}$$

As fragmentation decreases (moves closer to 1) more effort is put into a project. B. The cost reduction is also an increasing function of γ: as fragmentation decreases the potential cost savings increases or becomes more profitable.

$$\frac{\partial B}{\partial \gamma} = \frac{s}{\gamma^2\varphi\delta} > 0 \tag{13}$$

We see in both instances that fragmentation stifles innovation effort.

3.3 Research Costs and Implications

From equation 9 we see that R^* would have a corner solution $R^* = 0$ with $B^* = 0$ as well if:

$$\ln(\gamma\delta\varphi) - \ln(s) \leq 0 \tag{14}$$

Which can be simplified to:

$$\gamma\delta\varphi \leq s \tag{15}$$

In terms of IPR fragmentation, this means that if

$$\gamma \leq \frac{s}{\delta\varphi} \tag{16}$$

researchers will not explore this research path as their efforts will never payoff. This can lead to over or under investment in a specific technology pathway.

To further explore the social implications of the market failure generated by ill-defined property rights and the anticommons, we posit that the first-best social optimum is zero fragmentation or $\gamma = 1$. While that ideal may be impractical to achieve, or subject to rational second-best adjustments, a simple indicator of the social loss from the market failure is comparing B^* with the first-best outcome B^{**}, where B^{**} maximizes the value function when $\gamma = 1$:

$$B^{**} = \frac{1-s}{\gamma\sigma} \tag{17}$$

Since B^* and B^{**} are defined as percentage reductions in per-unit production costs, the per-unit social cost of fragmentation is equal to:

$$B^{**} - B^* = [\frac{(1-\gamma)}{\gamma}][\frac{s}{\gamma\sigma}]. \tag{18}$$

This expression reiterates that if $\gamma = 1$ there is no social loss. The total social loss from fragmentation equals this reduction multiplied by our initial production qualities.

3.3.1 Policy Options to Correct the Market Failure

From a policy perspective, the amount of social loss suggests the incentive needed to correct the poorly defined property rights. Alternatively, if that fix is impractical, the expressions above also imply that a subsidy to research input costs could correct the research effort distortion. Specifically, let σ be a percent subsidy reduction to s, the per-unit cost of research input, thus the effective cost per unit is σs. The benefit generated by the research subsidy is:

$$1-\frac{(1-\sigma)s}{\gamma\delta\varphi} \tag{19}$$

This benefit equals B** if the subsidy is:

$$\sigma^{*}=1-\gamma \tag{20}$$

If $\gamma = 1$, no subsidy is appropriate, and if $\gamma = 0$ the government must underwrite all costs for research to happen.

Alternatively, the subsidy could be given to patent examiners as an incentive to better screen patents. This policy reduces the uncertainties researchers face if it successfully achieves $\gamma = 1$ as originally intended by patent laws. In this instance the social and private incentives align and solve the market failure introduced by diffuse patent ownership.

3.4 Conclusion

This paper uses Nordhaus (1969) model of innovation incentives and expands the model to include fragmented property rights and diminishing returns to research effort inputs. Patents, a form of IPR, act as a barrier to information inputs when an inventor must navigate and often pay for access to existing IPR. Faced with potential litigation for infringement on existing patents, a researcher has little incentive to explore existing research pathways. This is counter to the original goal of patents: exclusive property rights over an idea with hopes of earning future royalties or other income streaming from the idea. When resources are devoted to a research path with high levels of fragmentation market failure results as those resources are not used in the most efficient way.

Theoretical models of innovation do not address the costs (including effort) to negotiate and find existing IPR that may be infringed upon. Recent literature on innovation theory focuses on inventor expected utility assuming the research team is already employed and have a limited amount of research paths to choose from. These multistage games and expected utility models tell only part of the story as they do not discuss access to existing IPR, but instead assume some level of access. If access to a resource is not as easy to obtain as originally thought, the research team may have to abandon their current research path in search of another, thus wasting resources and creating a market failure.

In the case of biofuels, research is inherently cumulative as it takes a series of steps to convert any feedstock to a final fuel. When patent rights are overlapping and fragmented, it makes it nearly impossible for any one researcher to navigate and afford the rights to each patent their idea might touch. In this instance, patents effectively block access to information inputs through onerous negotiations which hinders future innovations. This model shows this by introducing patent right fragmentation. The more IPR surround a particular technology, the more expensive it is to gain access to those resources. In these instances, intellectually property rights are hindering, not helping future inventions.

This model is not without limitations. First, we assume all researchers have some existing technology they are trying to improve. This assumption is relaxed when we view the benefit function as benefits to the researcher rather than a cost reduction as originally intended by Nordhaus. Second, this model does not differentiate access to existing IPR or other research inputs directly. This model is also a one-shot game as written, but could include dynamic decisions over time.

Future expansions of this model could include Bayesian updating, where each researcher learns more about the existing IPR within their research field as they move deeper into any one research space. This two period model would allow researchers to change research directions in period 2 if they uncovered onerous IPR hurdles in stage 1 of their research. Other possible expansions could include an IPR intermediary who helps the researcher navigate existing property rights, but this would require even more resources dedicated to each research path. This case follows the trend we've seen in the U.S. with land grant universities creating a technology transfer office. In the case of biofuels there are still large grants, subsidies, and other financial incentives for researchers to continue research in this field, even with overlapping patents in place. This is shown empirically in paper 3.

sectionPaper 3: Empirically Testing the Anticommons using Biofuel Patent Assignee Count as a Fragmentation Indicator

3.5 Introduction

When the development of a new technology requires the use of multiple overlapping patents or negotiating with several patent owners, the cost of developing the technology may increase since doing so requires the simultaneous agreement of several patent owners. Since any single patent owner may hold out in an attempt to reap a higher payoff, the situation has the potential to create a significant barrier to innovation. This problem, discussed in earlier chapters of this dissertation, is sometimes called the tragedy of the anticommons.

While the tragedy of the anticommons makes intuitive sense and can be motivated with theoretical economic models, there is very little work validating the hypothesis empirically. Two main obstacles have impeded efforts to test the hypothesis empirically. First, measuring fragmentation is complex and difficult. For example, in the biofuels context that I consider in this paper, bringing a final fuel to market requires three distinct steps: feedstock, processing, and final fuel. Ideally we could trace three different patents from feedstock to conversion to final fuel type. Unfortunately, most biofuel patents claim more than one technology, which makes it very difficult to assign a measure of fragmentation based on overlapping patent use within a given technology. Second, since the patent landscape has evolved quickly over time, the degree of interdependence between different patents has also evolved quickly. This non-stationary complicates efforts to empirically test the anticommons hypothesis.

Recognizing the challenges of empirically testing the anticommons hypothesis directly, this chapter takes a different approach. Rather than study the impact of patent fragmentation using a complicated fragmentation index, I instead study the relationship between the number of assignees on a given patent and subsequent non-self citations (a common measure of patent value). When there are multiple owners of a patent, there is a negotiation challenge similar (though not identical) to the negotiation challenge that arises as a result of patent fragmentation. This similarity suggests the potential for using count of patent authors as a proxy for the degree of fragmentation in the patent context.

This chapter considers the impact of diffused patent ownership on subsequent citations looking at U.S. patents related to biofuel production from 1964 to 2014. We find that the count of citing patents falls as the number of assignees increases, indicating the anticommons may be present. The data set includes 4,748 granted U.S. patents related to biofuel production. The assignee count ranges from 1 to 21 with a mean of 1.88 (1.77).

We find a negative relationship between the number of patent assignees and the count of non-self citations in subsequent years. On average we find a 4.5% decrease in follow on citations when assignee count increases by 1%. Interpreting the count of patent assignments as a proxy for patent fragmentation, these results provide evidence of the potential magnitude of the tragedy of the anticommons in the context of biofuels production.

3.6 Literature Review

There are few empirical models of the anticommons in economics literature. The models that do exist use fairly limited data sets as described below. This paper hopes to add to this liturature in a novel way by introducing ownership count as a proxy for ownership fragmentation.

3.6.1 Empirical Tests of the Anticommons

Murray and Stern (2007) constructed the first empirical test of the anticommons using a difference-in-differences estimator for 169 patent-paper pairs identified from Nature Biotechnology. They test the affect of IPR on the propensity of future researchers to build upon the protected knowledge in their own R&D by comparing pre and post patent grant citation rates. Patent-paper pairs are used to illustrate “dual knowledge“ in which a single discovery contributes to scientific research and commercial applications. They use a negative binomial model of citations produced per year for each article as a function of: time, individual publication quality (article fixed effects), publication age and citation year fixed effects, number of authors, author affiliation, location, annual citation counts, patent lag, number of claims, patent back citations and references, and a dummy variable for federal interests.

Through this set up they find that citation rates fall 10-20% after formal IPR are granted, and this result is particularly salient for researchers with public affiliations. During the year the patent is granted and in the subsequent 4 years they find patented articles have a significant citation advantage (20%) over citation rates for non-patented articles. Although their results support the existence of an anticommons effect, they neglect to identify the underlying institutional mechanisms by which patent grant shifts citation behavior. Further, their results do not address the issue of researchers choosing not to take a particular research path at time zero due to the existence of dense IPR within a specific technology trajectory or the existence of substitute information available to researchers, and cannot be generalized beyond this specific academic realm.

Murray et al. (2009) also use a difference-in-differences estimator to test the hypothesis that patent strategy affects the long run supply of public knowledge in human genetics. To do so they create paper-patent pairs for over 1,900 inventions. They assess the impact of patent grant on the rate of production of follow-on public knowledge by examining the annual number of papers citing a focal paper in the years before and after the patent (linked to the paper) is granted. Their analysis includes a patent-gene fragmentation index and uses a nonlinear regression approach. Using annual citations as their dependent variable, which they argue represents follow-on public knowledge accumulation; they use a negative binomial regression model. Patent grant serves as the "shock" to identify pre/post publication citations. Inputs into their econometric model include: the patent window, number of authors, number of inventors, number of assignees, number of addresses, U.S. addresses, public addresses, an impact factor (to proxy for the quality of journal the gene patent is published in), patent scope (as measured by the number of national classes the patent is categorized in), number of claims as a proxy for patent strength, paper age fixed effects, and citation year fixed effects (Huang and Murray (2009)).

Their results support the anticommons effect as they find increased fragmentation leads to decreases in follow-on invention as well as increased transaction costs. However, their model assumes random patenting and that a paper-patent pair claims the same piece of knowledge, thus neglecting to address the underlying incentives to apply for a patent as opposed to publishing ones research. And again, researchers choice to conduct research on a particular invention at time zero is not discussed in this context (Huang and Murray (2009)).

Another attempt to empirically test the anticommons was conducted by Galasso and Schankerman (2013) in which they measure patent citations before and after a patent is invalidated by the court. They limit their analysis to private sector patents. Given this, and the 1,397 invalidated patents used, they find that patent invalidation leads to an average increase of 50% in subsequent citations, but their results are heterogeneous between industries. They conclude “patent rights appear to block follow-on innovation only in the technology fields of computers, electronics and medical instruments”. Our dataset includes both patent applications and patents granted. Future research could include exploring those patents not granted.

The Anticommons hypothesis continues to pop-up in other economic literature, most notably in the natural resource space. Leonard and Parker (2021) explore the anticommons with regard to oil and gas drilling rights and royalties in the Bakken. Their study explores the production rates and royalties across 5 types of ownership covering 579,096 acres of land. These plots focus on the Fort Berthold Indian Reservation and are broken into trusts, which have an average of 17 co-owners: fee simple, tribal owners, government ownership, and private ownership. This unique example illustrates how various levels of ownership, including communal and private, change the outcomes and profitability of a potential oil well. They find that increased ownership fragmentation leads to lower levels of final output, which is consistent with the anticommons hypothesis.

Another resource related attempt at explaining the anticommons is the Koh and Rojas (2022) paper which explores franchise ownership rights in lodging units in Texas. They find that hotels with several owners charge higher prices than those owned by a single entity. Showing that increasing the number of owners increases costs.

Winikoff and Parker (2024) look at the composition of land ownership and uptake of land used for wind energy in the U.S. Their model controls for variables that impact wind production. They find that areas with generally the same amount of wind potential see fewer wind energy sites as the size of land plots decreases. They argue wind energy projects requiring access to many small land owners are more costly than those projects involving only one or a few land owners. They propose smaller land owners often demand higher royalties, making the overall project less profitable. Thus often proposed projects requiring many land owners' approval are abandoned while those on plots owned by a single owner are more fruitful for the developer. Additionally, they use an Herfindahl-Hirschmann Index to illustrate land ownership heterogeneity. Future work with our biofuels data set could include a similar index.

Other attempts to test the anticommons hypothesis include Hall and Ziedonis (2001) who use survey responses from the semiconductor industry, an industry characterized by inherently cumulative innovation, to conclude "semiconductor firms do not rely heavily on patents to appropriate returns to R&D"(Hall and Ziedonis, 2001). They find that firms often form large patent portfolios which can be used as bargaining chips for access to other patent pools and that "the 1980s strengthening of U.S. patent rights spawned 'patent portfolio races' among capital-intensive firms, but it also facilitated entry by specialized design firms', implying the anticommons may not be an issue within this industry.

However, this industry has been scrutinized for the existence of "Patent Trolls" or individuals who buy a large number of patents and patent portfolios to enforce infringement claims and reap the profits from doing so, as well as create a barrier to entry for other firms in the industry (Merges, 2009). Lemley (2008) argues that the 1980 Bayh Dole act and subsequent increase in technology transfer offices has created incentives for universities to become 'patent trolls' when profit incentives outweigh social benefits, thus further increasing the bargaining costs of gaining rights to patents held by universities (Lemley, 2008).

Biotechnology is a unique innovation space as patenting in this area is relatively naive and a few large companies hold large patent portfolios, effectually tying up important IPR (Graff et al., 2001). This situation gives rise to the anticommons hypothesis as any one step of a biotechnology invention can require access to several other steps. Biofuel technologies, a subset of the larger

Biotech industry is plagued with this problem farther as production of the final fuel requires access to each step of the often complicated conversion process (Graff and Zilberman, 2007).

Cumulative inventions require gaining access to others knowledge through exerting more work effort. The existing literature generally assume a researcher can partake in bargaining, in which case both parties must agree upon the terms of the license(s). Under incomplete information, where neither party knows the true value of the invention prior to its commercialization, this is a daunting task. If the innovator suffers from cognitive bias, in which they believe their patent has a higher value than it will actually appropriate, bargaining over the cost of licensing is further complicated as reasonable licensing terms will not be reached given this information asymmetry (Heller and Eisenberg, 1998).

Hall and Ziedonis (2001) end their paper with questions about the implications of patent pooling, they ask: “does this behavior simply represent the outcome of a non-cooperative strategic game and, therefore, an implicit ‘tax’ on innovation? Or do these portfolios provide an important backdrop for exchanges of intellectual property and more tacit ‘know-how’ that otherwise would not take place?”(Hall and Ziedonis, 2001). These examples illustrate a few of the problems and possible solutions surrounding intellectual property right fragmentation caused by patent right assignment.

3.6.2 Empirical Models using Patent Citations

The use of patents as innovation indicators must be discussed before diving into a discussion of the patent data set constructed for this paper. As noted above, patents only represent a piece of industrial innovation as not all inventions are patented and the value distribution of patented applications is quite skewed. Nagaoka et al. (2010) notes,

> Patent statistics should be used carefully and wisely as they are not free from problems nor do they correspond perfectly to innovation. They are affected by the idiosyncratic features of a particular patent system of a nation at a given point in time. It might not be easy to match other economic data. However, if used carefully and wisely, it will lead us to new insights into innovation.

Through careful data set construction and cleaning we are confident the patent data presented here overcomes many of the issues commonly discussed when using patent data. See section 1 for further details regarding data collection and cleaning.

It is hard to deduce how valuable an individual patent is. In 1990 Trajtenberg (1990) used count of citing patents as an indicator for patent value. This metric is still used today as no better metric for patent value has been discovered. If only companies would disclose how much money they spent on R&D and the incomes streaming from said patent...alas that information is held privately. Citation counts are public information and the best indicator we have for the value of a patent. If a patent was cited in other patent applications it holds research value. Trajtenberg (1990) method is still used today, including recent publications such as Hsu et al. (2021).

Attempts to create a fragmentation index using patent data include Hall and Ziedonis (2001); Hall and MacGarvie (2010); Bessen et al. (2009). In all cases the authors construct complex fragmentation indexes using patent claims as their indicator and creating trees to link them. Although an interesting question, these paper rely on small data-sets and their results are specific to specific technologies. This paper uses biofuel patents as a test, but could be expanded to other technologies as well.

Kim and Mitra-Kahn (2020) uses a difference in difference estimator to study the impacts of the USPTO's Peer-to-Patent pilot program. This program allowed crowd-sourcing of prior art on patent applications. Their study finds that this program had limited impacts on patent grants, but the patents within the study had higher forward citation rates. This implies that patents with more exposure are cited more often. This study was limited in the patents that participated in the Peer-to-Patent program so it is not a good avenue for us to take given our data.

Sun and Wright (2022) look at patent citations and the role of the patent examiner with regard to finding blocking patents. Their paper includes several important metrics, including the ability of researchers to fully search patent databases, which was very hard prior to 2000. Their data set consists of rejected patents, which is not a metric we can measure in our data. The module uses pre-grant forward citations as their value of a patent measurement. Our data looks at forward citations as the value metric, but does not differentiate between pre and post grant citations as that data is not available for the entire time range we study. Their dependent variable is patent grant and their independent variables include number of claims, number of inventors, filing year, and backward citations. These are all included in our model. Using their definition of blocking patents they find that patents have a lower probably of grant when a blocking patent is in the prior art search, yet said blocking patent has a higher probability of grant when cited. This is consistent with the anticommons hypothesis as these blocking patents lead to lower grant levels. The data used in their study is the USPTO Action Dataset which covers patents from 2008-2017. Our data consists of patents from 1965-2014, thus even if we had access to the Action Dataset it would not be fruitful in this study given the limited number of patents in our set published in that time frame.

Lastly, this paper introduces the nuanced idea that patent assignee count is a good proxy for patent right fragmentation. **?** discusses the use of patent assignee data and explains that this data was not reliable in the past. This paper is one of the first in economics literature to utilize the updated assignee database. Although there are some potential problems with assignee count accuracy[4], we are confident this independent variables offers new incites about the anticommons hypothesis not explored in previous literature.

3.7 Testing the Anticommons Hypothesis

Biofuel production is a multi-faceted process that hinges on three key elements. First, a suitable feedstock must be selected, with options ranging from energy-rich crops like corn and sugarcane to sustainable sources like algae and organic waste. Next, an appropriate conversion pathway must be chosen, utilizing either biochemical processes like fermentation or therochemical methods involving heat and pressure, to transform the feedstock into usable fuel. Finally, the desired final fuel type must be determined, whether it be biodiesel for diesel engines, bio-ethanol as a gasoline blend stock, or biogas for heating and electricity generation. Each of these choices influences the overall sustainability, efficiency, and applicability of the biofuel produced.

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[4] see (**?**) for more details

In principle, this setting provides an appealing context in which to explore patent fragmentation since viable commercial technologies require users to string together multiple overlapping patents that reach across these three domains of application as demonstrated in Figure 13 below. Unfortunately, most biofuel patents claim more than one technology, which makes it very difficult to assign a measure of fragmentation based on overlapping patent use within a given technology. For example, sugar is turned into ethanol via fermentation. If we limit our dataset to these three technology types there are 377 observations. A newer feedstock, such as algae (our set includes 338 algae patents), only 18 patents include a final fuel and process type. This makes creating a fragmentation index very hard. Most notably due to the heterogeneity in the patent data and wide range of patent claims. Additionally, sorting across feedstock type, process type, and final fuel type still only tells us a small piece of the puzzle. If the anticommons were truly blocking innovation we would not have over 4,000 published U.S. patents in this field. The data and analysis in paper 1 indicates patent ownership rights have been consolidated to some extent, which helps overcome negotiation costs as one firm now owns an entire package of related patents.

Many patents claim all three technology classes, while others claim just one piece. In the instances where a patent only claims one of our three technology classes it is impossible to track what process and final fuel that patent helped provide. The ideal anticommons test would trace each feedstock through to final fuel type, but our data does not allow us to do so. Instead, we use ownership rights via assignee count, as our fragmentation estimator.

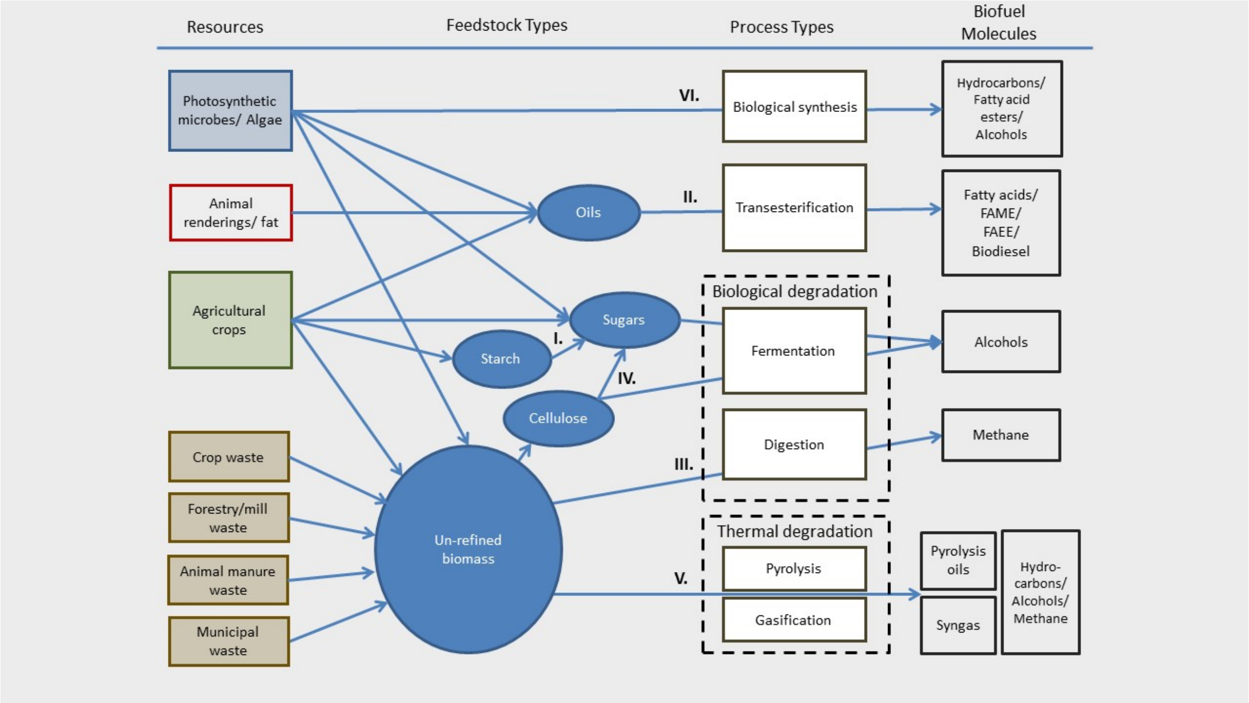


Figure 13: Fuel Conversion Pathways

3.7.1 Biofuel Patent Data

Biofuel production takes place via several different pathways as illustrated in Figure 1 above and discussed in paper 1. The data set constructed and explained in paper 1 includes many patent variables, but this empirical test uses those most consistent with the literature in this field, namely: count of cited patents, claims count, assignee count, age, and Derwent World Patents Index (DWPI) family members.

DWPI families are included to indicate the ex-ante value the owner(s) thought the patent had. DWPI families include all patents filed related to the original patent across all jurisdictions. If the owner(s) believe their patent is worth while they will file the patent with many patent offices and may even spin off related patents. The DWPI family construction includes these filings and spin offs. If an inventor or assignee believes their patent will make a large market impact, they will take the time and money to patent it globally.

This paper looks only at biofuel patents granted in the United States to standardize patent requirements. Further research could include all patents in our original data-set, but would require accounting for differences in patent office filing requirements, which is beyond the scope of this paper.

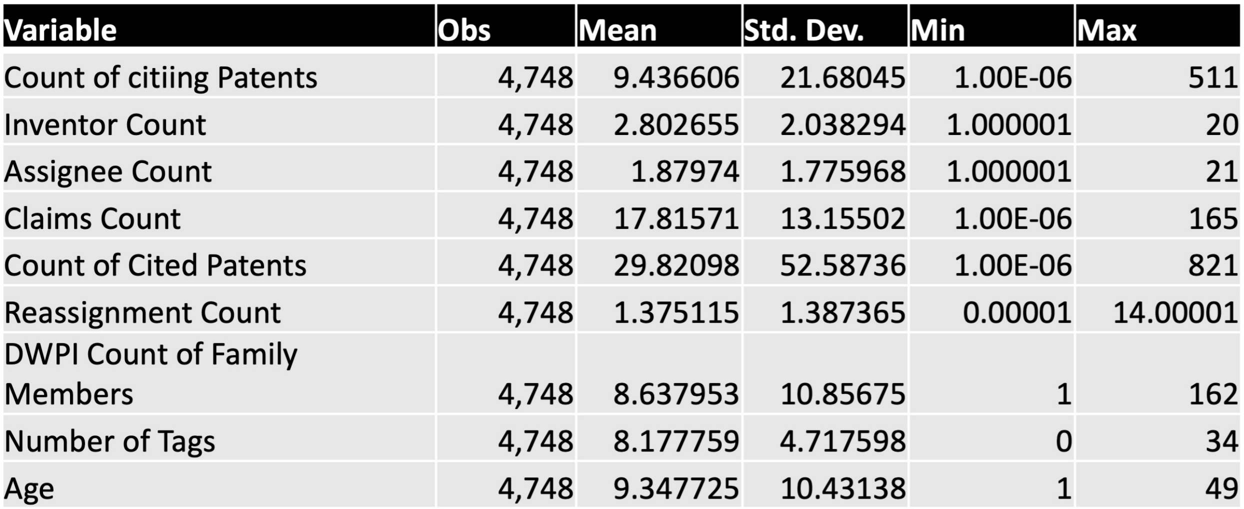
Using count of citing patents as our dependent variable and indicator for patent value has been used often in the literature as described above Trajtenberg (1990); Galasso and Schankerman (2013); Sun and Wright (2022); Murray and Stern (2007). However, there are some endogenous features to address. First, those patents filed in many different countries have a larger audience for future citations. This is most notable before the age of the internet when inventors had little access to patents filed in their home country, let alone abroad. Additionally, patents with more authors or assignees may have a greater audience as these authors mention their patent success to those around them. The more diverse the inventor team, the larger the network of people surrounding that patent is. Including DWPI count allows us to control for these features to some extent.

Additionally, I include cited patents, assignee count and inventor count in my regression. I also include the number of times the patent has been reassigned as a proxy for the worth of this patent to others. Worth in this instance may not mean actual profits from said patent, but instead patent profits from their own competing patents. If a company sees a patent as competition and has the means, why not buy that patent and shelf it to increase the value of the patent they have? Unfortunately this is not a question that my data set can answer. Entities do not disclose how much they paid for patents, spent in R&D for individual patents, or royalties and profits from each patent.

This data is also skewed due to the large range of publication dates. Those patents published 20 years ago are expected to have more citations as they've been around longer. Patents granted in 2014 (the last year we collected data for) will have no citations given their limited time in the public domain. To account for this I use an age variable equal to 2015 minus the year of publication. I used 2015 as my base year so that age count starts as 1 (those published in 2014). Future research in this area includes an updated data-set to see if these newer patents were cited more as expected with the uptick in use of programs such as Google patents.

3.8 Data Summary

Below is a summary of the data:



Variable	Obs	Mean	Std. Dev.	Min	Max
Count of citiing Patents	4,748	9.436606	21.68045	1.00E-06	511
Inventor Count	4,748	2.802655	2.038294	1.000001	20
Assignee Count	4,748	1.87974	1.775968	1.000001	21
Claims Count	4,748	17.81571	13.15502	1.00E-06	165
Count of Cited Patents	4,748	29.82098	52.58736	1.00E-06	821
Reassignment Count	4,748	1.375115	1.387365	0.00001	14.00001
DWPI Count of Family Members	4,748	8.637953	10.85675	1	162
Number of Tags	4,748	8.177759	4.717598	0	34
Age	4,748	9.347725	10.43138	1	49

Figure 14: Summary Statistics

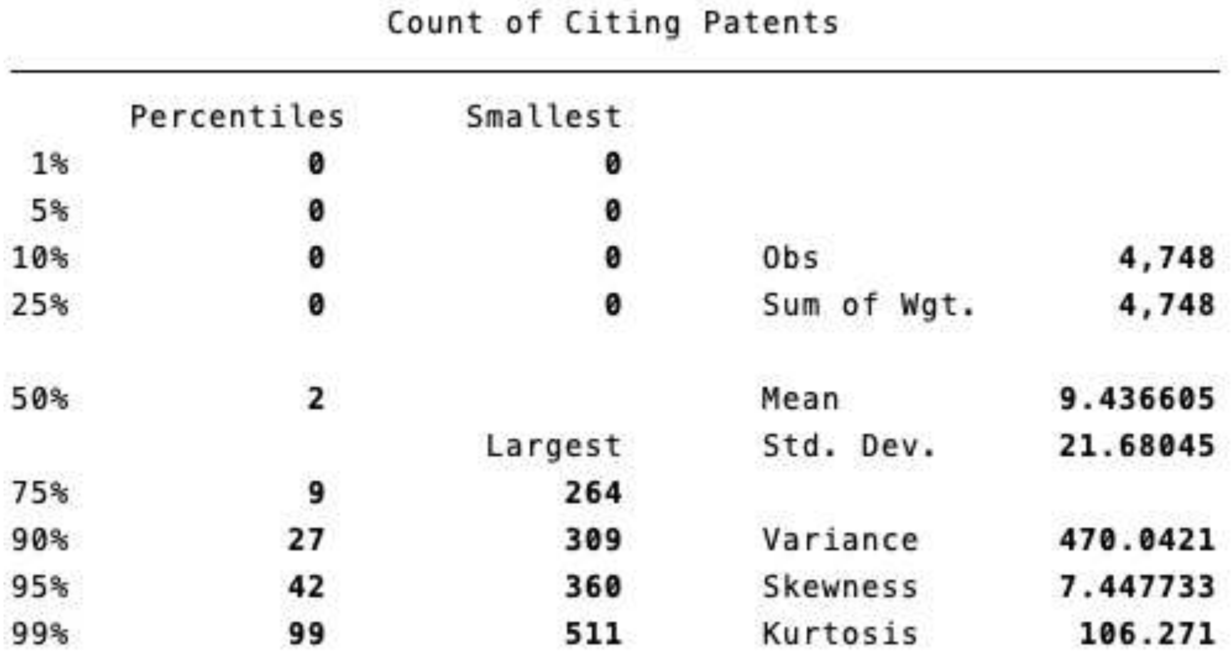
3.9 The Model

Following Trajtenberg (1990); Griliches (1990), we estimate the research outputs as measured by patent strength or non-self follow-on citations, with respect to research inputs including claims count, assignee count, inventor count, DWPI family members, and patent age. The more cited the patent is, the more useful the patent is in the specific area of research. These citations also come at a cost, as negotiated between the patent holder and patent applicant. The cost of information is measured by the number of citing patents, an indicator of the amount of IPR needed to move forward with an invention. We use logs of the standard production function to show percentage changes in outcomes given the input changes.

$$ln(citing_i) = \beta_1 ln(as_i) + \beta_2 ln(cited_i) + \beta_3 ln(cla_i) + \beta_4 ln(inv_i) + \beta_5 ln(DWPI_i) + \beta_7 (rea_i) \beta_7 (age_i) + \varepsilon_i \tag{21}$$

Using assignee count as a fragmentation index proxy we find that an 1% increase in patent assignee count leads to an average of 4.5% less follow on citations. This results indicates that diffuse ownership leads to less use of the existing patents or knowledge, all else equal.

The dependent variable, count of citing patents ($citing_i$), ranges from 0 to 511 with a mean of 9.44 and standard deviation of 21.67:



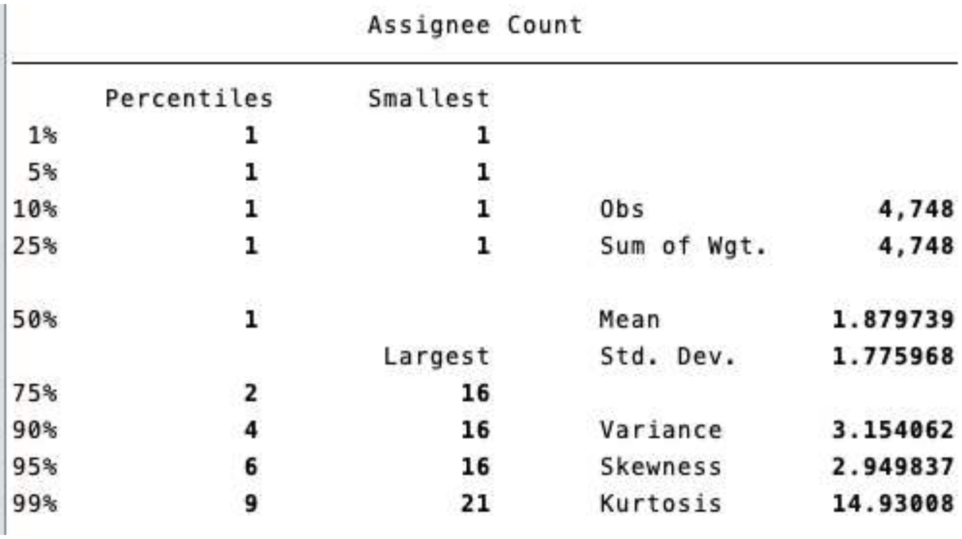
```
                     Count of Citing Patents
-------------------------------------------------------------

      Percentiles      Smallest
 1%            0              0
 5%            0              0
10%            0              0       Obs               4,748
25%            0              0       Sum of Wgt.       4,748

50%            2                      Mean           9.436605
                        Largest       Std. Dev.      21.68045
75%            9            264
90%           27            309       Variance       470.0421
95%           42            360       Skewness       7.447733
99%           99            511       Kurtosis        106.271
```

Figure 15: Summary Statistics for Citing Patents

The wide range of citing patents illustrated in these summary statistics show the potential to further explore the anticommons hypothesis. Why did some patents get cited hundreds of times and others never? Do the most cited patents have larger inventor teams? Do those highly cited patents belong to a large company with access to a plethora of prior art? Are there highly cited patents with a single author and no prior art?

The independent variables in this equation include:

- Assignee count (as_i): how many entities claim ownership over this patent. This differs from inventor count in an important way as it tells us who legally owns the patent or how many owners a potential inventor must negotiate with before applying for a patent using the existing knowledge base. The anticommons hypothesis suggests the more assignees a patent has, the lower the rate of follow-on inventions given the complexity of navigating access to prior art. We expect this coefficient to be negative. Assignee count ranges from 1 to 21 with a mean of 1.88 (1.77).



```
                        Assignee Count
-------------------------------------------------------------
      Percentiles      Smallest
 1%            1              1
 5%            1              1
10%            1              1       Obs               4,748
25%            1              1       Sum of Wgt.       4,748

50%            1                      Mean           1.879739
                        Largest       Std. Dev.      1.775968
75%            2             16
90%            4             16       Variance       3.154062
95%            6             16       Skewness       2.949837
99%            9             21       Kurtosis       14.93008
```

Figure 16: Summary Statistics for Assignee Count

- Count of cited patents ($cited_i$): how many patents the granted patent cited as prior art. This variable is an indicator for the existing knowledge base and tells us how many patents the patent in question cited in their references. The cost of access to prior work depends upon ownership and this data is not publicly available. Due to this, we cannot make assumptions about how prior art impacts costs, but assume inventors must pay for access to prior art. We expect this variable to be positive as more access to prior art increases the knowledge base and hypothetically makes it easier to push an invention forward, but comes at a higher initial cost. Cited patent count ranges from 0 to 821 with a mean of 29.79 (52.56) in our data set.

- Claims count (cla_i): how many different claims does the patent address? This variable shows how robust a patent is in terms of how many technology fields it claims to address. This ranges from 0 to 165 with a mean of 17.81 (13.16).

- Inventor count (inv_i): how many authors are listed on the patent. This variable tells us how many people worked on the patent and ranges from 1 to 20 with a mean of 2.80 (2.04). The more inventors involved in a process, the more access to prior art the team has. This includes increased access to prior art, most notably when joining a new team where they can leverage their relationships with past team members to access patent rights. We expect this variable to have a positive coefficient for this reason.

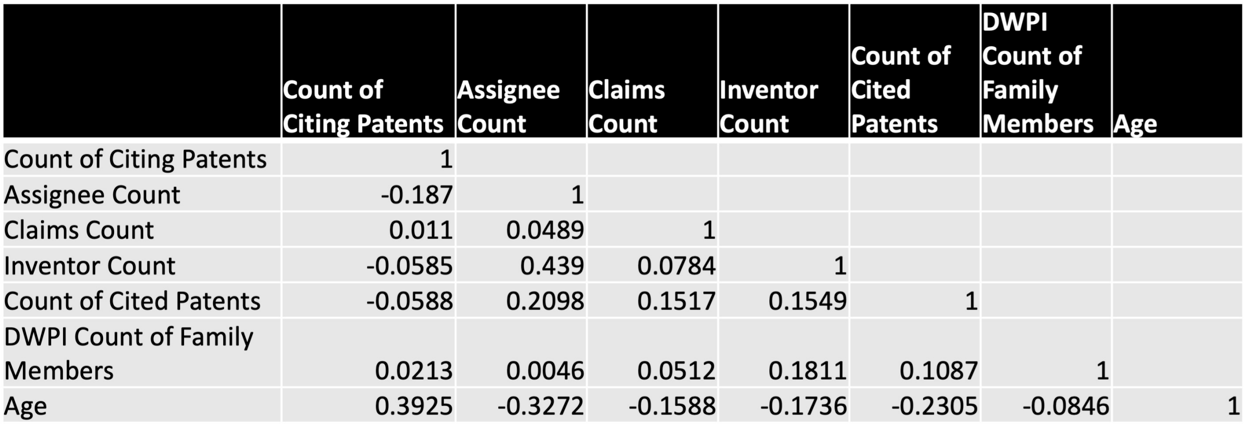
- Count of DWPI family members ($DWPI_i$): the more family members a patent is attached to the more prior art they have access to. For this reason, we expect this coefficient to be positive as more access leads to more inventions with less navigation required to traverse the patent landscape. DWPI family member count ranges from 0 to 162 with a mean of 8.63 (10.85).

- Age (age_i): the date the patent was published dictates the amount of prior art in existence when working on the invention. Our patents range from 1964 to 2014. We constructed an Age variable to account for how long the patent was published given the data set was constructed in 2016. Age is defined as 2015 minus the publication year. We would expect this coefficient to be positive as older patents have more opportunity to be cited over time. The data ranges from 1 year old (published in 2014) to 49 years old with a mean of 9.378 (10.43138).

- Reassignment (rea_i): the number of times a patent has been reassigned. Reassignment is another measure of patent value as only those deemed most valuable will transfer hands more than once. It is often the case that the original author or assignee reassigns the patent to their employer. For this reason patents with one reassignment are not our primary variable. However, we see that there are patents that changed hands as many as 14 times. I dug farther into the patents reassigned more than 2 times and in most instances the company of ownership changed hands or changed names. In a few instances the patents were reassigned to banks, possibly because the research was financed and the original assignees were not able to pay off that debt. The mean patent changed hands 1.375 (1.387) times. Further research on this topic could include diving deeper into the patents that changed hands more than 3 times, but this severely limits the dataset.

There are other variables in our dataset that could be explored in future research, including the number of times a patent was tagged for a particular technology type. However, this data is somewhat endogenous as it relates to the number of claims a patent had. The more a patent is tagged the more claims it covers as described in paper 1. It is important to note that there is overlap between technology types as many patents claim more than one of the categories listed. Future research could address this overlap and build a more formal fragmentation index. Within each category there are several technology types tagged. Feed stocks include: cellulose, algae, biomass, municipal and livestock waste, crop waste and animal fats. Process types include: pyrolysis, gasification, digestion, fermentation, and transesterification. The final fuel molecules include: fatty acids, alcohols general, butanol/propanol, syngas, ethanol and hydrocarbons.

It is also important to note that there is some correlation between our variables as shown below.



	Count of Citing Patents	Assignee Count	Claims Count	Inventor Count	Count of Cited Patents	DWPI Count of Family Members	Age
Count of Citing Patents	1						
Assignee Count	-0.187	1					
Claims Count	0.011	0.0489	1				
Inventor Count	-0.0585	0.439	0.0784	1			
Count of Cited Patents	-0.0588	0.2098	0.1517	0.1549	1		
DWPI Count of Family Members	0.0213	0.0046	0.0512	0.1811	0.1087	1	
Age	0.3925	-0.3272	-0.1588	-0.1736	-0.2305	-0.0846	1

Figure 17: Variable Correlation Statistics

To account for this correlation the model was run both with and without inventor count as discussed in the results section.

3.10 Results

When looking at the entire dataset we find that all variables are statistically significant. Most notably, assignee count has a negative and significant result in all variations of the model as shown below.

Table 1: Regression Results for all Patents

Variables	ln_countofcitingpatents1
ln_assigneecount1	-4.522***
	(0.157)
ln_reassignmentcount1	0.114***
	(0.0191)
ln_countofcitedpatents1	0.187***
	(0.0338)
ln_claimscount1	0.442***
	(0.0675)
ln_inventorcount1	1.040***
	(0.142)
ln_dwpicountoffamilymembers	0.143*
	(0.0862)
age	0.333***
	(0.00958)
Constant	-7.660***
	(0.291)
Observations	4,748
R-squared	0.403

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

These results are all statistically significant and show that a 1% increase in assignee count leads to a 4.522% decrease in follow-on citations. The more assignees a patent has, the less likely it is to be cited in the future. All other control variables have positive coefficients indicating that more inventors, higher DWPI count, age, claims and reassignment all increase the probability a patent is cited in the future. Additionally, we need to account for the correlation between inventors and assignees shown in Figure 17. To do so, we run the same regression without inventor count. These results are also statistically significant and again show that the number of assignees negatively impacts follow on citations.

Table 2: Biofuel Patent Regression without Inventor Count

Variables	Coefficient (Standard Error)
ln_assigneecount1	-4.178***
	(0.151)
ln_reassignmentcount1	0.125***
	(0.0191)
ln_countofcitedpatents1	0.180***
	(0.0340)
ln_claimscount1	0.445***
	(0.0678)
ln_dwpicountoffamilymembers	0.294***
	(0.0842)
age	0.332***
	(0.00964)
Constant	-7.168***
	(0.285)
Observations	4,748
R-squared	0.397

Standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

These results have a lower adjusted R-squared, but better P values for each variable. Assignee count also has a slightly smaller impact on follow-on citations (.344%) increase in citations when inventor count isn't included in our regression). This also helps eliminate the correlation between inventor count and assignee count show in Figure 17. However, existing patent literature discussed above illustrates the importance of including both inventor and assignee count, thus we include inventor count in the technology specific regressions below. Specifically, inventor count is a better indication of access to knowledge rather than knowledge ownership.

3.10.1 Feed Stock Types

When the above results are broken into the individual classifications we see assignee count continues to have a negative and significant coefficient. Looking at individual feedstocks we find a large difference between the magnitude and sign of the coefficients for these technologies within the same classification. One explanation for this is the age and application of each technology type: the older and more broad a feedstock is the more likely it is that ownership right holdups have been mitigated. Sugar, for example, has been produced for thousands of years and has many applications outside of biofuel production. For this reason we expect sugar to have a lower coefficient for assignee count as over time sugar producers have learned to work together to get around patent laws or share their knowledge. Algae on the other hand, was thought to be one of the next generation biofuel feedstocks and has little known other uses. Our results show that Algae patent ownership does have a higher negative impact on follow-on citations, possibly because algae inventors do not have access to the knowledge pipelines sugar inventors have. Alternatively, sugar production is consolidated in the U.S. while Algae production is dispersed, thus again showing the anticommmons may be at work.

Table 3: Results for Feedstocks Only

Variable	Coefficient (Standard Error)
ln_assigneecount1	-4.550***
	(0.280)
ln_reassignmentcount1	0.100***
	(0.0310)
ln_countofcitedpatents1	0.158**
	(0.0696)
ln_claimscount1	0.595***
	(0.126)
ln_inventorcount1	1.274***
	(0.234)
ln_dwpicountoffamilymembers	0.202
	(0.141)
age	0.339***
	(0.0156)
Constant	-8.466***
	(0.507)
Observations	1,577
R-squared	0.422

Standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

When using assignee count as a proxy for patent fragmentation we find that some technologies see lower follow on citations compared to others with similar assignee counts. For instance, Algae, a newer source of biofuel has a larger negative coefficient for assignees than all other feedstock types.

Table 4: Algae Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-5.774***
	(0.574)
ln_reassignmentcount1	0.109
	(0.0775)
ln_countofcitedpatents1	0.718***
	(0.128)
ln_claimscount1	0.00318
	(0.354)
ln_inventorcount1	1.452***
	(0.550)
ln_dwpicountoffamilymembers	-0.0454
	(0.307)
age	0.446***
	(0.0734)
Constant	-6.280***
	(1.194)
Observations	338
R-squared	0.384

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

For algae we see that a 1% increase in assignee count leads to a 5.77% decrease in follow-on citations. Interestingly algae is one of the only technology pathways for which claims count is not significant. One explanation for this is that algae patents have a higher claims count than many of the older technologies in the data set.

Biomass, a much older biofuel technology also has a negative and significant coefficient for assignee, but less than that for algae. In both cases we find DWPI count of family members is insignificant.

Sugar, another feedstock that has been around for a long time shows similar results, but the assignee coefficent is even lower than that of both biomass and algae.

Table 5: Biomass Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-4.336***
	(0.265)
ln_reassignmentcount1	0.104***
	(0.0339)
ln_countofcitedpatents1	0.177***
	(0.0620)
ln_claimscount1	0.796***
	(0.145)
ln_inventorcount1	1.425***
	(0.249)
ln_dwpicountoffamilymembers	0.136
	(0.148)
age	0.398***
	(0.0196)
Constant	-9.023***
	(0.563)
Observations	1,742
R-squared	0.375

Standard errors in parentheses

$*** p < 0.01, ** p < 0.05, * p < 0.1$

Table 6: Sugar Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-3.904***
	(0.398)
ln_reassignmentcount1	0.0891*
	(0.0526)
ln_countofcitedpatents1	0.186***
	(0.0690)
ln_claimscount1	0.823***
	(0.315)
ln_inventorcount1	1.266***
	(0.384)
ln_dwpicountoffamilymembers	0.298
	(0.219)
age	0.424***
	(0.0295)
Constant	-10.53***
	(1.075)
Observations	690
R-squared	0.401

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Assignee count has a smaller impact on sugar when compared to the data set as a whole. Sugar patents span beyond just biofuels and on average sugar patents are older than many of the other feedstocks. Have researchers learned ways or created collaborations to overcome fragmented property rights in this area?

3.10.2 Process Types

Process types also follow the overall results illustrated above. Namely a negative and significant coefficient for assignee count and year, but positive and significant coefficients for count of cited patents, claims count, inventor count, and count of DWPI family members. We see large variation in the size and sign of the coefficients for the various technology types in this category.

Table 7: Process Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-3.957*** (0.221)
ln_reassignmentcount1	0.109*** (0.0282)
ln_countofcitedpatents1	0.166*** (0.0444)
ln_claimscount1	0.668*** (0.114)
ln_inventorcount1	0.951*** (0.206)
ln_dwpicountoffamilymembers	0.224* (0.129)
age	0.372*** (0.0155)
Constant	-8.655*** (0.467)
Observations	2,212
R-squared	0.392

Standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

We again see assignee count is negative and significant, but less so than in the other 2 technology pathways. This could indicate that patent ownership is more binding for these newer technology types than those with a longer history. When looking among the process pathways we find that fermentation, a technology that has a long history for various uses has a lower coefficient for assignee than the other process paths, such as transesterification which is a relatively younger technology.

Table 8: Fermentation Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-3.980***
	(0.254)
ln_reassignmentcount1	0.106***
	(0.0335)
ln_countofcitedpatents1	0.162***
	(0.0447)
ln_claimscount1	0.696***
	(0.144)
ln_inventorcount1	1.171***
	(0.245)
ln_dwpicountoffamilymembers	0.183
	(0.150)
age	0.388***
	(0.0184)
Constant	-9.364***
	(0.574)
Observations	1,574
R-squared	0.405

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Transesterification shows a 1.5% decrease in follow-on citations per 1% increase in assignee count compared to fermentation. This could be due to the diverse use of fermentation in industries beyond biofuels, such as brewing. One could posit that the brewing industry is more collaborative than the biofuel industry where a few major companies have been able to take over the majority of production. Alternatively, since fermentation technologies have been around longer the processes involved maybe more standardized and rely less on patents for new innovations.

Table 9: Transesterification results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-5.347***
	(0.607)
ln_reassignmentcount1	0.125
	(0.0984)
ln_countofcitedpatents1	-0.0963
	(0.174)
ln_claimscount1	0.993*
	(0.531)
ln_inventorcount1	0.944
	(0.660)
ln_dwpicountoffamilymembers	0.190
	(0.369)
age	0.414***
	(0.0573)
Constant	-7.684***
	(1.735)
Observations	300
R-squared	0.427

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

3.10.3 Final Fuel Molecule

Final fuel molecules follow similar trends as mentioned above.

Table 10: Final Fuel Type Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-4.275***
	(0.247)
ln_reassignmentcount1	0.0844***
	(0.0307)
ln_countofcitedpatents1	0.154***
	(0.0543)
ln_claimscount1	0.507***
	(0.101)
ln_inventorcount1	1.270***
	(0.233)
ln_dwpicountoffamilymembers	0.193
	(0.142)
age	0.369***
	(0.0162)
Constant	-8.652***
	(0.449)
Observations	1,936
R-squared	0.393

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

The results for final fuel show a higher impact for assignee count than for process type. More interesting is the variation among different final fuel types. Ethanol, arguably the most developed biofuel on the market is statistically significant when looked at in isolation, but shows a lower coefficient than that for the other final fuel types. This indicates inventors in the ethanol space maybe able to better navigate existing property rights than those in newer fuel fields like butanol.

The results for Ethanol are very similar to those of the entire data set. Butanol and Propenol have a larger negative impact from assignee. This is consistent with our results for algae and in both fields there are fewer total patents than the first generation sources in their technology class.

Butanol and Propenol are the only final fuel type for which claims count is not significant.

Table 11: Ethanol Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-4.662*** (0.283)
ln_reassignmentcount1	0.136*** (0.0370)
ln_countofcitedpatents1	0.202*** (0.0592)
ln_claimscount1	0.594*** (0.177)
ln_inventorcount1	0.965*** (0.277)
ln_dwpicountoffamilymembers	0.286* (0.161)
age	0.377*** (0.0229)
Constant	-8.367*** (0.647)
Observations	1,306
R-squared	0.395

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Table 12: Butanol and Propenol Results

Variable	Coefficient (Standard Error)
ln_assigneecount1	-5.265***
	(0.446)
ln_reassignmentcount1	0.221***
	(0.0752)
ln_countofcitedpatents1	0.155
	(0.133)
ln_claimscount1	-0.0320
	(0.436)
ln_inventorcount1	1.503***
	(0.483)
ln_dwpicountoffamilymembers	0.895***
	(0.292)
age	0.301***
	(0.0427)
Constant	-6.650***
	(1.449)
Observations	372
R-squared	0.456

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

There are several possible reasons for this including the overlap between final fuel types. This is a question for future research.

3.10.4 Robustness checks

To further test our results we use a quadratic model for assignee count. We find that the results are still statistically significant and negative for assignee count. The results are smaller than when not squared, as expected.

Table 13: Quadratic Results

Variable	Coefficient (Standard Error)
ln_assigneecount1_squared	-2.260*** (0.0786)
ln_reassignmentcount1	0.114*** (0.0191)
ln_countofcitedpatents1	0.187*** (0.0338)
ln_claimscount1	0.442*** (0.0675)
ln_inventorcount1	1.040*** (0.142)
ln_dwpicountoffamilymembers	0.143* (0.0862)
age	0.333*** (0.00958)
Constant	-7.661*** (0.291)
Observations	4,749
R-squared	0.403

Standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

We see that assignee count is still negative and significant. These results also show that assignee count increases at a decreasing rate, which is consistent with the patent literature.

Additionally, we ran a mean shock model to test how our coefficients change when the mean for each variable is added to them. We again see statistical significance, but much lower levels as

Table 14: Mean Analysis

Variable	Coefficient (Standard Error)
ln_assingeemean	-0.286***
	(0.0224)
ln_reassignmentmean	0.168***
	(0.0166)
ln_citedmean	0.0919***
	(0.0139)
ln_claimsmean	0.192***
	(0.0224)
ln_inventormean	0.0593**
	(0.0237)
ln_dwpimean	0.0356**
	(0.0161)
age	0.0346***
	(0.000722)
Constant	1.338***
	(0.103)
Observations	4,748
R-squared	0.412

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

expected given we blew up the variable values by adding the mean to each.

3.11 Discussion and Conclusion

This paper shows that diffused ownership provides a drag on subsequent patent uptake. While this is distinct from the anticommons hypothesis, it does provide empirical evidence consistent with it. Along all technology pathways we see assignee count, our proxy for fragmentation, has a significant negative coefficient. This illustrates the anticommons is at work as the more fragmented, or dispersed, ownership rights are the less likely a patent is to be cited by others. Traditionally patents are introduced to inspire further innovation and share knowledge, but here we see that as patent ownership gets more fragmented follow-on inventions are stifled. To overcome this issue requires regulation on patent royalties and bargaining. Future research includes exploring trends for different countries as patent rights differ. Do countries with more open access policies innovate more?

Biofuel technologies such as algae expanded with the RFS in 2008 but dropped off in 2014. Our results suggest this drop-off was in part due to dispersed ownership rights for existing patents. Algae technologies expanded so quickly it became costly to negotiate rights to the existing patents an invention may infringe upon. How long did it take researchers in this field to realize their ideas would be extremely costly to bring to market?

Future studies of the anticommons using this data could include using an HHI index for patent fragmentation across technology fields. Exploring ownership characteristics (public, private, individual) could also offer a unique insight into the anticommons question. Expanding the data-set to include patent applications that were not granted could also lead to more insights about the anticommons. Comparing patents across countries is another avenue this data would allow, but controlling for international patent laws is beyond the scope of this paper.

The anticommons hypothesis posits fragmented property rights leads to under utilization of a resource. Here we have shown that as patent ownership, our proxy for fragmentation, follow-on citations decreases. Thus the anticommons hypothesis holds when using assignee count as a proxy for ownership fragmentation.

4 Conclusion

These three papers illustrate the tragedy of the anticommons using both a theoretical and empirical model. The methods and results from paper 3 could be used to further explore the anticommons in other technology fields. Assignee count, our proxy for fragmentation, is a relatively new variable in the economics literature with large potential as illustrated here.

Paper 1 explores biofuel patent trends from the early 1960's to 2014 and finds an uptick in patenting activity following government policy announcements. The paper shows patent trends across countries and biofuel technology pathways. It finds increased patent activity in all jurisdictions from 2004-2008. Advanced biofuels, such as algae and biomass, increase substantially between 2004 and 2008 with a large drop off after 2008. In the same time period traditional biofuels, such as ethanol, experience a plateau which continues beyond 2008.

Paper 2 is a theoretical model of researcher incentives. The model builds on previous innovation models by adding a parameter for diminishing returns to research inputs and potential negotiation costs in the case of fragmented patent rights. We find that if fragmentation exists research efforts and benefits are less than those achieved with no fragmentation. Finally, the paper argues a subsidy to research effort could mitigate the impacts of fragmentation on market outcomes.

Paper 3 empirically tests the anticommons using the biofuel patent data set from Paper 1. The anticommons argument is that resources are underused if it is too costly to gain access from multiple property owners. Rather than constructing a complex fragmentation index similar to other economic papers in this field, we introduce the nuanced idea of using assignee count as a fragmentation proxy. Gaining patent rights from multiple owners on one patent is considered equally as hard as gaining access to several single-owner patents. For this reason we believe patent assignee count is a good indicator of fragmentation.

Along all biofuel technology pathways explored we find a decrease in follow-on citations by 4.52% for each 1% increase in patent ownership. For advanced biofuel technologies such as algae we find a 5.77% decrease in follow-on citations. More traditional fuel sources such as sugar see only a 3.9% decrease in follow on citations with a 1% increase in assignee count. These results suggest older technologies have found ways to work around existing patent ownership rights. These findings are consistent with the anticommons hypothesis and suggest a new way of testing this hypothesis.

Building upon these results we anticipate future work including adding patent ownership type and collaborations. Our methods and results could also be broadened to other technology fields to further test the anticommons hypothesis. The nuanced idea of using assignee count as a proxy for fragmentation is a first step at showing the anticommons exists within patent ownership. These results imply U.S. patents may be hindering innovation more than helping it as originally intended, leaving room for policy intervention.

5 Appendix: Public, Private, and Individual Ownership Trends

Table 15: Individual Owner Results

Variable	Coefficient (Standard Error)
ln_reassignmentcount1	0.144*
	(0.0803)
ln_countofcitedpatents1	0.0751
	(0.180)
ln_claimscount1	0.0741
	(0.310)
ln_inventorcount1	0.767
	(3.004)
ln_assigneecount1	-1.367
	(2.942)
ln_dwpicountoffamilymembers	-0.412
	(0.463)
age	0.307***
	(0.0315)
Constant	-4.659***
	(1.304)
Observations	226
R-squared	0.343

Standard errors in parentheses

$***p < 0.01, **p < 0.05, *p < 0.1$

Table 16: Private Owner Results

Variable	Coefficient (Standard Error)
ln_reassignmentcount1	0.199^{***}
	(0.0326)
ln_countofcitedpatents1	0.236^{***}
	(0.0527)
ln_claimscount1	0.304^{***}
	(0.101)
ln_inventorcount1	0.957^{***}
	(0.211)
ln_assigneecount1	-4.747^{***}
	(0.226)
ln_dwpicountoffamilymembers	0.180
	(0.124)
age	0.308^{***}
	(0.0145)
Constant	-7.140^{***}
	(0.421)
Observations	2,111
R-squared	0.415

Standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

Table 17: Publicly Owned Results

Variable	Coefficient (Standard Error)
ln_reassignmentcount1	0.0423
	(0.0708)
ln_countofcitedpatents1	0.106
	(0.0677)
ln_claimscount1	0.904^{***}
	(0.179)
ln_inventorcount1	1.438^{***}
	(0.423)
ln_assigneecount1	-4.254^{***}
	(0.382)
ln_dwpicountoffamilymembers	0.212
	(0.254)
age	0.423^{***}
	(0.0316)
Constant	-10.20^{***}
	(0.836)
Observations	692
R-squared	0.440

Standard errors in parentheses
$***p < 0.01, **p < 0.05, *p < 0.1$

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