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Has COVID-19 Affected Patenting in the US?

Johnny Allen Cope

A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of
Master of Science

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ABSTRACT

Has COVID-19 Affected Patenting in the US?

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Scholars have studied how exogenous shocks affect innovation, yet the effects of COVID-19 on one measure of innovative activity, numbers of patent applications, are not well understood. This study looks at what effect disruptions related to COVID-19 have had on numbers of patent applications submitted by inventors in the United States. Using the Patent Examination Research Dataset from the United States Patent and Trademark Office and the Oxford COVID-19 Government Response Tracker, I examine how numbers of patent applications have changed in 2020 and what effect economic disruptions, health disruptions, and nonpharmaceutical interventions related to COVID-19 have had on numbers of patent applications submitted among US states. Descriptive analysis shows that patent applications for large firms, small firms, and independent inventors have dropped from 2019 to 2020, yet small firms had the smallest decrease. Statistical models indicate that percent change in GDP is positively associated with patents applications per capita while COVID cases, COVID deaths, and nonpharmaceutical interventions have no little to no association with patent applications per capita.

Keywords: patents, COVID-19, innovation resilience, nonpharmaceutical interventions

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Has COVID-19 Affected Patenting in the US?

The COVID-19 pandemic has disrupted all facets of society—millions of people have suffered and died, and the ways people work, socialize, shop, recreate, travel, and communicate have changed. Many people have lost jobs and economies, workplaces, governments, and other institutions have struggled to adapt to coronavirus and the challenges it has imposed. As the world gradually overcomes and recovers from the pandemic, research that investigates the effects of COVID-19 on individuals and society is valuable. In the short term, understanding how the pandemic has harmed society and who it has harmed the most can help us know where to allocate resources to aid recovery. In the long term, understanding effects of COVID-19 on society can help us understand what parts of society are more vulnerable to health-related exogenous shocks, and what parts we should prioritize strengthening. Another benefit that can come from research on the effects of COVID-19 is an improved understanding of how economic strain, health disruption, and changes in work structure and setting affect society. One aspect of our society that may have been affected by the economic and social pressures of COVID-19 is innovation, measured by numbers of patent applications.

Creating sustainable patterns of innovation is important to scholars, policy makers, and business leaders due to the direct relationship between innovation and economic success. As the Information Technology & Innovation Foundation says, “innovative new products and services... raise incomes and improve quality of life (Nager et al. 2016:5).” Empirical evidence shows the clear link between innovation and economic growth and resilience. For instance, Hasan and Tucci (2010) showed that countries with more patents and higher quality patents (measured by number of citations) have higher economic growth. Kogan et al. (2017) showed that highly cited patents are associated with increases in the economic value of private

companies. Filippetti et al. (2020) showed that more innovative nations were more economically resilient during the global financial crisis of 2008. Furthermore, countries with higher levels of R&D expenditures were linked to lower levels of unemployment during and after the peak financial crisis.

Innovation scholars have long studied how exogenous shocks affect innovation, often using numbers of patents, patent citations, or patent applications as proxies for innovative output. Yet the effect of COVID-19 on patenting in the United States is not well understood, partly because of data availability. The relationship between COVID-19 and patenting is still playing out, and it is hard to assess that relationship while we are still amid it. Yet using recent batches of patent application data from the United States Patent and Trademark Office's PatEx dataset, which can be analyzed sooner than patents or patent citations, we can begin to study its effects.

What is the effect of COVID-19 on innovation output in the US? The outbreak of COVID-19 has caused economic disruption, health disruption, and changes in the setting and structure of work due to nonpharmaceutical interventions such as stay at home orders and restrictions on gatherings—all relevant factors that could affect innovation output. In my thesis, I investigate how each of these factors—economic disruption, health disruption, and nonpharmaceutical interventions—has affected innovation output measured by patent applications at the state level. In doing so, I seek to answer the following questions. Have the numbers of patent applications submitted in 2020 changed compared to 2019? How do those numbers vary according to the entity status—independent, small organization, large organization—of the inventor? Are economic disruptions, health disruptions, or various nonpharmaceutical interventions implemented to mitigate the spread of COVID useful predictors of numbers of patent application submissions in 2020? By investigating these questions, this

paper contributes to the literature on innovation resilience during exogenous shocks and the literature on effects of nonpharmaceutical interventions on work. Specifically, this paper helps us understand how one measure of innovative activity—patent application submissions—has been affected by various forces during a global pandemic.

To answer these questions, I study the effect of COVID-19 on the number of patent applications submitted by US inventors to the United States Patent and Trademark Office (USPTO) in two ways. First, using descriptive statistics, I assess whether there are changes in the number of patent applications submitted to the USPTO between 2019, the year right before the pandemic, and 2020, the first year of the pandemic in the US. I examine changes in patent application rates between 2019 and 2020 by inventor entity status (whether an inventor is independent or belongs to a small or large organization). Second, using statistical models, I examine whether variables that represent economic disruptions, health disruptions, and nonpharmaceutical interventions can explain variation in patent applications per capita in 2020 among US states.

Descriptive analysis indicates that numbers of patent applications submitted between 2019 and 2020 have dropped, especially for micro and large entities. Statistical models show that percent change in GDP is positively associated with patent applications per capita. COVID cases and COVID deaths are not associated with patent applications per capita, except in the case of independent inventors. Some nonpharmaceutical interventions are associated with increases in patent applications per capita, though these associations disappear when accounting for common patenting control variables and share of democratic voters in a state.

LITERATURE REVIEW

Economic Disruption and Innovation

The first year of the COVID-19 pandemic led to dramatic disruption in GDP, employment, consumer spending, and global supply chains, causing an economic recession. During this year, the stock market experienced a huge drop that was negatively correlated with growth in COVID-19 cases (Yilmazkuday 2021). While global pandemics with the magnitude and impact of COVID-19 are rare, economic recession is not, and the link between recession and innovation is well established. Empirical evidence shows many examples of the negative effects of recession on the innovative output of countries. For example, Yamashita (2021) showed that compared to the rest of the innovating world, Japan, a powerhouse of innovation in the 1980s, suffered a decrease in patent citations, a measure of patent quality, since the Japanese recession of 1991 from which it has yet to completely recover. Filippetti et al. (2020) showed evidence that the global recession of 2008 led to a decrease in R&D spending, a measure for innovative input, in Europe.

While evidence of economic recession harming countries is clear, some scholars argue that the effect of recession has varying effects on companies and individuals. According to these scholars, recession disrupts and harms many companies, but it also creates new opportunities for creative innovation that some inventors and firms can exploit (Filippetti and Archibugi 2011). For example, Hoegl, Gibbert, and Mazursky (2008) showed that financial constraints sometimes compel innovators to do things more efficiently, citing an example of the history of jet propulsion technology. German teams that had a much smaller budget were able to outcompete American teams, due, in part, to finding efficiencies in cheaper alloys. Though certain industries like communications technology and biotechnology may have been able to exploit new

opportunities during 2020, it is likely that the overall effect of the COVID-19 recession on innovation output for the whole US will be negative.

Though different in many ways, the global financial crisis of 2007-2009 serves as a useful case study to compare to the recession caused by COVID-19. The initial months of the COVID-19 pandemic caused an unprecedented disruption to the United States economy that in many ways was worse than the global financial crisis (GFC) of 2007-2009 (Li et al. 2021; Ashraf 2020). The first year of COVID-19 saw GDP, consumer spending, industrial production, and employment rates fall more dramatically than during the previous recession. One difference between that financial crisis and the COVID-19 recession is that the 2007-2009 recession had long overdue economic causes while the COVID-19 recession was caused by a rapid health-related exogenous shock. And while it is still too soon to know what the long-term economic consequences of COVID-19 are, recovery in terms of GDP and the stock market has been faster for the COVID-19 recession than the previous financial crisis (Xu 2021).

The effect of the 2007-2009 recession on patenting rates among US firms has been examined in a study by Breitzman (2013). Breitzman found that small firms (under 500 employees) experienced an immediate drop in patent applications during the early stages of the 2007-2009 recession. Patent applications for large firms (over 500 employees) did not change significantly until they took a small hit during the later stages of the recession. Small firms experienced long-term negative effects from their initial drop, with amounts of patent applications growing much slower than large firms by the end of 2009.

If the COVID-19 recession affects innovative output in a similar way to how innovation has been affected by other recessions, we might expect decreases in the number of patent applications in 2020. Since previous literature has established the relationship between economic

hardship and a reduction in innovation, we might expect to find that US states that faced higher levels of economic disruption, in terms of a decrease in GDP and an increase in unemployment, experienced a greater reduction in numbers of patent applications. Based on the study of patent application rates during the 2007-2009 recession, we might expect that large firms were more resilient than small firms, experiencing less overall reduction in patent applications during 2020.

Health Disruption, NPIs, and Innovation

Besides the clear effects of COVID-19 on economies and employment, COVID-19 has dramatically affected health as well as the settings and structures of work. Death from the pandemic could lead to a reduction in the total number of individuals engaged in inventive work. Sickness from the pandemic, whether directly affecting inventors or family members that inventors care for, can lead to a reduced capacity for individuals to perform inventive work. Grinza and Rycx (2020) finds that among employees at Belgium firms, sickness absenteeism reduces firms' productivity, especially for smaller firms. If sickness and death from the pandemic affect US innovators in similar ways to the Belgium study, we might expect to find that as COVID cases and COVID deaths increased in US states, patent applications decreased. We might also find that small US firms suffered decreases in patent applications more than large US firms.

Nonpharmaceutical interventions, including social distancing and restrictions on gathering, that have taken place during the pandemic could lead to a reduced ability for individuals and teams to innovate and collaborate. Government interventions implemented to mitigate spread of disease are not unprecedented. One study investigates the effects of government mandated social restrictions to combat the influenza pandemic of 1918 on innovation. In the study, Berkes et al. (2020) shows that US cities with longer non-

pharmaceutical interventions (NPIs), including measures like social distancing and restrictions on gathering, did not experience a decline in patenting compared with cities with shorter NPIs. Instead, the cities with longer NPIs experienced an increase in patenting rates after the pandemic ended. While the mechanism for this surprising trend is undetermined, Berkes et al. hypothesizes that longer NPIs may have resulted in less death, a sense of control, and increased motivation and morale for innovators during the 1918 pandemic, which in turn may have positively affected rates of patenting.

Socially distanced collaborative work has been enabled by Zoom and other online infrastructures during the COVID-19 pandemic in a way that was not present during the 1918 pandemic. Yet if the effect of social distancing and other measures taken to prevent the spread of COVID-19 has a similar association with increased innovative activity as NPIs did during the 1918 pandemic, we might see US states with stricter and longer COVID restrictions to experience an increase in numbers of patent applications submitted in 2020.

Demographics of US Innovators

Because COVID-19 has affected groups of people in the United States differentially, understanding who is most likely to innovate in the United States is an important part of making sense of COVID-19's effect on innovation. For instance, a growing body of literature suggests that COVID-19 has exacerbated health inequities of racial and ethnic minorities including African Americans, Hispanic Americans, and Native Americans (Bauer et al. 2020). Furthermore, unemployment has affected women more than men during this pandemic (Albanesi and Kim 2021). Because women and People of Color are more likely to experience distress or disadvantage due to COVID-19, one might expect that less patent applications were submitted by people in these demographic groups in 2020.

A report by the Information Technology and Innovation Foundation looked at the demography of high-impact inventors in the United States (Nager et al. 2016). The study found that innovators who received awards and recognition for their inventions tend to be male, middle-aged, highly educated with advanced STEM degrees, and centralized in California, the Northeast, and areas near sources of public research funding. Compared to the US population and even college educated Americans with PhDs in science or engineering, women and US-born People of Color were under-represented, and immigrants were over-represented. Small businesses, large businesses, and public research institutions all contributed significantly to high-impact inventions. So, while it is unfortunate that People of Color and women are not well represented among successful innovators in the US, the pandemic may have less impact on innovative activity than one might presume due to most innovators tending to be already privileged members of society that may have more structural resilience in their job security and health outcomes. Should this be the case, we may not see a large drop off in numbers of patent applications in 2020.

Hypotheses

Based on previous literature that economic recession hurts innovation, I expect that the total number of patent applications decreased between 2019 and 2020. However, since most inventors in the US are part of a privileged group, I expect that the decrease was small (Hypothesis 1). Individuals and organizations involved in patenting tend to have access to health resources and social capital and are more financially secure, and I suspect they were adaptable and resilient, and able to continue close to normal levels of innovative activity. I expect that small organizations experienced a greater decrease in total numbers of patent applications than large organizations, since large organizations have more resources to adapt to exogenous shocks,

and research on patenting during the 2008 financial crisis shows large organizations fared better than small ones (Hypothesis 2). I predict that independent inventors, having more time at home to work on innovative projects due to stay at home orders and workplace closings, experienced an increase in patent applications in 2020 (Hypothesis 3).

I hypothesize that states with more economic disruption, in terms of decrease in GDP and increase in unemployment, experienced a reduction in patent applications (Hypothesis 4). I expect that states with more health disruption, measured by numbers of COVID cases and COVID deaths, experienced a decrease in patent applications due to a decrease in worker productivity (Hypothesis 5). Finally, I suspect that states with stricter NPIs had increases in numbers of patent applications, because working from home may have given innovators more time and flexibility and stricter government measures may have given them a greater sense of security and morale, as suggested by Berkes et al. (2020) in reference to the 1918 pandemic (Hypothesis 6).

METHODS

Sample

The sample in my descriptive analysis comes from patent applications submitted by US inventors to the United States Patent and Trademark Office in both 2019 and 2020. Numbers of patent applications for 2019 and 2020 are based off data aggregated from the USPTO's 2019 and 2020 releases of the PatEx dataset. The sample includes every patent application that has been made publicly available as of the dataset's release date. Data for patent application submissions are released on a rolling basis with a consistent systematic lag. As such, patent application submission counts are increasingly underrepresented with each later month of the year. Nevertheless, I compare the number of 2019 patent applications found in the 2019 dataset to the

number of 2020 patent applications found in the 2020 dataset so while neither number represents the total number of patent applications filed, they are comparable samples.

The unit of analysis for my statistical models is the state-year for all 50 US states and Washington DC. Each of the 51 entities has numbers of patent applications for the entire years of 2019 and 2020. The 51 entities also have measures for economic disruption, health disruption, and nonpharmaceutical interventions for the year of 2020. While a fixed-effects analysis of patent application submissions by state-month would be especially useful in studying the effects of COVID-19 disruptions within each state as the pandemic developed, the data for such an analysis are not yet available, due to the truncation bias issue mentioned above. For this reason, the sample I use contains a count of all patent applications filed in 2020 that have been released to the public so far. Instead of looking at the variation in numbers of patent applications within states over time, I study the variation between states' numbers of 2020 patent applications. While patent applications are underrepresented in later months of 2020, each state experiences the same bias, and thus can be compared.

Measures

Dependent variables. The measure for innovative activity I am using in my descriptive analysis is the number of patent applications in the US during 2020. This is then broken down by entity status of the inventor. Entity status is an indicator of the size of the organization an inventor is associated with. Each patent application is categorized as one of three entity statuses: small—nonprofit organizations or companies with less than 500 employees, large—organizations or companies with over 500 employees, or micro—independent individuals that are not named on more than four previously filed applications, do not have an income of more than three times the median household income, and are working independently from any small or

large entity. Breaking down numbers of patent applications by inventor entity status is important because we know that inventors from varying entity status are affected differentially during exogenous shocks like the 2008 recession (Breitzman 2013).

The measure I am using for innovative activity in my statistical analysis as a dependent variable is patent applications per 1000 people by US state. This also includes a breakdown by entity status of inventor and is only needed for the year 2020, since I will be creating models that predict for variation in patents per capita among US states in 2020 and not variation in numbers of patents over time. Using some form of patents or patent applications per capita rather than total numbers is not uncommon in quantitative studies that predict for patents by US state (McCann 2011). Using a per capita measure controls for the effect of population size on patent output and allows more variation for analysis (Berkes et al. 2020).

The variables for patent applications for 2019 and 2020 are created from the 2019 and 2020 batches of the Patent Examination Research Dataset (PatEx), a dataset released yearly by the United States Patent and Trademark Office (USPTO) designed for academic research on patent applications through US history (Graham, Marco, and Miller 2016). While the 2019 and 2020 batches of PatEx data have truncation bias as discussed earlier, they are released a year apart, and thus are equally affected by the time lag of patent applications being released. Correspondence with the USPTO confirms that the time lag of patent applications in the 2020 PatEx dataset has not been exacerbated by any pandemic-related workplace difficulties. Thus, while the 2019 and 2020 numbers from PatEx do not reflect the entirety of patent applications released during their respective years, the 2019 and 2020 batches can be assumed to be equally time-lagged and can be compared in descriptive analysis. Using the variables in PatEx for

inventor country, inventor region, inventor city, and inventor entity status, I aggregated number of patent applications by US state and entity status for 2019 and 2020.

While patent applications are not the best proxy for innovation, their use for this study is justified by data availability and precedence in the literature. Other measures such as patents granted, patent citations, new products introduced on the market, and new product sales are seen as better indicators of the quality of innovation (Reeb and Zhao 2020). Nevertheless, explaining innovation quality is beyond the scope of this study. Patent applications take about 2 years on average before they become granted patents, and patent citations take years to accrue. An analysis that uses such variables in a model to predict COVID-19's effect on innovation could not be performed for several more years. Using current releases of patent applications, we can begin to investigate patenting trends during the early stages of the COVID-19 pandemic immediately. Despite many scholars criticizing the use of patent applications as a measure of innovation, its relation to innovative output has been validated in the literature and many studies use patent applications in their predictive models (Breitzman 2013; Thomas, Sharma, and Jain 2011).

Independent variables. The measures I use as independent variables in my statistical analysis represent economic disruption, health disruption, and NPIs, three major effects of the COVID-19 pandemic that could have impacted innovative output. Measures for economic disruption include percent change in GDP from 2019-2020 by US state and change in unemployment from 2019-2020 by US state. These variables are taken from the US Bureau of Economic Analysis website.

Measures for health disruption include total numbers of COVID cases and COVID deaths during 2020 by US state, sourced from the Oxford COVID-19 Government Response Tracker

(OxCGRT). The OxCGRT is a dataset that collects information on numbers of COVID cases, COVID-related deaths, vaccinations, and various policy measures taken by governments in response to COVID for every day since January 1st, 2020 (Hallas et al. 2021). The US version of the dataset includes data for each US state.

Measures for nonpharmaceutical interventions include several daily ordinal scale scores averaged out for the year of 2020 for each US state that indicate the strictness of government policy. These index score variables include school closing, workplace closing, restrictions on gathering, canceled events, stay at home orders, and movement restrictions. School closing is an ordinal scale of 0–3 indicating (0) no school closing measures, (1) school closing recommended, (2) some schools required to be closed, and (3) all schools required to be closed. Workplace closing is an ordinal scale of 0–3 indicating (0) no workplace closing measures, (1) workplace closing recommended or open with alterations, (2) some workplaces required to be closed, and (3) all workplaces closed excluding essential workplaces. Restrictions on gathering is an ordinal scale of 0–4 indicating (0) no restrictions, (1) restrictions on very large gatherings (1000 people), (2) restrictions on gatherings of 101-1000 people, restrictions on gathering of 100-10 people, and (3) restrictions on gatherings of 10 people or less. Canceled events is an ordinal scale of 0–2 indicating (0) no measures for canceling public events, (1) canceling public events recommended, and (2) canceling public events required. Stay at home requirements is an ordinal scale of 0–3 indicating (0) no stay at home measures, (1) recommend not leaving house, (2) required to not leaving house except for exercise, grocery shopping, and essential trips, and (3) measures requiring people to stay at home with minimal exceptions. Finally, movement restrictions is an ordinal scale of 0–2 indicating (0) no restrictions on internal movement between

cities and regions, (1) recommended not to travel between regions/cities, and (2) internal movement restrictions in place.

Control variables. While there are many important control variables that could be used in statistical models that predict for numbers of patent applications, my dataset only includes a sample size of 51. Thus, the number of variables I can include in my models is limited (Tabachnick and Fidell 1989). While I started with many state-level demographic, social, and economic variables commonly used as controls in innovation literature, the variables I ended up including in my models were 2019 R&D spending per capita, 2019 percent of population with a college degree, 2019 percent of population that lives in urban areas, and share of population that voted democrat in the 2020 Presidential election. These variables are commonly used as control variables in literature that studies innovation through numbers of patents and patent applications (Hidalgo and Gabaly 2013). These variables were accessed through Social Explorer (<http://socialexplorer.com>), which publishes data collected by the United States Census Bureau, the 2020 Occupational Employment Survey, and the U.S. Bureau of Economic Analysis.

In literature that studies the effects of various factors on patents and patent applications, variables for R&D spending and human capital, e.g., percent of population with a college degree, were the most common control variables used (Thomas, Sharma, and Jain 2011). In such a framework, innovative output is largely determined by how much money is allocated to innovative work and how much human talent is available to work on innovative activities. Percentage of people living in urban settings is an important control in models of health disruptions, as COVID caused more damage in urban communities in 2020, and innovation also tends to occur in urban hubs. Share of population that voted democrat in the 2020 election is a

proxy for average political affiliation that is linked to both creative output and COVID-19 related government restrictions (McCann 2011).

Analytic procedure

The first analysis will use descriptive statistics to assess changes in numbers of US inventor patent application submissions to the USPTO between 2019 and 2020. The second analysis will use statistical models to determine whether measures of economic disruptions, health disruptions, and NPIs caused by COVID-19 are useful predictors of numbers of patent applications submitted among US states in 2020. For more information regarding the type of statistical model I propose to use and my rationale for using it, see the section below that outlines my plan for the statistical analysis.

Descriptive Analysis

Batches from the 2019 and 2020 editions of the USPTO PatEx dataset will be compared to determine whether there are any important differences in the numbers of patent applications between the two years. As discussed earlier, while batches for both years are right-lagged and do not contain the complete set of patent applications submitted, we can assume that the delay for when applications become publicly available in both years is consistent, and thus we can compare the data on 2019 found in the 2019 dataset to the data on 2020 found in the 2020 dataset. I will compare 2019 and 2020 by the total number of patents as well as the number of patents by entity status.

Statistical Analysis

Using multiple linear regression models, patent applications per capita (dependent variable) will be regressed against measures of economic disruption, health disruption, and NPIs (independent variables) that have emerged during the first year of the pandemic to determine whether there are any statistical links between patent application numbers and the three categories of disruptions from COVID-19. Regular multiple linear regression will be used rather than regressions for count variables, because although number of patent applications is indeed a count variable, the outcome variable used in this analysis, patent applications per capita, is not. Models will include simple linear regressions with single explanatory variables and multiple linear regression models with control variables.

Regression models will seek to answer whether measures of economic disruptions, health disruptions, and nonpharmaceutical interventions that emerged due to COVID-19 can explain variation in patent applications per capita in 2020 among US states. They will also seek to answer whether there are differences among the models depending on entity status of inventor.

RESULTS

Descriptive Analysis

My first analysis compares the change in numbers of patent applications from 2019 to 2020 based on my sample taken from the USPTO PatEx dataset. Table 1 shows that total applications slightly decreased from 2019 to 2020, with a drop of about 5.4%. Surprisingly, patent applications for small organizations (under 500 people) had the lowest reduction in applications at -3.2%, followed by large organizations (over 500 people) at -6.5%, and micro inventors at -9.7%. I expected large organizations to fare better than small organizations because

large corporations usually have more resources and funding—something that might help sustain high levels of patent application output. Large organizations also did not experience as drastic a drop off in patent applications compared to small organizations during the 2008 recession. The large drop off for independent inventors is also surprising, because I expected them to have more time to work on inventive activities due to quarantining and social distancing. I also predicted that patent applications from micro inventors would increase due to individuals having more time at home to work on inventive projects during stay-at-home orders and workplace closings.

[See Table 1]

The first year of the pandemic brought with it many drastic economic, health, and social disruptions to society, and it is likely that the overall drop in numbers of patent applications is due to the various effects of COVID-19. While my data for patent applications in 2019 and 2020 is a sample, the USPTO releases the complete number of patent applications submitted each year in a yearly report. These reports do not include counts of applications by entity status or geographic location, but they do differentiate applications from US residents and foreigners.

From data in the 2020 year-end report, we see that the decrease in patent applications submitted by US inventors in 2020 is the largest drop that has occurred in 20 years (see Figure 1). The last two decades show a gradual increase from 164,795 applications in 2001 to 269,586 applications in 2020. Over the 20-year span, patent applications increased by 63.59% with an average yearly increase of 3.18%. The years between 2007 and 2009 show single year changes of -4.04% in 2008 and -2.88% in 2009, coinciding with the global financial crisis. While applications have slightly decreased from 2017 to 2019, with an average yearly change of -1.16% during those years, 2020 shows a considerable drop off. Compared to 2019, numbers of patent applications in 2020 have decreased by 15,527 applications, or a change of -5.45%.

Among yearly changes over the last 20 years, -5.45% is about two standard deviations away from the mean. While we cannot be sure, it is reasonable to assume that the disruptions of COVID-19 may have been at least partially responsible for the decrease in patent applications. Statistical analysis will further investigate whether there is a direct link between economic disruptions, health disruptions, and NPIs and numbers of patent applications among US states.

[See Figure 1]

Statistical Analysis

Effect of Economic Disruptions. A major part of COVID-19's effect on society has been the economic disruption it has caused. In the US, GDP decreased by 3.4% from 2019 to 2020 and unemployment rose from 3.67% in 2019 to 8.31% in 2020. Based on the negative effect of economic recession on innovative output established in the literature, I model the effect of percent change in GDP and change in unemployment on patent applications per capita among US states in 2020. For control variables, I use share of population with a bachelor's degree and share of population that is urban. These variables are used in literature predicting for patents and patent applications, but they are also particularly relevant to models dealing with economic analysis of job loss. While many individuals lost jobs during the pandemic, most job loss has been in low-wage and medium-wage industries (Food 2020). Thus, increases in unemployment may not be as important as the size of the college educated workforce in predicting patent applications per capita. Furthermore, innovation tends to occur in urban centers, and urban areas also experienced more job loss than rural areas (Cho, Lee, and Winters 2020).

Model 1 in Table 2 shows that both percent change in GDP and increase in unemployment were positively associated with patent applications per capita. A 1% percent increase in state GDP from 2019 to 2020 was associated with .027 more patent applications per 1000 people. This result is not surprising, since previous literature indicated that economic

recession is associated with decreased innovative output. A 1% increase in unemployment in US states was associated with .051 more patent applications per 1000 people. This would be surprising, except for the fact that innovation occurs more in urban states, and urban areas also suffered greater job loss than rural areas, as mentioned above. In Model 2 when the control variable percent urban population is added, the effect of change in unemployment is no longer statistically significant, indicating that the relationship in model 1 between unemployment and patent applications per capita was likely spurious. Models 3 and 4 show that the percent of state population with a bachelor's degree is also statistically significant and associated with higher patent applications per capita.

[See Table 2]

Similar models using patent applications per capita of different entity statuses as outcome variables reveal that the independent variables had virtually the same association for applications connected to large and small organizations, yet slightly different results for micro inventors. In models with the same independent and control variables as models 1-4 but using micro applications per capita as the outcome variable, change in GDP was not statistically significant, indicating that drops in GDP during the pandemic did not seem to affect independent inventors the same way they affected small and large firms.

Effect of Health Disruptions. The most direct impact of COVID-19 on society is the sickness and death it caused among millions of individuals. In the US, there were 20,013,459 confirmed cases of COVID in 2020, and there were 350,280 confirmed deaths from COVID in the same year. Because sickness and death of individuals leads to a disruption to work productivity (Grinza and Rycx 2020) and a decrease in the number potential inventors, one would expect that states with higher COVID cases and COVID deaths might experience a

reduction in patent applications. The control variable used in this model is percent of population living in an urban setting. This variable is important as COVID-19 spread faster in urban communities than rural communities in 2020, and innovation also largely occurs in urban hubs.

Table 3 shows that after controlling for states' urban population, there was no statistically significant association between COVID cases per capita or COVID deaths per capita and patent applications per capita. This effect holds true for total patent applications, applications from large firms, and applications from small firms. However, an increase of 1 COVID death per 1000 people in a state is associated with a decrease of 0.00305 micro patent applications per capita. According to these models, there is a statistically significant association between COVID deaths and a reduction in micro patent applications, but no other associations between COVID cases or COVID deaths and patent applications per capita.

[See Table 3]

Effect of NPIs. A unique effect of COVID-19 that is different than previous recessions is the implementation of nonpharmaceutical interventions. The last major time the US implemented nonpharmaceutical interventions to mitigate the spread of a pandemic was in 1918. Analysis of this era shows that cities with stricter NPIs did not experience a reduction in patents per capita during the 1918 pandemic and after the pandemic ended, they experienced an increase in patents per capita (Berkes et al. 2020). Based on this, we might expect that NPIs implemented in 2020 to combat COVID-19 did not lead to a reduction in numbers of patent applications. If anything, we may expect that patent applications in states with stricter NPIs might increase.

Variables created from the Oxford COVID Government Response Tracker are used as independent variables in models to estimate the effect of NPIs on patent applications per capita among US states in 2020. These variables include an average score for the year of 2020 for

school closing, workplace closing, restrictions on gathering, canceled events, stay at home orders, and movement restrictions. Control variables used in these models include 2019 R&D spending per capita, the percent of population with a college degree, and the share of the population that voted democrat in the 2020 election. These variables are important controls because states with stricter NPIs tend to be more liberal, more educated, wealthier, and have more high-tech firms—all variables associated with more patent applications per capita. If these controls are not included in models that estimate the effects of NPIs on patent applications per capita, the NPIs may appear to have an association with patent applications per capita that is explained by other characteristics of states with strict NPIs.

The OxCGRT dataset is new, and literature that uses specific NPIs variables within the dataset is also rare. There is a precedent for using NPIs in predicting patents, but the study that examines the effect of NPIs during the 1918 pandemic simply codes NPIs as either more strict or less strict. Since there are not strong conceptual models for the specific types of NPIs found in the OxCGRT dataset, I ran regression models for every NPI with every inventor entity status for patent applications. There are good reasons to investigate the effect of NPIs on different entities of inventors, because small companies, large companies, and individuals likely responded somewhat differently to changes to the structure and setting of work.

Most of the models indicated that NPIs did not have statistically significant associations with patent applications per capita even in simple linear regression models with only one NPI as an explanatory variable. Yet for the models that did estimate a statistically significant association between an NPI and patent applications, these associations disappeared after including controls for 2019 R&D spending, percent of population with a college degree, and share of population that voted democratic in the 2020 Presidential election.

The results of some of these regression models are shown in Tables 4, 5, and 6. Stricter school closing restrictions were associated with an increase in large patent applications per capita in model 1 (no controls), model 2 (R&D per capita added), and model 3 (% of population with college degree added) (see Table 5). Yet, when share of population that voted democrat in the 2020 election is the control variable in model 4, the effect of school closing is no longer statistically significant. A similar pattern emerges for other NPI variables that are found to be statistically significant in single variable models. Whether it is the effect of workplace closing on total patent applications per capita (see Table 6) or canceled public events on micro applications per capita (see Table 7), after adding control variables, any statistically significant relationship between NPIs and patent applications per capita disappears. This is likely because states that are more educated and liberal tend to be places with innovation hubs as well as places that were more likely to enact strict NPIs to combat COVID-19.

[See Tables 4–6]

DISCUSSION

The descriptive analysis that compares numbers of patent applications in 2019 and 2020 by inventor entity status showed a decrease in number of patent applications for each category, though surprisingly patent applications from small firms dropped less than large firms and independent inventors. This finding is surprising given that during the 2008 recession, the patent application rates of large firms did not drop as quickly or as drastically as the patent application rates of small firms. Why was the patent application output of large firms less resilient than that of small firms during the first year of the pandemic? It could be that small firms, which might have more localized employees, were able to adapt to workplace changes faster than large firms, whose employees are spread out in many locations. Employees at small firms might have exhibited a greater sense of comradery during the early stages of the pandemic. In-house patent

lawyers at large firms that help inventors find things to patent at the end of each quarter might have been stymied by stay-at-home orders and workplace closings. I was surprised by the drop-off of independent inventors in 2020, because I expected independent inventors to have more time to work on inventive projects at home due to NPIs. This could be due to school closings placing a greater burden on parents or because fear and uncertainty of the pandemic limited independent inventors' ability to be productive.

Models that looked at the relationship between economic disruptions and states' numbers of patent applications in 2020 confirmed my prediction that economic disruption was associated with less patent applications. Percent change in GDP from 2019 to 2020 proved to be an important predictor of patent applications per capita, while change in unemployment was not as useful of a predictor as expected. Increased change in GDP was associated with higher patent applications per capita in 2020, and descriptive statistics show that most states experienced a decrease in GDP. So, the association could also be described as smaller decreases in GDP in US states were associated with more patent applications per capita. Increases in unemployment were associated with higher patent applications per capita which would be surprising, expect that the effect disappears when controlling for percent of population that is urban in a state. Since urban centers are both innovation hubs and places where employment was more negatively affected than rural areas (Cho 2020), the association makes sense. And while job loss was a huge issue for all Americans, individuals with high-wage jobs were largely unaffected (Bauer et al. 2020). Another interesting finding in the economic disruption analysis is that changes in states' GDP did not seem to influence independent inventors. This may be because research and development funding in small and large firms is affected by immediate economic changes, while independent

inventors have low operating costs and may be able to continue projects with saved personal funds.

The findings from models that used COVID cases and COVID deaths as measures of health disruption during the pandemic were mostly unexpected. There was no statistically significant association between COVID cases or COVID deaths per capita and total patent applications per capita when controlling for urban population. This is unexpected because sickness, death, and taking care of family members would seem to lead to a decrease in productive output, yet there was no association found between COVID cases or COVID deaths and patent applications per capita for small and large firms. However, COVID deaths did have an association with patent applications per capita from micro inventors. An increase in COVID deaths in US states was associated with a decrease in patent applications per capita for independent inventors. This could be because some potential inventors died from COVID during 2020, or because inventors lost productivity because they were grieving death. Small and large firms might not have had the same association because work projects are not halted in the same way that personal projects are stopped when an individual dies or experiences loss of loved ones.

Nonpharmaceutical interventions largely had no association with patent applications per capita in my analysis. Literature that studies the effect of NPIs on innovation is rare, and to the best of my knowledge, the NPI variables in the OxCGRT dataset have not been used to predict measures of work productivity by country or state. Most NPIs had no association with patent applications per capita in simple linear regressions, and for the ones that did have an association, the effect disappeared after including control variables including 2019 R&D spending, percent of population with a college degree, and share of population that voted democrat in the 2020 election.

Why did the association of NPIs disappear after controlling for these variables? Florida (2014) argues that creative talent is not spread out evenly across the US but tends to cluster in specific geographic locations—urban areas that are known for diversity, tolerance, and openness, which are characteristics of liberal values. Members of the creative class, or people that work in industries associated with knowledge work or creative projects, are major drivers of culture and innovation and although these individuals are not all liberal, they go to where opportunities abound. Innovation hubs tend to emerge in liberal cities because that is where creative talent is concentrated, which then attracts more creative talent. Liberal states tend to have more high-tech firms and college educated people which leads to greater innovation output. In the US, there is a strong relationship between stricter NPIs and liberal government, as pointed out by Hallas et al. (2021). Therefore, the relationship between certain NPIs and patent applications is likely to be spurious. Why were school closing, workplace closing, and cancelled public events the only NPIs that were statistically significant in linear regression models? While some NPIs were implemented with little variation regardless of the politics of states, school closings, workplace closings, and cancelled public events had much more variation, with liberal states tending to have much stricter policies than conservative states.

The findings from the analysis of nonpharmaceutical interventions are important because there has been much speculation about the effects of policies like stay-at-home orders and workplace closings on work, the economy, and productivity. While there may have been negative effects of certain NPIs on work, there was no association found between stricter NPIs and patent applications per capita in US states during the first year of the pandemic. This could be an important finding to support the use of NPIs in the future, as it does not appear to have negative effect on innovation.

One relevant critique of my analysis is the question of whether effects of economic disruption, health disruption, or NPIs could show up in patent applications for 2020, since it is the first year of the pandemic, and innovation takes time. Perhaps the negative effect on innovation would not show up in patent application rates until a year or two after the start of the pandemic. While the effect of COVID-19 on patent applications may be clearer in data after 2020, the trends of patent applications over the last 20 years show that patent applications dropped immediately from 2007 to 2008, suggesting that the effects of an exogenous shock affect patent application numbers quickly.

CONCLUSION

My paper set out to study the effects of COVID-19 on numbers of patent applications submitted by US inventors to the USPTO in 2020 with simple descriptive analysis and statistical models. I first used a sample of applications from 2019 and 2020 created from the USPTO's PatEx database to see how numbers of patent applications have changed between 2019 and 2020, and how they have varied by inventor entity status. Then I used statistical models to estimate the effect of economic disruption, health disruption, and NPIs on patent applications per capita. Economic disruption was measured by percent change in GDP and change in unemployment, health disruption was measured by total COVID cases and COVID deaths in 2020, and NPIs were measured by the average ordinal score of variables representing the strength of government social restrictions in 2020.

In my analyses, I sought out to answer how numbers of patent applications have changed according to inventor entity status in 2020 and whether variables that represent economic disruptions, health disruptions, and NPIs caused by COVID are useful predictors of patent application submissions per capita among US states in 2020. I found that patent applications

decreased overall and for each inventor entity status, though surprisingly small firms experienced the least drop, maybe because they were more adaptable to the changes to work that occurred during the first year of the pandemic than large firms and independent inventors. I hypothesized that independent inventors would experience increases in patent applications in 2020, since quarantining and social distance measures during 2020 might give them more time to focus on inventive projects at home. Yet this prediction was incorrect, as micro inventors had the greatest drop in patent application numbers, perhaps due to increased child care, emotional strain, or anxiety about the pandemic.

Percent change in GDP was a useful predictor for patent applications per capita among US states, though change in unemployment was not as useful a predictor, perhaps because individuals who work at high-paying patenting companies did not lose jobs as much as people who work in medium or low wage industries. Change in GDP was not a good predictor for independent inventors however, perhaps because economic disruption most directly effects R&D budgets of companies rather than individuals.

COVID cases and COVID deaths were not useful predictors for patent applications per capita except in the case of COVID deaths and independent inventors. Increases in COVID deaths in states were associated with less patent applications from independent inventors. This effect was not seen for applications from large firms and small firms, perhaps because death or grieving can more easily stop personal projects than work projects.

Finally, NPIs were not useful predictors for patent applications per capita, because while there were initial associations found in models using NPIs as single explanatory variables, the associations disappeared when including control variables. This is probably because liberal states with high innovative output tended to be places where stricter NPIs were implemented.

The fact that patent applications from US inventors have dropped in 2020 means that companies may have to spend extra on R&D to catch up to previous levels of innovation. However, while a decrease of 5% is the largest we have seen in the last 20 years, it is not a shockingly bad figure. With how much the pandemic has negatively affected the world, a decrease in 5% shows that our system of innovation is resilient. This may be due to the fact that innovation tends to occur in privileged research universities and tech firms and inventors tend to be highly educated, upper-middle class men (Nager et al. 2016). This demographic tends to have more wealth and access to resources than women and People of Color, and the effects of the pandemic may not have negatively impacted inventors as much as the average person in the US.

My study is limited in several ways. The biggest constraint on studying the effects of COVID-19 on innovative activity is lack of data. Data for patent applications is lagged such that months in 2020 that are closer to the present are underrepresented, even despite the fact that it is now 2022. This constrain makes a fixed effects analysis that compares variation within states over time impossible. Such a study would be a useful contribution as more data becomes available in the next couple years. Furthermore, the effects of COVID-19 on innovation may be clearer when analyzes patent application trends in 2021 or 2022. Conducting a similar analysis when patent application data is available for these years might also be a useful contribution. To do a study that uses better measures for innovative activity like patent grants or patent citations on the other hand, researchers would have to wait several more years for such data to become available and useful.

The data available from OxCGRT and USPTO allowed for an analysis at the granularity of the state level. While this is a simple analysis and can be undertaken with publicly available secondary data, other methods may be better suited to answer the question of how economic

disruption, health disruption, and NPIs caused by COVID-19 affected innovation. The effect of health disruption and NPIs on productivity and creativity may be better understood through survey data from interviewing creative professionals, science and technology workers, or business leaders.

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TABLES

Table 1. US Inventor Patent Application Counts by Entity Status

Year	Total	Micro	Small	Large
2019	117245	5358	43220	68667
2020	110860	4840	41829	64191
% Change	-5.4%	-9.7%	-3.2%	-6.5%

Source: Data Aggregation from USPTO PatEx Dataset

Table 2: Regression Estimating Total Patent Applications Per Capita: Coefficients and Standard Errors

	Model 1	Model 2	Model 3	Model 4
% Change in GDP	.115** (.056)	.0220* (.0085)	.0180** (.0081)	.0172* (.0080)
% Change in unemployment	.0513** (.0091)	.0209 (.017)	.0384** (.013)	.0261 (.016)
% Urban population		.00542** (.017)		.00262 (.0019)
% Bachelor's degree			.0134*** (.0031)	.0109** (.0036)

N=51. * = $p > 0.05$, ** = $p > 0.01$, *** = $p > 0.001$

Table 3: Regression Estimating Total Patent Applications Per Capita (Models 1–3) and Micro Patent Applications Per Capita (Model 4): Coefficients and Standard Errors

	Model 1	Model 2	Model 3	Model 4
COVID cases per 1000	-.00157 (.0010)		-.00179 (.0012)	
COVID deaths per 1000		-.0205 (.049)	.0216 (.056)	-.00305* (.0013)
% Urban population	.00624*** (.0015)	.00653*** (.00011)	.00604*** (.0016)	.00024*** (.000040)

N=51. * = $p > 0.05$, ** = $p > 0.01$, *** = $p > 0.001$

Table 4: Regression Estimating Large Patent Applications Per Capita: Coefficients and Standard Errors

	Model 1	Model 2	Model 3	Model 4
School closing	.204* (.081)	.0127* (.048)	.0135** (.048)	.144 (.075)
R&D per capita		.0000847*** (.000086)	.0000776*** (.000010)	
% College Degree			.00208 (.0017)	
% Democrat				.433** (.12)

N=51. * = $p > 0.05$, ** = $p > 0.01$, *** = $p > 0.001$

Table 5: Regression Estimating Total Patent Applications Per Capita: Coefficients and Standard Errors

	Model 1	Model 2	Model 3
Workplace closing	.285** (.082)	.0526 (.057)	.136 (.10)
R&D per capita		.000131*** (.000015)	
% Democrat			.571* (.23)

N=51. * = $p > 0.05$, ** = $p > 0.01$, *** = $p > 0.001$

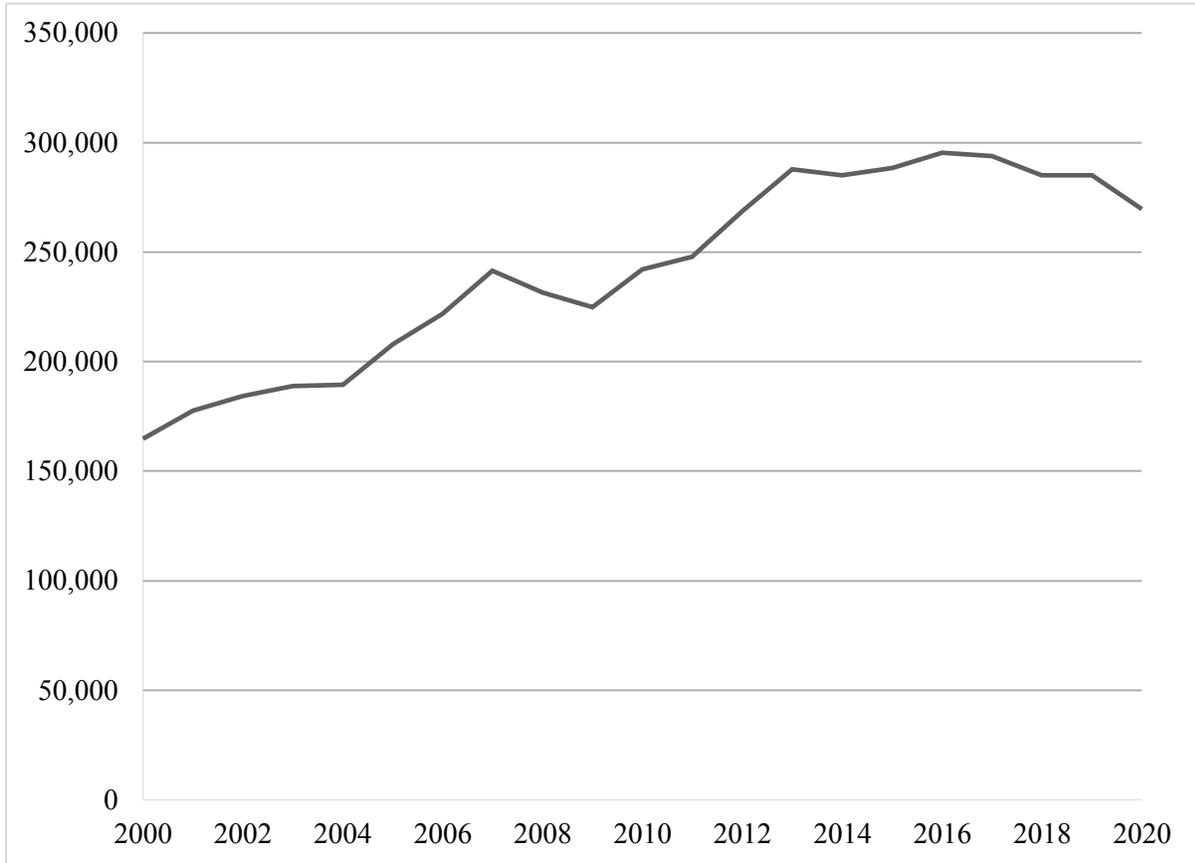
Table 6: Regression Estimating Micro Patent Applications Per Capita: Coefficients and Standard Errors

	Model 1	Model 2	Model 3	Model 4
Cancelled Public Events	.00628* (.0026)	.00484* (.0024)	.00484 (.0024)	.00434 (.0025)
% College Degree		.000379*** (.000097)	.000378* (.00017)	
% Democrat			.000050 (.0093)	.0170** (.0057)

N=51. * = $p > 0.05$, ** = $p > 0.01$, *** = $p > 0.001$

FIGURES

Figure 1. Domestic Patent Applications Submitted to the USPTO by Year



Source: USPTO 2020 Year-End Report