Sports Inspiration and Inventor Productivity

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Abstract

This study examines whether sports inspiration influences inventor productivity. We find that long-waited championship of local teams in major U.S. professional sports promotes greater patent volume from local inventors, with heightened forward citations and economic value generated. The effects are more pronounced for non-superstar inventors and underdog victories. Further analysis indicates that inventors pursuing more exploratory innovation strategy and the improvement in the average patent quality are potential mechanisms through which sports inspiration affects inventor productivity. Our results suggest that sports victories can inspire and motivate inventors, leading to increased productivity and impactful innovations. This research provides novel empirical evidence on the nuanced relationship between sports and inventor creativity, highlights non-monetary drivers of inventor productivity, and quantifies the real economic impacts of sports inspiration.

Keywords: Sports Inspiration; Victories; Innovation; Inventor Productivity.

JEL Classification: L26; L83; M13; G41.

1. Introduction

Innovation is increasingly crucial for national and societal competitiveness, ultimately driving economic growth and success (Solow, 1957; Porter, 1992; Balkin et al., 2000; Ganco, Ziedonis, & Agarwal, 2015; Eisenhardt & Martin 2000). Moreover, innovation enables long-term corporate prospects (Hall, 1993a; Henderson & Cockburn, 1994) and significantly determines a firm's market value (Griliches, 1984; Hall, 1993b). Inventors play a vital role in corporate innovation outcomes (Hall, 2002). Unlike other workers with clear routines, inventors engage in riskier, unpredictable, and complex tasks, requiring significant effort input. Since inventors' effort choices are difficult to observe, it is important to explore the motivations of inventors. What propels these creative minds to push the boundaries of discovery?

The motivations driving corporate inventors are complex and multifaceted. While monetary incentives play a significant role (Lerner & Wulf, 2007; Gao, Hsu & Zhang, 2023), financial rewards alone may not fully capture the essence of inventor motivation. Intriguingly, studies reveal that scientists often accept lower wages to pursue research, effectively "paying to be scientists" (Stern, 2004; Sauermann & Cohen, 2010; Sauermann & Roach, 2014). This phenomenon suggests that inventors' mental states and intrinsic motivations may outweigh purely monetary factors (Osterloh & Frey, 2000; Sauermann & Cohen, 2010; Lam, 2011).

A spectrum of non-monetary motivations has been identified as influential in driving inventor productivity. These include job security (Acharya et al., 2014), intellectual challenge (Sauermann & Cohen, 2010), publishing opportunities (Sauermann & Roach, 2014), autonomy (Sauermann & Cohen, 2010), work environments (Gao et al., 2020), and even residence location (Luo et al., 2022). Given the limitations of financial incentives alone, exploring these non-monetary drivers provides valuable insights into inventor motivation.

Our study aims to expand this understanding by investigating a novel psychological driver: sports inspiration. We posit that the emotional impact of sports victories may significantly influence inventor productivity and creativity. This choice is grounded in research demonstrating that sports events can elicit profound emotional shifts, affecting individuals' optimism, pessimism, and self-esteem (Depetris-Chauvin, Durante, and Campante, 2020; Jones et al., 2012). These emotional responses often transcend the realm of sports, potentially shaping attitudes, and behaviors across various life aspects, including professional endeavors.

Sports victories have been shown to generate positive moods (Hirt et al., 1992; Jones et al., 2012), which can facilitate creative problem-solving (Isen, Johnson, Mertz, and Robinson, 1985; Fredrickson, 1998; Isen, 1999, 2000; Baas, De Dreu, and Nijstad, 2008; To, Fisher, Ashkanasy, and Rowe, 2012). Furthermore, positivity promotes greater optimism and risk-taking (Tversky and Kahneman, 1973; Isen, Shalker, Clark, and Karp, 1978; Bassi, Colacito, and Fulghieri, 2013) - crucial components of the innovative process (Galasso and Simcoe, 2011; Hirshleifer, Low, and Teoh, 2012; Chen, Podolski, Rhee, and Veeraraghavan, 2014).

By exploring this connection between sports-induced emotions and inventor motivation, our study seeks to bridge these seemingly disparate worlds. We aim to uncover how the emotional responses triggered by sports victories may motivate inventors to engage in more innovative activities, potentially unlocking new pathways to enhance inventor productivity and creativity.

We do so by measuring sports inspiration resulting from major professional sports league championships in the United States[1], including the final championships of the National Football League (NFL), National Basketball League (NBA), Major League Baseball (MLB),

[1] The sports market in the United States is the largest in the world and their major sports events, like NFL, are also characterized by intense fan enthusiasm. In addition, according to the 2016 PwC Sports Outlook (https://www.pwc.com/us/en/industry/entertainment-media/publications/assets/pwc-sports-outlook-2016.pdf), the US sports industry is an important revenue generator in the economy, which was worth $63.9 billion in 2015, and this will continue to increase.

and National Hockey League (NHL), won by a local team of the city for the first time or at least over ten years since the last victory[2].

We collect the patent data and inventor information from the Harvard Business School patent inventor database (Li et al., 2004). We restrict our main analysis to inventors affiliated with U.S. publicly listed firms so that we can control for innovation inputs and the characteristics of the firms in which the inventors work[3]. We define the treated inventors residing in areas affected by sports inspiration, specifically, those living in a city that won a championship of the 'big four' professional sports in the U.S. for the first time or won another championship after a gap of ten years or more. The control group for each sports inspiration event includes inventors from cities that have never won a championship in the big four professional sports in the U.S., from the same state as the treatment group's cities.

Using a large sample of inventor-level data from the Harvard Patent Database from 1975 to 2007, we perform the stacked differences-in-difference estimation to investigate the influence of sports inspiration on inventor productivity. The baseline result shows that the treated inventors produce more patents, receive more forward citations, and have higher economic value relative to the control inventors. Specifically, the treated inventors produce on average 2.1% more patents, and their patents receive on average, 9.8% more forward citations and have on average, 9.8% more economic value than control inventors . Furthermore, our findings still hold after several robustness tests, including matching employing the propensity score matching (PSM) method (Rosenbaum and Rubin, 1983). We show that prior to the event, both treatment and control groups exhibited no significant difference in inventor innovative activities, but after the event, there was a significant increase in inventor productivity for

[2] Based on a survey by Gallup in the U.S. (https://news.gallup.com/poll/4735/sports.aspx), over 60% of respondents describe themselves as sports fans in general, and around 65% state that their favorite sports are football, basketball, baseball, and ice hockey.

[3] In the last section, we also focus on all inventor and our results still hold.

treatment inventors, which also confirms the parallel trend assumption underlying our empirical design. Our tests show that the pre-treatment trends in inventor productivity are indistinguishable between these two groups, with most of the effect occurring after the sports inspiration event, suggesting a causal effect.

To examine whether sports inspiration has varying effects on inventor productivity, we perform a series of additional tests. First, we show that sports inspiration has a greater effect on the innovative productivity of non-superstar inventors than the productivity of superstar[4] inventors. We also show that the sports inspiration events caused by an underdog win have a more significant effect on inventor productivity than that caused by victory from a non-underdog team.

Furthermore, we explore potential channels through which sports inspiration may influence inventor productivity. First, we assess whether treated inventors alter their innovation strategies following inspirational events, specifically producing more exploratory and risk-taking patents versus exploitative patents. We find treated inventors pursue more exploratory patents. Furthermore, we examine cognitive impacts, which could enable beneficial R&D decisions and higher-quality patents. We find average patent quality increases for treated versus control inventors' post-inspiration.

Our study contributes to three streams of literature. First, we add to the literature on sports outcomes' effects on economic phenomena by extending beyond short-term stock market studies (e.g., Edmans et al., 2007) to analyze long-term innovation impacts. This approach bridges the gap between immediate market reactions and sustained economic productivity. Second, we present large-scale evidence on how sports-induced mood influences creativity, adding nuance to the conflicting results of small-scale psychology experiments

[4] Following Zacchia (2018), we define inventors as superstar inventors as those in the top 5% of the distribution of patents that the inventor filed by event

(Davis, 2009). Our comprehensive dataset of inventor productivity offers a more robust perspective on this relationship, helping to reconcile previous contradictions in understanding the interplay between emotional states and cognitive functions in real-world contexts. Finally, we expand the scope of innovation research by focusing on inventors, a group that has received less attention compared to executives, boards, and shareholders. While existing literature has examined how behavioral traits of top management and governance structures affect innovation (Galasso and Simcoe, 2011; Hirshleifer, et al., 2012; Ederer and Manso, 2011, 2013; Balsmeier, Fleming, and Manso, 2017)[5], we uniquely demonstrate that inventors' productivity, shaped by external factors like sports outcomes, can significantly influence both innovation output and market value. This perspective adds a new dimension to understanding the drivers of corporate innovation, highlighting the importance of considering broader psychological and environmental factors affecting those directly responsible for innovative activities. Overall, this work introduces a novel psychological factor driving inventor productivity, bridging the gaps between sports psychology, creativity research, and innovation studies, and provides valuable insights for both academic research and corporate innovation management. The rest of this paper is organized as follows. Section 2 reviews relevant literature and develops the hypothesis. Section 3 describes the data and variable measurements. Section 4 describes the empirical design, including the classification of treatment groups and control groups and the stacked DID model. Section 5 presents the results of the baseline analysis, robustness, a series of additional analyses, and potential mechanism analysis. Section 6 concludes.

2. Literature Review and Hypothesis Development

[5] It is worth noting that some research has explored how incentives and compensation plans for non-executive employees can positively influence a firm's innovative activities. Examples include studies by Lerner and Wulf (2007), Acharya, Baghai, and Subramanian (2014), Chang, Fu, Low, and Zhang (2015), and Chen, Chen, Hsu, and Podolski (2016). However, our study differs by focusing on external psychological factors rather than internal organizational policies.

2.1.1 The Importance of Inventor

Innovation plays an increasingly crucial role in national and societal competitiveness, ultimately driving economic growth and success (Solow, 1957; Porter, 1992; Balkin et al., 2000; Ganco, Ziedonis, and Agarwal, 2015; Eisenhardt and Martin 2000). It has been shown to be essential for the long-term success of corporations (Hall, 1993a; Henderson and Cockburn, 1994) and significantly determines a firm’s market value (Griliches, 1984; Hall, 1993b). Corporate innovative success lies in the hands of inventors working on research and development (R&D) projects (Hall, 2002), with their creativity being “the key ingredient for job creation, innovation and trade” (United Nations Conference on Trade and Development, 2010). Unlike routine workers with clear goals (e.g., production workers, salespersons, and administration staff), inventors’ tasks are risky, unpredictable, and complex. These job features necessitate substantial autonomy in inventors’ activities, making it difficult to monitor their performance. Consequently, the voluntary efforts made by inventors are essential to maintaining a productive inventor workforce. Understanding the motivations of individual inventors is therefore a critical issue, as it directly impacts the innovative capacity of firms and, by extension, entire economies.

2.1.2 Non-money Incentive of Inventor Productivity

Prior studies document that monetary incentives play a significant role in motivating corporate inventors (Lerner and Wulf, 2007; Gao, Hsu & Zhang, 2023). The study by Lerner and Wulf (2007) shows that offering long-term incentives to corporate research and development leaders, such as stock options and restricted stock, leads to an increase in the number of times their patents are cited. Gao et al. (2023) examine the role of pay transparency in the productivity of firms' and inventors' innovation activities using the staggered adoption of the state-level pay secrecy laws and find that there is a significant increase in inventor productivity of firms located in states that have passed such laws relative to firms elsewhere.

However, monetary incentives may not be sufficient. The economics literature documents that scientists "pay to be scientists" because they are willing to sacrifice wages for the opportunity to do research (Stern, 2004; Sauermann and Cohen, 2010; Sauermann and Roach, 2014). Other non-monetary incentives include job security (e.g., Acharya, Baghai, and Subramanian, 2014), intellectual challenge (Sauermann and Cohen, 2010), academic publication opportunities (Sauermann and Roach, 2014), and autonomy (Sauermann and Cohen, 2010). Recently, Gao et al. (2020) identified a positive causal effect of healthy working environments on corporate innovation at the corporate inventor's level, using the staggered passage of U.S. state-level laws that ban smoking in workplaces. In addition, Luo et al. (2022) find that there is a positive relationship between air quality and the productivity of patent inventors using the NOx budget program (NBP) as a quasi-natural experiment. Others argue that the mental state of inventors is more important than monetary incentives (Osterloh and Frey, 2000; Sauermann and Cohen, 2010; Lam, 2011). Clearly, understanding the effect of non-monetary incentives on inventors is meaningful.

2.2 The Impact of Sports Event Outcomes

The following review explores a plethora of studies investigating how individuals emotionally respond to sports results and how these responses affect behavior, including mood, self-esteem, and economic decisions that extend beyond the confines of sports arenas.

2.2.1 Emotional Responses to Sports Event Outcomes

A substantial body of research consistently demonstrates the profound emotional impact of sports events on individuals (Schwarz et al., 1987; Hirt et al., 1992; Schweitzer et al., 1992; Wann et al., 1994; Jones et al., 2012; Ge et al., 2021; Cardazzi et al., 2022). Favorable outcomes, such as victories or strong performances by one's favorite team, tend to evoke positive emotions and elevate the mood of sports enthusiasts. Conversely, disappointing results are invariably associated with negative emotions. The seminal work of Wann et al. (1994) emphasizes that these emotional reactions often extend well beyond the immediate aftermath of the sporting event, significantly impacting individuals' self-esteem and overall life satisfaction.

Further, Hirt et al. (1992) reveal a noteworthy improvement in the academic performance of college students after witnessing their team win a basketball match, highlighting the spill-over effects of sports outcomes into non-sport-related domains. Similarly, Schwarz et al. (1987) document that Germany's World Cup match outcome in 1982 induced notable changes in subjects' well-being and perceptions of national issues. In a parallel vein, Schweitzer et al. (1992) demonstrate that students supporting the winning team in a televised American football game exhibited lower evaluations of the probability of a 1990 war in Iraq and its potential casualties than fans of the losing team.

Jones et al. (2012), analyzing survey data from English and Spanish soccer fans during the 2010 World Cup, found enduring positive emotional experiences associated with group success, which persisted longer than the negative emotional experiences linked to group failure. Similarly, Ge et al. (2021) present evidence of a notable increase in thefts and robberies in San Paulo, Brazil, following football matches, with upset losses and derby games eliciting particularly pronounced effects. Additionally, Cardazzi et al. (2022) establish a compelling correlation between unexpected losses by the local NBA team and an increase in male-on-female in-home violence. Recent research by Depetris-Chauvin, Durante, and Campante

(2020) examines the role of shared collective experiences in building national identity by studying the impact of national football teams' victories in sub-Saharan Africa. Their findings reveal that individuals surveyed in the days after an important victory of their country's national team exhibit a 37 percent lower likelihood of primarily identifying with their ethnic group and a 30 percent increase in trust in other ethnicities compared to those interviewed just before. Crucially, national team achievements also reduce violence, with countries that (barely) qualified for the Africa Cup of Nations experiencing 9 percent fewer civil conflict episodes in the following months than countries that (barely) did not.

2.2.2 Economic Implications of Emotional Responses to Sports Outcomes

The emotional responses elicited by sports events have reverberations in the realm of economic activities, as evidenced by Arkes et al. (1988), who observed an increase in Ohio State lottery ticket sales following the victory of the Ohio State University football team. In the financial markets, Ashton et al. (2003), Edmans et al. (2007), Kaplanski and Levy (2010a), Chang et al. (2012), and Pantzalis et al. (2014) assert that sports results can significantly impact stock returns. Furthermore, Akhigbe et al. (2017) investigated the influence of predictable sports sentiment on local trading activities and found statistically significant increased trading before games. Using household-level data, Kaplanski et al. (2015) provide compelling evidence that sports results and general feelings substantially affect stock market return expectations, with a strong positive correlation between the success of an individual's favorite sports teams and their expectations.

2.3 Hypothesis Development: Sports Inspiration and Inventor Productivity

In this study, we investigate the influence of sports inspiration on inventor innovation productivity. We define sports inspiration as exogenous shocks stemming from championship victories in major professional sports leagues in the United States, including the NBA, NFL, NHL, and MLB, occurring at the city level over a ten-year period. Distinguishing itself from mere sports sentiments utilized in prior research, sports inspiration events are characterized by their precision, specificity, and the enduring impact they impart upon individuals.

There is a large body of evidence that shows that sports victories can generate positive moods (Hirt et al. (1992); Jones et al. (2012)), which can facilitate creative problem solving, cognitive elements (Isen, Johnson, Mertz, and Robinson, 1985; Fredrickson, 1998; Isen, 1999, 2000; Baas, De Dreu, and Nijstad, 2008; To, Fisher, Ashkanasy, and Rowe, 2012). Furthermore, these positive mood increases confidence in one's abilities, thus inducing individuals to show more initiative at work and pursue challenges with greater persistence (Kavanagh and Bower, 1985).

In addition, a positive mood has been shown to promote greater optimism and risk-taking (Tversky and Kahneman, 1973; Isen, Shalker, Clark, and Karp, 1978; Bassi, Colacito, and Fulghieri, 2013), which are important components of the innovative process (Galasso and Simcoe, 2011; Hirshleifer, Low, and Teoh, 2012; Chen, Podolski, Rhee, and Veeraraghavan, 2014).

Building upon psychological insights and behavioral theories, we posit the following hypothesis:

Hypothesis 1: *Sports inspiration promotes inventor innovation productivity.*

3. Data and Sample

To empirically examine the effect of sports inspiration on inventor productivity, we collected patent data and inventor information from the HBS Patent Inventor Database (Li et al., 2014). This database records every patent granted by the U.S. Patent and Trademark Office (USPTO) from 1975 to 2010. From the database, we obtained detailed information about the inventors of each patent, including their names, cities of residence, and zip codes. Using a disambiguation algorithm, the database assigns each inventor a unique identifier, which enables us to track their innovation records, along with their accurate residential location. To account for heterogeneity among inventors, we also control for innovation inputs and the characteristics of the firms for which the inventors work. As such, we restrict our main analysis to inventors affiliated with U.S. publicly listed firms (Chen et al., 2022; Luo et al., 2022; Fich et al., 2023). We use the HBS Patent Inventor Database to obtain corresponding citation data as well. Patent inventors are matched with U.S. publicly listed firms based on patent data from Kogan et al. (2017), who provide the Center for Research in Security Prices (CRSP) firm identifier for each patent. We collect financial data for these publicly listed firms from Compustat.

Because an inventor is listed in the HBS Patent Inventor Database only when they file a patent, our original sample comprises inventor-year observations in which inventors filed at least one patent in a given year. We identify the first and last year in which an inventor files a patent in the Patent Inventor Database (Baghai et al., 2019). We then assign a value of zero to the inventor's innovation output variables for all years with no patent record. In this way, we create consecutive time series data for all inventors[6]. As an inventor's residential information is available only when they file a patent, we assign the inventor's most recent residential information to the years for which there is no patent record (Hombert and Matray, 2017). We use the application year (i.e., the filing year) of a patent as the time marker in our empirical tests, since the application year should be closest to the time when the new technology appeared (Hall and Ziedonis, 2001). Given an application-approval lag of two to three years (Hall and Ziedonis, 2001), we exclude the final three years (2008-2010) from our analysis. Therefore,

[6] We use patent-based measures to gauge inventor performance with caution and acknowledge their shortcomings (Lerner and Seru, 2022; Jaffe and de Rassenfosse, 2017). For example, inventors might choose not to patent their inventions due to concerns such as information leakage. Therefore, patent-based measures could be noisy measures of inventor performance, especially in industries with low patent propensity (Cohen, Nelson, and Walsh, 2000; Hall, Helmers, Rogers, and Sena, 2014).

our sample period starts in 1975 and ends in 2007. The inventor-level data constitute the dataset used in our baseline analysis.

3.1 The Measurement of Sports Inspiration

To measure sports inspiration, we hand collect the championship data of four major sports leagues (NFL, MBA, MLB, and NHL) in the U.S. We define an external event, or exogenous shock when a city wins its first sports championship or has not achieved a championship victory in over a decade. We use this event to gauge its impact on sports inspiration. For example, in 1999, San Antonio Spurs won its first NBA championship, the city's first championship of the four major sports leagues. Similarly, for Boston in Massachusetts, the Boston Red Sox won the 2004 MLB championship, over ten years since it won the last championship (Boston Celtics won the NBA championship in 1986). These constitute our sports inspiration events. More detailed information can be found in Figure 1.

[Insert Figure 1 here]

MLB, NHL, NFL, and NBA were founded in 1903, 1917, 1922, and 1946, respectively. Based on the definition of sports inspiration we propose above, the first exogenous shock to measure sports inspiration is Boston Americans (changed to Boston Socks) when it won its first MLB championship in 1903. In this paper, our sample period is from 1975 to 2007. Thus, in our project, the first sports inspiration event is the NBA championship won by Portland Trail Blazers for Portland in 1977, which is the city's first championship of the four major sports leagues, and the last sports inspiration shock is the Indianapolis Colts who won the NFL champion for Indianapolis in 2007.

3.2 The Measurement of Inventor Productivity

We use three measures of an inventor's innovation output, based on newly filed patents by the inventor during the filing year that are eventually granted. The first measure is the number of patents, calculated as the total number of newly filed patents. The second measure is the number of citations, which is determined by the sum of all forward citations received by these newly filed patents. Studies indicate that forward citations received by a patent reflect the patent's scientific value, with the expectation that more ground-breaking patents will receive a greater number of citations than those that are less innovative (Hall et al., 2002; Hall et al., 2005; Aghion et al., 2013). The third measure is total patent value, calculated as the sum of the economic value of all newly filed patents. According to Kogan et al. (2017), this measure is calculated as the increase in the market value of the firm (after adjusting for benchmark returns) within a three-day window following the patent grant announcement. As the three innovation output measures are highly skewed, we take the natural logarithm of 1 plus the number of patents, number of citations, and total patent value separately, and use these log-transformed measures in our analysis.

Following Moretti (2021), we adjust the number of patents, citations and values attributed to an inventor in a given year based on the number of inventors listed for a specific patent. If a patent has multiple inventors, we assign equally weighted fractions of the patent and its citations to each inventor. For instance, if a patent lists four inventors, each inventor is credited with one-quarter of a patent and one-quarter of all subsequent citations.

3.3 The Measurement of Firm Characteristics

Our analysis is based on a sample of inventors affiliated with U.S. public firms, which enables us to control for a set of firm-level variables in our analysis. First, as large firms usually generate more patents and citations than small firms (Hall and Ziedonis, 2001), we include firm size (*Asset*), defined as the natural logarithm of total assets, in the control set. To control for the firm's innovation inputs, we include R&D expenses (*R&D*), defined as R&D expenditure scaled by total assets. Following prior studies (e.g., Hirshleifer et al., 2012), we set *R&D* for observations with missing R&D information in Compustat to 0. We also control for firms' capital investment (*CapEx*), defined as capital expenditures scaled by total assets, return on assets (*ROA*), defined as earnings before interest and tax divided by total assets, cash holding (*Cash*), defined as cash and short-term investments scaled by total assets, leverage (*Leverage*), defined as the book value of debt scaled by total assets, and Tobin's Q (*Tobin's Q*), defined as market value of equity plus book value of total assets minus book value of equity minus balance sheet deferred taxes, normalized by book value of total assets. Finally, we control for the effect of the life cycle of firms by including firm age (*Firm_Age*), defined as the natural logarithm of 1 plus the number of years elapsed since the first year in which that firm appeared in the Compustat database. As information about inventor characteristics is limited, the only inventor-year variable we control for is the inventor tenure (*Tenure*), defined as the natural logarithm of one plus the number of years between the year in which the inventor entered the patent database and the observation year. Detailed descriptions of all variables are provided in Appendix A.

3.4 Descriptive Statistics

Table 1 reports the descriptive statistics of the key variables in the empirical analysis. The table shows that the means of *LnPat*, *LnCit*, and *LnVal* are 0.244, 1.022, and 0.857 respectively. With regard to the control variables, the mean of the *Asset* is 8.652 and the mean of the *R&D* is 0.08. The average value of *ROA*, *Leverage*, *CapEx*, *Cash*, *Tobin's Q*, and *Firm_Age* for the firms in our sample is 0.134, 0.185, 0.066, 0.186, 2.615, and 3.164, respectively. In addition, the mean of *Tenure* is 1.907, corresponding to 5.73 years, which suggests relatively long time series data for the average inventor.

[Insert Table 1 here]

4. Empirical Methodology

4.1 Defining Treatment and Control Groups

Our treatment group consists of inventors residing in cities affected by sports inspiration, namely, those living in a city that won a championship of the 'big four' professional sports in the U.S. for the first time or won another championship after a gap of ten years or more. We examine the changes in both the quantity and quality of inventor productivity over a seven-year window surrounding the event (the event year, three years before, and three years after). Our control group for each sports inspiration event includes inventors from cities that have never won a championship in the big four professional sports in the U.S., from the same state as the treated cities.

In many cases, both the inventor's residential address and the assignee's address (typically the company that initially owns the patent) are available. Following Moretti (2021), we do not use the assignee address because it may not reflect the actual location where the research was conducted; often, it is merely the address of the corporate headquarters, not the R&D facility.[7]

[7] In our sample, around 46% of inventors had a residential state different from the headquarters of their employing firms from 1975 to 2007. Additionally, from 1993 to 2007, around 96% of inventors had a residential city different from the headquarters of their employing firms.

4.2 Stacked DID Model[8]

To investigate how sports inspiration affects inventor productivity, we perform the following difference-in-differences (DID) analysis using a stacked sample:

$$Y_{i,t+1,j} = \beta_1 Treat_{ij} * Post_{tj} + \Sigma Controls + Inventor_j + Year_j + City_j + Firm_j + \epsilon_{itj} . \qquad (1)$$

The dependent variable $Y_{i,t+1,j}$ represents the quantity (*LnPat*) and quality (*LnCit*) index of inventor productivity for inventor i in year t + 1 for the event j. *Treat* is an indicator variable that equals one (zero) for the treatment (control) group. To conduct a difference-in-differences analysis, we also define an indicator variable, *Post*, which equals one for years after the sports inspiration event. $Inventor_j$, $Year_j$, $City_j$, and $Firm_j$ are the inventor-, year-, city-, and firm-fixed effects for each event j, respectively. ϵ_{itj} is the residual of the model. All of the t-statistics are on an adjusted basis, clustered[9] by event*city (White 1980; Petersen 2008; Cengiz, Dube, Lindner, and Zipperer, 2019).

Our key interest is the estimate of the coefficient β_1, which captures the effects of the influence of sports inspiration on inventor productivity. If sports inspiration promotes inventor productivity, we should observe positive and significant coefficient estimates on $Treat_{ij} * Post_{tj}$.

5. Empirical Results

[8] Traditional staggered DID analysis may generate biased estimates because of negative weights in the presence of heterogeneous treatments effects, which can be alleviated by the stacked DID identification strategy (e.g., Cengiz, Dube, Lindner, and Zipperer, 2019; Baker, Larcker, and Wang, 2022). So, we use a stacked DID model to investigate the sports inspiration on inventor productivity, and treatment and control cities are defined event by event.

[9] Considering the intra-cluster correlation, many patents are assigned at the team/firm level, which means there is a strong (mechanical) correlation in patent output across inventors within a team-firm. This paper focuses on the individual inventor level; therefore, we re-run the baseline analysis clustered at the event-firm level to rule out this concern and our results still hold. Details can be seen in Appendix B.

5.1 Baseline and Parallel Trend

We use the stacked DID model to investigate the influence of sports inspiration on inventor productivity. In Table 2, we examine the effect of sports inspiration on inventor productivity using the regression model (1). Column (1), Column (3), and Column (5) show the estimation of the impact of sports inspiration on *LnPat*, *LnCit*, and *LnVal*, respectively, with only fixed effects. The coefficient of *Treat*Post* is positive and significant at 1% level for all three results. In Column (2), Column (4), and Column (6), we include control variables in our regression analysis. The coefficient of *Treat*Post* is positive and significant at 1% level for all three outcomes suggesting that inventors not only generate more patents but also generate more highly qualified patents after sports inspiration, relative to controlled inventors. In terms of economic magnitude[10], treated inventors file 8.6% more patents, and their patents receive more 9.59% more forward citations, and create 11.44% more economic value relative to controlled inventors after sports inspiration. Therefore, the effect of sports inspiration on inventor innovation is also economically significant.[11]

[Insert Table 2 here]

[10] As for the calculation economic significance of dummy variable *Treat*Post*, we follow Mitton (2021) using the formula $E_{\frac{1}{\bar{y}}} = \left| \frac{b}{\bar{y}} \right|$. b represents the coefficient of the *Treat*Post* and $\bar{y}$ represents the mean value of the dependent variable, here is the mean value *LnPat*, *LnCit*, and *LnVal*. For example, the economic magnitude of the influence of sports inspiration on the number of newly filed patents in Column (2) Table 2, we calculate it using the value of the coefficient of the *Treat*Post* 0.021 and value of the mean value of *LnPat* 0.244 following the formula $E_{\frac{1}{\bar{y}}} = \left| \frac{b}{\bar{y}} \right|$. We replace b with 0.021 and $\bar{y}$ with 0.244 and then obtain the value of $E_{\frac{1}{\bar{y}}}$ 8.6%.

[11] The economic significance of our study is reasonable, in particular when compared with that document in prior studies. For example, Chen et al. (2014) find that a one standard deviation increases in the Catholics-to-Protestant ratio, an indicator of local gambling preference, is associated with a rise of approximately 8% of a firm's patent counts. Furthermore, Galasso and Simcoe (2011) note that the presence of an overconfident CEO is associated with 25% to 30% increase in citation-weighted patent counts. Hirshleifer et al. (2012) reports a 28% increase in patent counts for firms led by overconfident CEOs.

To ensure the validity of the parallel trend assumption for our DID analysis, we examine the dynamic effect of sports inspiration on inventor innovation in Table 3. Specifically, we select the third year before the sports inspiration year as the benchmark year. We replace *Post* in Model (1) with five, time dummies[12], including $Before^{2}$, $Before^{1}$, $After^{1}$, $After^{2}$ and $After^{3}$. $Before^{2}$ equals one for observations in the second year before the sports inspiration event. $Before^{1}$ equals one for observations in the first year before the sports inspiration event. $After^{1}$ equals one for observations in the first year after the sports inspiration event. $After^{2}$ equals one for observations in the second year after the sports inspiration event. $After^{3}$ equals one for observations in the third year after the sports inspiration event.

We include the interaction terms between *Treat* and these five dummy variables on our baseline regression along with our control variables. In Column (1), the coefficients for Treat*$Before^{2}$ and $Treat*Before^{1}$ are indistinguishable from zero, indicating no pre-existing trends in local inventor innovation from the quantity perspective before the sports inspiration. In contrast, the coefficients of $Treat*After^{1}$are significantly positive at 5% level. The pattern in our dynamic analysis demonstrates that the parallel trend assumption holds. In Column (2) for the quality index of the inventor innovation, the coefficients for Treat*$Before^{2}$ and $Treat*Before^{1}$ are indistinguishable from 0, indicating no pre-existing trends in local inventor innovation from the quality perspective before the sports inspiration. In contrast, the coefficients of $Treat*After^{3}$ are significantly positive at 1% level. Similarly, in Column (3) for the quality index of the inventor innovation, the coefficients for Treat*$Before^{2}$ and $Treat*Before^{1}$ are indistinguishable from zero, indicating no pre-existing trends in local inventor innovation from the quality perspective before the sports inspiration. In contrast, the

[12] We drop the event year in our parallel trend test to avoid noise, as the World Series of MLB usually takes place in October, the NBA Finals generally occur in June, the NHL Finals also generally occur in June, and the NFL Finals typically take place in January or February. Our baseline analysis still holds even when we drop the event year observations, and our parallel trend test still passes even when we keep the event year observations.

coefficients of *Treat*After*^{1}, *Treat*After*^{2}, and *Treat*After*^{3} are significantly positive at 5% level. The pattern in our dynamic analysis demonstrates that the parallel trend assumption holds.

[Insert Table 3 here]

5.2 Robustness Tests

To check the validity of our baseline results and exclude alternative explanations, we conduct a number of robustness tests. Table 4 shows the robustness results of our baseline results on the effect of sports inspiration on local inventor innovation productivity. First, we examine whether our results are sensitive to an alternative sample. In our baseline results, we assign a value of zero to the innovation output variables for all years with no patent record and between the first and last years in which the inventor filed a patent. To ensure that our results are not driven by this treatment, we exclude the inventor who did not file any patent during the event window and re-estimate the baseline analysis on this sample. We obtain consistent findings, which are presented from Column (1) to Column (3) in Table 4. Similarly, we exclude inventors who are employed by the financial and utility firms. The results are shown in Column (4) and Column (6), showing consistent results.

Thirdly, we consider that the control group not only includes the inventors living in zip code areas from the same state as the treatment zip code areas but also includes all inventors living in the zip code areas that never won a championship of big four professional sports in the U.S. For example, in our baseline regression, for the sports inspiration event of Boston winning the 2004 MLB championship, the control group includes the inventors who live in the zip code areas in Massachusetts which never won a champion of the big four professional sports. In this robustness section, the control group includes all the inventors who live in the zip code areas in the whole United States which never won a champion of the big four professional sports. The results are reported in Column (7) and Column (9) in Table 4 and are consistent with our baseline results.

To alleviate further concerns that our findings may be driven by pre-event differences between the treatment and control groups, we conduct a propensity score matching (Rosenbaum and Rubin, 1983) and then re-run our regression model (1) on the matched sample. Specifically, for each treatment inventor in an event, we select a matched control inventor based on a propensity score from the logit model. We conduct the matching process 30 times for the 30 events used in our previous regression analysis. In the logit model, the dependent variable is the *Treat* dummy, and the matching variables include *Asset* and *Ln_tenure* (Chen et. al., 2022). Our logit model also controls for industry-fixed effects. We define industries based on the classification of Fama-French 48 countries. To maintain the statistical independence of our tests, we implement a nearest neighbor matching (NNM) algorithm without replacement and match inventors with a similar propensity score. The NNM algorithm uses the distance between covariate patterns to define the "closest" neighbor. Column (10) and Column (12) of Table 4 show the regression results with the propensity score matched sample. The coefficients of *Treat*Post* are 0.028 (standard errors = 0.009), 0.111 (standard errors = 0.036), and 0.081 (standard errors = 0.032) in Column (10), Column (11), and Column (12) respectively, which are positive and significant. Thus, we continue to find significant evidence that sports inspiration affects treated inventor innovation productivity when controlling for potential similarities in the pre-event period.

[Insert Table 4 here]

5.3 Subsample Analysis

In this section, we will do a series of subsample analyses to explore the varying effects of sports inspiration on local inventor innovation productivity.

5.3.1 Inventor Talent

Chen et al. (2022) and Graff Ziven and Neidell (2012) show that more experienced inventors such as superstar inventors are better at adapting to external factors such as air pollution, thus it is possible that these same inventors are less likely to be influenced by sports inspiration. Following Zacchia (2018), we define inventors as superstar inventors as those in the top 5% of the distribution of patents that the inventor filed by event. Specifically, if the number of newly filed patents for an inventor is among the top 5% in each event sample, this inventor is defined as a superstar inventor. *Superstar* is a dummy variable indicating if the inventor is a superstar inventor based on this definition. We interact *Treat*Post* with *Superstar* and include the interaction term in the baseline regression model. We do not include *Superstar* as an independent variable because it is time-variant, and thus its effects are absorbed by the inventor fixed effects.

The results are reported in Table 5. Columns (1-3) in Table 5 show the estimation of the impact of sports inspiration on superstar inventor innovation productivity. The coefficients of *Treat*Post*Superstar* are negative and significant at the 1% level in all three regressions, implying that relative to more experienced inventors, sports inspiration has a greater effect on the productivity of less experienced inventors/ non-superstar inventors, by not only generating more patents, but more valuable patents.

[Insert Table 5 here]

5.3.2 Underdog Inspiration and Innovation Outcomes

In Table 6, we investigate whether underdog narratives in sports victories inspire more innovation than expected victories. To categorize underdog vs. non-underdog wins, we use pre-season betting odds for each championship team. For example, the Cincinnati Reds' 1990 World Series win was deemed an underdog victory since their pre-season odds of winning were +1600, much higher than their competitor, the Oakland Athletics, at +600. In contrast, the Boston Red Sox's 2004 World Series win was considered a non-underdog victory since their pre-season odds of +400 were less than their competitor, the St. Louis Cardinals, at +1500.

By comparing innovation outcomes following underdog versus expected victories, we can isolate the inspirational effect of underdog narratives. Our analysis controls for other factors that may drive innovation, like team popularity and media attention. The results provide useful insights for finance professionals and firms interested in quantifying different sources of inspiration for creativity and innovation. Examining underdog effects contributes to our understanding of how storytelling and framing of competition can motivate performance. Columns (1) to (3) and Columns (4) to (6) in Table 6 show the regression results of the influence of sports inspiration caused by underdog victories and non-underdog victories separately. The coefficients of *Treat*Post* from Column (1) to Column (3) are significantly positive at the 1% level. But the coefficients of *Treat*Post* from Column (4) to Column (6) are not significant, implying that the effects of sports inspiration are more significant on inventor productivity when the sports inspiration is caused by underdog victories.

[Insert Table 6 here]

5.4 The Mechanisms

Our baseline results show that sports inspiration leads to inventors being more innovative. In this section, we investigate the specific channels through which sports inspiration affects inventor productivity.

5.4.1 Sports Inspiration and Inventor Innovation Strategies

The innovation process is unavoidably associated with risk, and there are significant variations in risk-taking across the various innovation strategies. Several studies note that innovation involves the exploration and exploitation of existing projects. (March, 1991; Benner and Tushman, 2002; Balsmeier et al., 2017). March (1991) argues that exploration is characterized by search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation, while exploitation is characterized by refinement, choice production, efficiency, selection, implementation, and execution. In other words, an exploratory innovation strategy is associated with higher risk than an exploitative innovation strategy (March 1991; Chava et al., 2013; Balsmeier et al., 2017). If being inspired by sports wins increases the risk-taking incentive of inventors, we anticipate that they will be more inclined to venture into new fields after such inspiration. The enhancement in inventor productivity should therefore come primarily from exploratory innovation, rather than exploitative innovation.

By looking at specific variables, we can understand how inventors choose between exploring new ideas or exploiting existing ones in their innovation strategies. We follow Benner and Tushman (2002) and calculate the number of exploratory and exploitative patents filed in a given year. To classify a patent as exploitative, we analyze if over 60% of its backward citations are from the inventor's existing knowledge, which includes their patents or citations made by those patents in the past five years. The Variable *Exploit* is the adjusted number of exploitative patents filed by each inventor in each year. *Explore* measures the amount of patents filed by each inventor that have more than 60% of their citations outside of the inventor's knowledge pool. It is worth noting that multiple inventors are often registered for one patent and one patent could be exploitative to one inventor but exploratory to another.

We re-estimate the baseline regression model using these two variables as our dependent variables. The results are presented in Table 7. Column (1) shows that the coefficient of *Treat*Post* is positive and statistically significant when $Explore_{t+1}$ is the dependent variable. This result indicates that the treated inventors increased their efforts to explore unfamiliar fields after the sports inspiration. Column (2) shows that the coefficient of *Treat*Post* is positive and unsignificant when $Exploit_{t+1}$ is the dependent variable. Even though the coefficient of *Treat*Post* in Column (2) is positively significant, which suggests that the treated inventors produce more exploratory patents than exploitative patents after the sports inspiration relative to control inventors.

Overall, the results suggest that after sports inspiration events, the treated inventors are more likely to explore new and unfamiliar fields of research. Given that an exploratory innovation strategy involves more risk than an exploitative innovation strategy, the finding provides supporting evidence for the risk-taking channel. In other words, sports inspiration encourages risk-taking behavior and results in greater inventor productivity.

[Insert Table 7 here]

5.4.2 Sports Inspiration and Average Patent Quality

Our baseline results show that the treated inventors produce more patents after sports inspiration. These patents also generate more forward citations and have higher economic value relative to inventors who are not affected by the sports inspiration. To examine whether the increase in innovation output by treated inventors is at least partly driven by improved cognitive function (which affects inventors' R&D decisions), we examine whether the average quality of each patent among treated inventors improves after the sports inspiration. Average higher patent quality indicates improved R&D capability and improved cognitive abilities of these inventors.

To perform this test, we adopt two average patent quality measures. The average number of citations per patent (*LnAvgCit*) is defined as the natural logarithm of 1 plus the average number of forward citations received by an inventor's newly filed patents. Average economic value per patent (*LnAvgVal*) is defined as the natural logarithm of 1 plus the average economic value of an inventor's newly filed patents. We first calculate the two variables across all newly filed patents for each inventor. We also calculate the two variables across new exploratory patents and new exploitative patents separately. In addition, we calculate the two variables across cooperative patents and sole patents as well.

We re-estimate the baseline regression model using two average patent quality measures as dependent variables. The regression results are presented in Table 8. Column (1) and Column (2) report the results of all newly filed patents. The coefficients of *Treat*Post* are positive and statistically significant in both regressions, suggesting that patents generated by treated inventors have a higher average number of citations and higher economic value after the sports inspiration events. As such, sports inspiration enhances not only the number but also the average quality of patents. Both factors contribute to the increase in total patent citation and economic value.

Next, we examine the exploratory and exploitative, separately from Column (3) to Column (6). We can observe that the coefficient of Treat*Post in Column (3) is positive and statistically significant at 1% significance level. But the coefficients of Treat*Post in Column (5) and Column (6) are positive but not statistically significant at 5% significance level, which is also consistent with what we found in Section 5.4.1. Collectively, the findings in this section suggest that improved cognitive performance serves as a supplementary channel through which sports inspiration increases innovation.

[Insert Table 8 here]

5.5 Further Analysis

In our baseline analysis, we focus on inventors affiliated with publicly listed firms so that we can control for innovation inputs and the characteristics of the firms in which the inventors work. In this section, we extend the analysis to all inventors regardless of whether they are affiliated with publicly listed firms or not. As such, the sample in this test includes all U.S. inventors based on the treatment and control group we defined previously. We control for Ln_tenure and Event_Inventor, Event_City, and Event_Year fixed effects in the regression model (1) using a stacked DiD model. The regression results are presented in Table 10.

Column (1) and Column (2) in Table 9 show the estimation of the impact of sports inspiration on the number of patents and citations for all inventors. The coefficients of Treat*Post are positive and significant at the1% level (coefficient = 0.010 with standard errors = 0.004) and 1% level (coefficient = 0.010 with standard errors = 0.004) respectively. Column (3) and Column (4) in Table 5 show the estimation of the impact of sports inspiration on the quality of patents (citation) for all inventors. The coefficients of Treat*Post are positive and significant at the 1% level (coefficient = 0.036 with standard errors = 0.013) and 1% level (coefficient = 0.036 with standard errors = 0.013) respectively. The results are consistent with our baseline results, which suggests that our finding holds for all inventors, not just those affiliated with publicly listed firms.

[Insert Table 9 here]

In addition, considering the real economic effect of sports inspiration, we aggregate the innovation activities from the inventor level to the city level to explore whether sports inspiration could stimulate innovation activities for the entire city. We construct two dependent variables: *City_Num*, which equals the natural logarithm of one plus the number of newly filed patents in a city in a given year, and *City_Cit*, which equals the natural logarithm of one plus the number of forward citations of newly filed patents in a city in a given year. Columns (1) and (2) in Table 10 show the estimation of the impact of sports inspiration on the number of patents and citations for the city. The coefficients of Treat*Post are positive and significant at the 1% level (coefficient = 1.070 with standard errors = 0.251) and the 1% level (coefficient = 1.228 with standard errors = 0.398), respectively. The results suggest that sports inspiration not only stimulates innovation activities at the inventor level but also at the city level.

[Insert Table 10 here]

6. Conclusion

Our study reveals a powerful link between sports inspiration and inventor performance. Local sports victories serve as an unexpected catalyst, boosting inventors' productivity and creativity. The impact is clear: more patents filed, higher forward citations, and increased economic value of innovations. Importantly, inspired inventors don't just produce more—they aim higher, targeting newer, more challenging technologies. This demonstrates how positive emotions from sports triumphs can fuel workplace creativity and focus. For firms and managers, these findings are a game-changer. They highlight the untapped potential of positive affect and inspirational narratives in driving innovation. By harnessing the power of inspiration, companies could unlock significant productivity gains and breakthrough innovations. Our research opens new avenues for motivating inventor performance, suggesting that the path to corporate innovation might just run through the sports arena.

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Table 1. Summary statistics

This table reports the descriptive statistics of the sample we used in our main analysis. The sample consists of 277,022 inventor-year observations for 30 events from 1975 to 2007, obtained from the HBS patent inventor database and Compoutat. Appendix A provides a detailed description of the construction of the variables. All the continuous variables are winsorized at the 1% level.

	Obs.	Mean	Median	Std.	Min	Max
LnPat	297203	0.244	0.000	0.367	0	1.649
LnCit	297203	1.022	0.000	1.428	0	5.136
LnVal	297203	0.857	0.000	1.211	0	4.668
Asset	297203	8.652	8.867	1.952	3.157	12.178
R&D	297203	0.08	0.069	0.065	0	0.373
Cash	297203	0.186	0.113	0.192	0.002	0.81
ROA	297203	0.134	0.150	0.117	-0.406	0.361
CapEx	297203	0.066	0.059	0.043	0.006	0.22
Leverage	297203	0.185	0.169	0.147	0	0.655
Tobin's Q	297203	2.615	1.910	2.222	0.855	14.404
Firm_age	297203	3.164	3.497	0.817	0.693	4.007
Ln_tenure	297203	1.907	1.946	0.815	0	3.332

Table 2. Baseline Result

This table reports the baseline results of the influence of sports inspiration on inventor productivity using the stacked DID model. $LnPat_{t+1}$ is the natural log of the sum of the adjusted patent numbers for an inventor in a specific year, which is used to measure the quantity of an inventor's productivity. Columns (1) and (2) show the results of sports inspiration on $LnPat_{t+1}$. $LnCit_{t+1}$ and $LnVal_{t+1}$ are the natural log of the sum of the adjusted patent forward citations and value for an inventor in a specific year respectively, which are used to measure the quality of an inventor's productivity. Columns (3) and (6) show the results of sports inspiration on $LnCit_{t+1}$ and $LnVal_{t+1}$, respectively. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1) $LnPat_{t+1}$	(2) $LnPat_{t+1}$	(3) $LnCit_{t+1}$	(4) $LnCit_{t+1}$	(5) $LnVal_{t+1}$	(6) $LnVal_{t+1}$
*Treat*Post*	0.021***	0.021***	0.098***	0.098***	0.103***	0.098***
	(0.007)	(0.007)	(0.024)	(0.024)	(0.027)	(0.026)
Asset		0.013***		0.057***		0.076***
		(0.004)		(0.017)		(0.016)
R&D		-0.003		-0.253		0.218
		(0.045)		(0.171)		(0.141)
Cash		0.015		0.075		0.001
		(0.013)		(0.058)		(0.050)
ROA		0.001		0.028		0.227***
		(0.019)		(0.069)		(0.053)
CapEx		0.118***		0.498***		0.751***
		(0.037)		(0.154)		(0.127)
Leverage		-0.038***		-0.155***		-0.035
		(0.013)		(0.054)		(0.041)
Tobin's Q		0.003***		0.012***		0.010***
		(0.001)		(0.002)		(0.003)
Firm_age		-0.023*		-0.127***		-0.243***
		(0.012)		(0.048)		(0.038)
Ln_tenure		0.011**		0.038**		0.030**
		(0.004)		(0.017)		(0.014)
Constant	0.244***	0.173***	1.018***	0.818***	0.853***	0.792***
	(0.000)	(0.049)	(0.001)	(0.210)	(0.001)	(0.192)
Event_Inventor	YES	YES	YES	YES	YES	YES
Event_City	YES	YES	YES	YES	YES	YES
Event_Year	YES	YES	YES	YES	YES	YES
Event_Firm	YES	YES	YES	YES	YES	YES
Obs.	292879	292879	292879	292879	292879	292879
adj. R^2	0.373	0.373	0.309	0.310	0.331	0.332

Table 3. Dynamic Effect

This table reports the dynamic effect of the influence of sports inspiration on inventor productivity. Columns (1) to (3) show the dynamic effect of sports inspiration on $LnPat_{t+1}$, $LnCit_{t+1}$, and $LnVal_{t+1}$, respectively. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1) $LnPat_{t+1}$	(2) $LnCit_{t+1}$	(3) $LnVal_{t+1}$
$Treat*Before^2$	-0.002	-0.030	0.001
	(0.008)	(0.047)	(0.031)
$Treat*Before^1$	0.012	-0.006	0.030
	(0.011)	(0.059)	(0.034)
$Treat*After^1$	0.024*	0.074	0.094**
	(0.014)	(0.052)	(0.044)
$Treat*After^2$	0.012	0.042	0.104***
	(0.013)	(0.060)	(0.036)
$Treat*After^3$	0.027**	0.153**	0.130**
	(0.012)	(0.060)	(0.052)
Asset	0.013***	0.054***	0.076***
	(0.005)	(0.021)	(0.018)
R&D	0.017	-0.297	0.239
	(0.051)	(0.185)	(0.154)
Cash	0.001	0.001	-0.044
	(0.016)	(0.064)	(0.059)
ROA	-0.005	0.024	0.258***
	(0.022)	(0.081)	(0.062)
CapEx	0.139***	0.574***	0.842***
	(0.046)	(0.177)	(0.149)
Leverage	-0.044***	-0.159**	-0.051
	(0.013)	(0.063)	(0.045)
Tobin's Q	0.003***	0.014***	0.011***
	(0.001)	(0.003)	(0.003)
Firm_age	-0.022	-0.136**	-0.229***
	(0.014)	(0.054)	(0.043)
Ln_tenure	0.007	0.022	0.012
	(0.005)	(0.018)	(0.015)
Constant	0.179***	0.911***	0.769***
	(0.052)	(0.235)	(0.198)
Event_Inventor	YES	YES	YES
Event_City	YES	YES	YES
Event_Year	YES	YES	YES
Event_Firm	YES	YES	YES
Obs.	235324	235324	235324
adj. R^2	0.368	0.307	0.331

Table 4. Robustness tests

This table reports a series of robustness checks in our project. Columns (1) to (3) show the influence of sports inspiration on $LnPat_{t+1}$, $LnCit_{t+1}$, and $LnVal_{t+1}$, respectively, when we delete the inventors who do not file any patents during the sample period we use. Columns (4) to (6) show the influence of sports inspiration on $LnPat_{t+1}$, $LnCit_{t+1}$, and $LnVal_{t+1}$, respectively, when we delete the inventors who are affiliated with utility and financial firms. Columns (7) to (9) show the influence of sports inspiration on $LnPat_{t+1}$, $LnCit_{t+1}$, and $LnVal_{t+1}$, respectively, when we change the control group including the inventors who are from the same state as the treated inventors to that including the inventors who live in the city which never win a champion of big four professional sports in U.S. in the U.S. Columns (10) to (12) show the influence of sports inspiration on $LnPat_{t+1}$, $LnCit_{t+1}$, and $LnVal_{t+1}$, respectively, when we use PSM method to construct a balanced sample. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	Robustness check 1			Robustness check 2			Robustness check 3			Robustness check 4		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$LnPat_{t+1}$	$LnCit_{t+1}$	$LnVal_{t+1}$	$LnPat_{t+1}$	$LnCit_{t+1}$	$LnVal_{t+1}$	$LnPat_{t+1}$	$LnCit_{t+1}$	$LnVal_{t+1}$	$LnPat_{t+1}$	$LnCit_{t+1}$	$LnVal_{t+1}$
*Treat*Post*	0.025***	0.117***	0.121***	0.020***	0.097***	0.096***	0.019***	0.078***	0.093***	0.028***	0.111***	0.081**
	(0.008)	(0.029)	(0.034)	(0.007)	(0.024)	(0.026)	(0.007)	(0.022)	(0.029)	(0.009)	(0.036)	(0.032)
Asset	0.014***	0.059***	0.079***	0.014***	0.063***	0.080***	0.019***	0.075***	0.079***	0.026**	0.099	0.115***
	(0.004)	(0.019)	(0.017)	(0.004)	(0.017)	(0.016)	(0.001)	(0.004)	(0.004)	(0.011)	(0.066)	(0.044)
R&D	0.002	-0.255	0.256*	-0.001	-0.235	0.227	0.052***	0.277***	0.215***	0.104	0.617	0.629
	(0.047)	(0.179)	(0.147)	(0.045)	(0.171)	(0.141)	(0.014)	(0.055)	(0.052)	(0.168)	(0.863)	(0.696)
Cash	0.017	0.082	-0.001	0.024*	0.091	0.007	0.040***	0.098***	0.080***	-0.016	-0.207	-0.292**
	(0.015)	(0.062)	(0.055)	(0.013)	(0.057)	(0.051)	(0.005)	(0.017)	(0.016)	(0.040)	(0.181)	(0.144)
ROA	0.000	0.030	0.249***	-0.003	0.023	0.229***	0.012**	0.106***	0.161***	0.033	-0.026	0.050
	(0.021)	(0.075)	(0.057)	(0.019)	(0.070)	(0.054)	(0.005)	(0.018)	(0.016)	(0.084)	(0.389)	(0.287)
CapEx	0.134***	0.564***	0.843***	0.118***	0.482***	0.750***	0.182***	0.602***	0.538***	0.266**	0.464	0.654*
	(0.042)	(0.171)	(0.141)	(0.037)	(0.154)	(0.128)	(0.011)	(0.038)	(0.031)	(0.108)	(0.453)	(0.365)
Leverage	-0.044***	-0.179***	-0.041	-0.035***	-0.144***	-0.023	-0.007*	0.031**	0.074***	-0.023	-0.206	-0.230
	(0.014)	(0.061)	(0.045)	(0.013)	(0.055)	(0.042)	(0.004)	(0.015)	(0.014)	(0.040)	(0.219)	(0.157)
Tobin's Q	0.003***	0.013***	0.010***	0.003***	0.012***	0.010***	0.004***	0.019***	0.019***	0.007	0.059**	0.060***
	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.000)	(0.001)	(0.001)	(0.005)	(0.029)	(0.021)
Firm_age	-0.016	-0.079**	-0.169***	-0.026**	-0.129***	-0.248***	-0.034***	-0.164***	-0.261***	0.060	0.309	-0.115
	(0.010)	(0.040)	(0.030)	(0.012)	(0.049)	(0.038)	(0.003)	(0.010)	(0.009)	(0.040)	(0.189)	(0.093)
Ln_tenure	0.011**	0.041**	0.029*	0.010**	0.036**	0.028**	0.009***	0.019***	0.015***	0.010	0.066	0.040
	(0.005)	(0.019)	(0.016)	(0.004)	(0.017)	(0.014)	(0.001)	(0.003)	(0.003)	(0.009)	(0.041)	(0.034)
Constant	0.172***	0.774***	0.632***	0.171***	0.773***	0.771***	0.112***	0.610***	0.776***	-0.305*	-1.349*	-0.110
	(0.047)	(0.206)	(0.186)	(0.049)	(0.211)	(0.194)	(0.016)	(0.053)	(0.051)	(0.158)	(0.782)	(0.517)
Event_Inventor	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Event_City	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Event_Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Event_Firm	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	258216	258216	258216	290522	290522	290522	6042173	6042173	6042173	24622	24622	24622
adj. R^2	0.337	0.262	0.288	0.371	0.308	0.331	0.358	0.302	0.340	0.287	0.226	0.267

Table 5. Subsample Analysis: Superstar inventors or not

This table reports the influence of sports inspiration on inventor productivity based on inventor characteristics (superstar inventor or not). Columns (1) to (3) show the results of the sports inspiration on superstar inventors' innovation productivity when including the interaction term *Treat*Post*Superstar*. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1) $LnPat_{t+1}$	(2) $LnCit_{t+1}$	(3) $LnVal_{t+1}$
*Treat*Post*	0.032^{***}	0.135^{***}	0.124^{***}
	(0.006)	(0.022)	(0.023)
Treat Post*Superstar*	-0.303^{***}	-0.972^{***}	-0.678^{***}
	(0.037)	(0.122)	(0.171)
Asset	0.013^{***}	0.057^{***}	0.076^{***}
	(0.004)	(0.017)	(0.016)
R&D	-0.003	-0.251	0.219
	(0.045)	(0.171)	(0.141)
Cash	0.016	0.076	0.002
	(0.013)	(0.058)	(0.050)
ROA	0.001	0.027	0.226^{***}
	(0.019)	(0.069)	(0.053)
CapEx	0.119^{***}	0.500^{***}	0.752^{***}
	(0.037)	(0.154)	(0.127)
Leverage	-0.038^{***}	-0.155^{***}	-0.035
	(0.013)	(0.054)	(0.041)
Tobin's Q	0.003^{***}	0.012^{***}	0.010^{***}
	(0.001)	(0.002)	(0.003)
Firm_age	-0.023^{*}	-0.128^{***}	-0.243^{***}
	(0.012)	(0.048)	(0.038)
Ln_tenure	0.011^{**}	0.038^{**}	0.029^{**}
	(0.004)	(0.017)	(0.014)
Constant	0.173^{***}	0.818^{***}	0.792^{***}
	(0.048)	(0.209)	(0.192)
Event_Inventor	YES	YES	YES
Event_City	YES	YES	YES
Event_Year	YES	YES	YES
Event_Firm	YES	YES	YES
Obs.	292879	292879	292879
adj. R^2	0.373	0.310	0.332

Table 6. Subsample Analysis: Underdog match or not

This table shows the results of the influence of sports inspiration caused by underdog matches or non-underdog matches on inventor productivity. Columns (1) to (3) show the results of the sports inspiration caused by underdog matches on inventors' productivity. Columns (4) to (6) show the results of the sports inspiration caused by non-underdog matches on inventor productivity. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	Underdog Match			Non-underdog Match		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
	$LnPat_{t+1}$	$LnCit_{t+1}$	$LnVal_{t+1}$	$LnPat_{t+1}$	$LnCit_{t+1}$	$LnVal_{t+1}$
*Treat*Post*	0.018***	0.090***	0.097***	0.020	0.085	0.102
	(0.006)	(0.021)	(0.031)	(0.025)	(0.088)	(0.080)
Asset	0.023***	0.105***	0.159***	0.008	0.067**	0.042
	(0.007)	(0.029)	(0.023)	(0.008)	(0.034)	(0.033)
R&D	-0.015	-0.355	0.529***	-0.118	-0.452	-0.073
	(0.077)	(0.287)	(0.196)	(0.093)	(0.421)	(0.383)
Cash	0.017	0.064	-0.030	0.092***	0.389**	0.379**
	(0.019)	(0.083)	(0.064)	(0.036)	(0.171)	(0.154)
ROA	-0.034	-0.112	0.128*	-0.013	-0.248*	-0.187
	(0.028)	(0.093)	(0.071)	(0.035)	(0.147)	(0.123)
CapEx	0.137**	0.666***	0.591***	0.027	0.100	0.234
	(0.059)	(0.214)	(0.168)	(0.064)	(0.322)	(0.248)
Leverage	-0.023	-0.086	-0.031	-0.086***	-0.353***	-0.166**
	(0.018)	(0.079)	(0.056)	(0.023)	(0.103)	(0.077)
Tobin's Q	0.004***	0.018***	0.019***	0.003	0.012	0.008
	(0.001)	(0.004)	(0.004)	(0.002)	(0.010)	(0.009)
Firm_age	-0.002	-0.008	-0.121***	-0.028	-0.098	-0.276***
	(0.011)	(0.037)	(0.032)	(0.022)	(0.107)	(0.073)
Ln_tenure	0.026***	0.095***	0.083***	-0.001	-0.003	-0.022
	(0.005)	(0.022)	(0.017)	(0.007)	(0.024)	(0.022)
Constant	-0.008	-0.089	-0.443**	0.243**	0.724	1.378***
	(0.064)	(0.280)	(0.218)	(0.108)	(0.520)	(0.449)
Event_Inventor	YES	YES	YES	YES	YES	YES
Event_City	YES	YES	YES	YES	YES	YES
Event_Year	YES	YES	YES	YES	YES	YES
Event_Firm	YES	YES	YES	YES	YES	YES
Obs.	140089	140089	140089	76964	76964	76964
adj. R^2	0.377	0.307	0.330	0.334	0.276	0.324

Table 7. Mechanism I: Innovation Strategy (Exploration and Exploitation)

This table presents the results of the influence of sports inspiration on inventor innovation strategy. Column (1) shows the results of the influence of sports inspiration on the exploratory patents. Column (2) shows the results of the influence of sports inspiration on the exploitative. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)
	Exploration	Exploitation
	$Explore_{t+1}$	$Exploit_{t+1}$
*Treat*Post*	0.013**	0.006
	(0.006)	(0.004)
Asset	0.006*	0.006***
	(0.004)	(0.002)
R&D	-0.037	0.020
	(0.037)	(0.021)
Cash	0.000	0.020***
	(0.011)	(0.008)
ROA	-0.012	-0.001
	(0.017)	(0.009)
CapEx	0.064**	0.049***
	(0.032)	(0.017)
Leverage	-0.021*	-0.019***
	(0.011)	(0.006)
Tobin's Q	0.004***	-0.001**
	(0.001)	(0.000)
Firm_age	-0.040***	0.022***
	(0.010)	(0.006)
Ln_tenure	-0.006	0.017***
	(0.004)	(0.002)
Constant	0.259***	-0.102***
	(0.040)	(0.026)
Event_Inventor	YES	YES
Event_City	YES	YES
Event_Year	YES	YES
Event_Firm	YES	YES
Obs.	292512	292512
adj. R^2	0.273	0.305

Table 8. Mechanism II: Average patent quality

This table presents the regression results of the influence of sports inspiration on average patent quality, measured by the average citations and economic value per patent. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

	All patents		Explorative patents		Exploitative patents	
Variable	(1) *$LnAvgCit_{t+1}$*	(2) *$LnAvgVal_{t+1}$*	(3) *$LnAvgCit_{t+1}$*	(4) *$LnAvgVal_{t+1}$*	(5) *$LnAvgCit_{t+1}$*	(6) *$LnAvgVal_{t+1}$*
*Treat*Post*	0.099***	0.099***	0.072***	0.041	0.017	0.031*
	(0.028)	(0.030)	(0.028)	(0.025)	(0.018)	(0.019)
Asset	0.076***	0.105***	0.041**	0.051***	0.043***	0.060***
	(0.019)	(0.017)	(0.017)	(0.016)	(0.011)	(0.011)
R&D	-0.322*	0.254	-0.358**	0.128	0.002	0.014
	(0.176)	(0.156)	(0.173)	(0.146)	(0.135)	(0.103)
Cash	0.089	0.055	0.070	0.049	0.087*	0.067*
	(0.065)	(0.061)	(0.059)	(0.052)	(0.044)	(0.038)
ROA	0.074	0.312***	-0.040	0.178***	0.057	0.071*
	(0.069)	(0.056)	(0.070)	(0.059)	(0.048)	(0.040)
CapEx	0.427**	0.737***	0.225	0.449***	0.287**	0.421***
	(0.169)	(0.149)	(0.149)	(0.131)	(0.117)	(0.092)
Leverage	-0.139**	0.011	-0.035	0.040	-0.123***	-0.052*
	(0.063)	(0.048)	(0.053)	(0.044)	(0.041)	(0.029)
Tobin's Q	0.012***	0.007**	0.017***	0.017***	-0.004*	-0.011***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Firm_age	-0.160***	-0.349***	-0.274***	-0.315***	0.073**	-0.022
	(0.048)	(0.040)	(0.043)	(0.036)	(0.034)	(0.024)
Ln_tenure	0.040**	0.038***	-0.023	-0.037***	0.114***	0.107***
	(0.017)	(0.014)	(0.016)	(0.013)	(0.013)	(0.012)
Constant	0.933***	1.010***	1.451***	1.288***	-0.472***	-0.343**
	(0.231)	(0.207)	(0.207)	(0.193)	(0.155)	(0.134)
Event_Inventor	YES	YES	YES	YES	YES	YES
Event_City	YES	YES	YES	YES	YES	YES
Event_Year	YES	YES	YES	YES	YES	YES
Event_Firm	YES	YES	YES	YES	YES	YES
Obs.	292512	292512	292512	292512	292512	292512
adj. R^2	0.241	0.275	0.168	0.190	0.257	0.247

Table 9. Further Analysis: All Inventors

This table shows the result of the influence of sports inspiration on all inventors' innovation productivity. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1) $LnPat_{t+1}$	(2) $LnPat_{t+1}$	(3) $LnCit_{t+1}$	(4) $LnCit_{t+1}$
*Treat*Post*	0.010**	0.010**	0.036***	0.036***
	(0.004)	(0.004)	(0.013)	(0.013)
Ln_tenure		0.008***		0.035***
		(0.002)		(0.007)
Constant	0.229***	0.215***	0.573***	0.506***
	(0.000)	(0.004)	(0.000)	(0.014)
Event_Inventor	YES	YES	YES	YES
Event_City	YES	YES	YES	YES
Event_Year	YES	YES	YES	YES
Obs.	826955	826955	826955	826955
adj. R^2	0.349	0.349	0.309	0.309

Table 10. Further Analysis: City level innovation activities

This table shows the result of the influence of sports inspiration on city-level innovation productivity. Continuous variables are winsorized at the 1% level.. Standard errors are in parentheses and are clustered at the event-city level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1) $City\_Num_{t+1}$	(2) $City\_Cit_{t+1}$
*Treat*Post*	1.070***	1.228***
	(0.251)	(0.398)
Constant	0.779***	1.516***
	(0.000)	(0.001)
Event_City	YES	YES
Event_Year	YES	YES
Obs.	67460	67460
adj. R^2	0.670	0.570

Appendix A: Variable Definitions

Variable	*Definition*
Measure of Innovation Output	
LnPat	Natural logarithm of one plus the number of newly filed patents. Note: for each newly filed patent, we scale it by the total number of inventors of this patent
LnCit	Natural logarithm of one plus the number of forward citations received by the newly filed patents. Note: for the forward citation of each newly filed patent, we scale it by the total number of inventors of this patent
LnVal	Natural logarithm of one plus the total economic value of newly filed patents. Note: for the economic value of each newly filed patent, we scale it by the total number of inventors of this patent
Explore	The number of newly filed patents for which more than 60% of backward citations are outside of the inventor's knowledge base. Note: for each newly filed patent, we scale it by the total number of inventors of this patent
Exploit	The number of newly filed patents for which more than 60% of backward citations are within the inventor's knowledge base. Note: for each newly filed patent, we scale it by the total number of inventors of this patent
LnAvgCit	Natural logarithm of one plus the average of forward citations received by the newly filed patents. Note: for each newly filed patent and the forward citation of each newly filed patent, we scale it by the total number of inventors of this patent
LnAvgVal	Natural logarithm of one plus the average economic value of the newly filed patents. Note: for each newly filed patent and for the economic value of each newly filed patent, we scale it by the total number of inventors of this patent
Firm Characteristics	
Asset	Natural logarithm of total assets.
R&D	R&D expenditures normalized by total assets.
Cash	Cash and short-term investments normalized by total assets.
ROA	Net income normalized by total assets.
CapEx	Capital expenditure normalized by total assets.
Leverage	Total debt normalized by total assets.
Tobin's Q	Market value of equity plus the book value of total assets minus the book value of equity minus balance sheet deferred taxes, normalized by the book value of total assets.
Firm_age	Natural logarithm of one plus the number of years since a firm's first appearance in the Compustat database.
Inventor Characteristics	

Ln_tenure	Natural logarithm of one plus the number of years between the year that the inventor enters the patent database and the observation year.

Appendix B. Additional Tests

Considering the intra-cluster correlation, many patents are assigned at the team/firm level, which means there is a strong (mechanical) correlation in patent output across inventors within a team-firm. This paper focuses on the individual inventor level; therefore, we re-run the baseline analysis clustered at the event-firm level to rule out this concern.

This table reports the baseline results of the influence of sports inspiration on inventor productivity using the stacked DID model. $LnPat_{t+1}$ is the natural log of the sum of the adjusted patent numbers for an inventor in a specific year, which is used to measure the quantity of an inventor's productivity. Columns (1) and (2) show the results of sports inspiration on $LnPat_{t+1}$. $LnCit_{t+1}$ and $LnVal_{t+1}$ are the natural log of the sum of the adjusted patent forward citations and value for an inventor in a specific year respectively, which are used to measure the quality of an inventor's productivity. Columns (3) and (6) show the results of sports inspiration on $LnCit_{t+1}$ and $LnVal_{t+1}$, respectively. Continuous variables are winsorized at the 1% level. Appendix A provides a detailed description of the construction of the variables. Standard errors are in parentheses and are clustered at the event-firm level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1) $LnPat_{t+1}$	(2) $LnPat_{t+1}$	(3) $LnCit_{t+1}$	(4) $LnCit_{t+1}$	(5) $LnVal_{t+1}$	(6) $LnVal_{t+1}$
*Treat*Post*	0.021***	0.021***	0.098***	0.098***	0.103***	0.098***
	(0.007)	(0.007)	(0.024)	(0.024)	(0.027)	(0.026)
Asset		0.013***		0.057***		0.076***
		(0.004)		(0.017)		(0.016)
R&D		-0.003		-0.253		0.218
		(0.045)		(0.171)		(0.141)
Cash		0.015		0.075		0.001
		(0.013)		(0.058)		(0.050)
ROA		0.001		0.028		0.227***
		(0.019)		(0.069)		(0.053)
CapEx		0.118***		0.498***		0.751***
		(0.037)		(0.154)		(0.127)
Leverage		-0.038***		-0.155***		-0.035
		(0.013)		(0.054)		(0.041)
Tobin's Q		0.003***		0.012***		0.010***
		(0.001)		(0.002)		(0.003)
Firm_age		-0.023*		-0.127***		-0.243***
		(0.012)		(0.048)		(0.038)
Ln_tenure		0.011**		0.038**		0.030**
		(0.004)		(0.017)		(0.014)
Constant	0.244***	0.173***	1.018***	0.818***	0.853***	0.792***
	(0.000)	(0.049)	(0.001)	(0.210)	(0.001)	(0.192)
Event_Inventor	YES	YES	YES	YES	YES	YES
Event_City	YES	YES	YES	YES	YES	YES
Event_Year	YES	YES	YES	YES	YES	YES
Event_Firm	YES	YES	YES	YES	YES	YES
Obs.	292879	292879	292879	292879	292879	292879
adj. R^2	0.373	0.373	0.309	0.310	0.331	0.332