ABSTRACT

Title of dissertation: ESSAYS ON AWARDS AND ACHIEVEMENT

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This dissertation comprises three essays on the intended and unintended consequences of achievement. The introductory essay discusses the growing literature on awards in organizational contexts. I summarize the theoretical and empirical work on awards and integrate across these literatures to identify unanswered questions.

The next essay explores an unintended organizational consequence of patenting. Building on theories of appropriability and firm-specificity, prior studies support the notion that patents constrain inventors from leaving their employer. I argue, however, that by patenting an inventor's idea, firms unintentionally send signals about the employee inventor's quality to their labor-market competitors, thereby increasing the probability of inventor mobility and entrepreneurship. I match US patent data to linked employee-employer Census microdata at the individual level. This novel dataset allows me to observe the near-complete patent, wage, and employer history of most US inventors between 1995 and 2008. To causally identify the effect of patenting, I use the historical leniency of quasi-randomly assigned patent

examiners to instrument for whether a patent is granted. I challenge prior work by finding support for the signaling, rather than constraining, effects of patents. To test whether signaling is the operant mechanism, I show that patenting also increases the inventor's wages and future productivity. My findings reveal an interesting paradox for innovative firms: by patenting an inventor's idea, firms send signals to their labor market competitors and dramatically increase the probability that the inventor will leave to join or start another firm.

My final essay explores the effect of prestigious awards on artist's subsequent productivity and performance. There is a large body of literature that finds award-winners have higher status, greater access to resources, and enhanced self-confidence; all of which may lead to increased performance and productivity. However, in this essay, I argue that prestigious awards may *decrease* ex post productivity for three reasons: (1) winners may become complacent after winning a prestigious award, and (2) winners may be freed to explore alternative career paths, and (3) winners may be more selective in choosing new projects. I investigate these conjectures in the US film industry from 2002-2018. I use prediction market odds to estimate the probability of winning an Academy or Golden Globe Award. I then condition on the probability of winning an award using a propensity score design to estimate the causal effect winning an award on subsequent productivity and performance. My results suggest that winning does lead to a decrease in the actor's future productivity. Further analysis suggests that winning an award also leads the winner to explore other careers (e.g., actors become directors) and to take less important roles. Award winners subsequently join movies that receive higher artistic ratings, but less commercial success. I find no effect on the number of screens the movie is released on or the movie's budget size. The results suggest that the productivity-enhancing effects in the pre-award period may be reversed after an award is granted.

ESSAYS ON AWARDS AND ACHIEVEMENT

by

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Chapter 1: Introduction

Modern corporate life is awash with symbolic awards, trophies, and accolades. Seemingly every resume has a section dedicated to the numerous awards bestowed on the candidate. Executive hallways and employee desks are similarly decorated with plaques and trophies boasting of the recipient's many achievements. Despite the abundance of awards in modern economic life, the theoretical and empirical understanding of their origins and consequences are lacking. This introductory chapter takes stock of the existing perspectives and empirical investigations of awards, discusses some of the most important questions remaining, and positions the other empirical essays of this dissertation within this existing literature.

1.1 Perspectives on Awards

Awards have been studied in Management and related disciplines from two primary lenses. Scholars from economics and sociology have investigated the effects that awards have on how others *perceive* the award winner. By award, I mean any public recognition or distinction given in honor of an achievement.[1] Often drawing on signaling theory, these studies generally find that awards provide information to

[1] Here I am primarily focused on symbolic awards, as opposed to financial rewards, though the two are often paired.

others about the underlying quality of the award winner and that, holding quality constant, awards increase the status and perceived quality of the winner (Gallus and Frey, 2015; Sauder et al., 2012a; Malmendier and Tate, 2009). This perspective assumes two parties: a sender and a receiver. The sender is the person, product, or firm to which the award is bestowed. The receiver is the party that observes the signal. In the signaling model, the signal provides information that changes the receiver's perception of the sender after the award is granted.

In addition to the body of work that investigates the ex post signaling effects of awards, there is a body of work that seeks to understand the ex ante effects on behavior. This literature suggests that if awards are desirable, perhaps because they boost the status and reputation of the winner as suggested by signaling theory, then award contests should motivate the contestants to work harder. Importantly, the 'awards as incentive' perspective differs from the literature on 'awards as signals' on two important dimensions. First, it focuses, though not exclusively, on the ex ante effects of awards. Second, this work focuses on how award contests affect the *behavior* of the contestant, rather than how others view her. See Table 1.1 for a visual representation of the relevant literatures along these dimensions.

[Table 1.1 about here.]

Before summarizing the literature further, I will briefly describe where the essays in this dissertation fall within this landscape. The second essay asks "how do patents affect the careers of the inventors?" This essay argues that patents act as signals, not just for the firm that owns them, but for the employees that invented them. I argue that by patenting an idea, firms not only secure the property rights for the idea and signal their quality to other firms, but they also signal the quality of their employees to their labor market competitors. I show that patenting leads to increased mobility and entrepreneurship of the inventors listed on the patent. I add to the signaling literature by pointing out that–though the standard signaling model focuses on a single sender and a single receiver–the value that awards provide may be captured by multiple parties. Thus, firms should concentrate, not just on the value that a patent award generates, but on who can best appropriate the value of the award. The third essay integrates across the 'awards as signal' and 'awards as incentive' literatures by examining the behavioral effects of awards on the ex post period. Here I argue that, though awards do have positive effects on how other's perceive the winner, they may also have unintended negative effects on the goals and motivations of the winner after the award has been granted.

1.2 Awards as Signal/Status

1.2.1 Information Asymmetry and Signaling

Signaling theory stems from the insight that information affects how firms and individuals make decisions. Information becomes particularly important when it is asymmetrically held. When "different people know different things" (Stiglitz, 2002, p. 496), markets and decisions are impacted. Though many scholars previously recognized the problem of information asymmetry, Stiglitz (2000) made significant strides by distinguishing between two broad types of information where asymmetry is consequential: information about *quality* and information about *behavior*. In this essay, I exclude discussions of moral hazard and related problems that stem from information asymmetry about a person's behavior. Instead, I focus on cases where one party in an exchange is not fully informed about the quality of the good being exchanged.

Spence's (1973, 2002) signaling theory addressed the problem with the observation that signals can reduce information asymmetries between two parties (Akerlof, 1970; Stigler, 1961).[2] In his classic study on labor markets, Spence (1973) recognized that employers commonly lack information about the quality of a job applicant. He argued that a job applicant may engage in certain behaviors, like obtaining a college degree, to reduce the information asymmetry between herself and a potential employer. In his formulation of the theory, he argued that reliable signals must be observable, correlated with quality, and the costs of obtaining the signal must inversely correlate with quality.

The signaling model has been deployed to explain phenomena in a wide range of fields, including management, to examine the role of information asymmetry, perception, and strategic action. Within management, signaling theory has been used to explain how firms use names (Belenzon et al., 2017), board membership (Certo, 2003), top management team members (Cohen and Dean, 2005), venture capital (Elitzur and Gavious, 2003), and patenting (Balasubramanian and Sivadasan, 2011; Farre-Mensa et al., 2017) to signal their quality to the market. See Connelly et al.

[2] I argue in the second essay of this dissertation that scholars and practitioners may benefit from considering more than two parties.

(2010) for a review of signaling theory and its use in management. In the next section, I discuss the key features of the signaling framework.[3]

1.2.2 Key Features of the Signaling Framework

Signaling theory, in its original formulation and its subsequent extensions, has primarily focused on two parties—the signaler and the receiver—as well as the signal. Signaling theory, as applied to awards, tends to view the award winner as the signaler who is trying to credibly communicate their quality to outsiders through the acquisition of an award. The signal is the award, itself, and the receiver is the outsider perceiving or otherwise judging the quality of the award winner.

The Signaler. The signaler is a person or organization with private information about their quality, broadly defined. The term 'quality' can include the intelligence of an individual, the innovativeness of a company, or the durability of a product. The private information that is held by the signaler, but not outsiders, creates information asymmetry between the signaler and the receiver. Organizational scholars and labor economists primarily focused on signals sent by individuals such as employees, recruiters, and managers.

The Signal. The signal, often the award, is a way for the signaler to reduce information asymmetry between the signaler and the receiver. The award usually contains positive information about the signaler, though there examples of negative signals in the literature (Myers and Majluf, 1984). To act as a credible Spencian

[3] I leave the technical discussion of separating equilibrium and signal costs to others (Connelly et al., 2010; Spence, 1973) and instead focus on the component parts of the model.

(1973) signal the award must be observable to outsiders. Second, the award must be correlated with the underlying quality of the signaler. Finally, the cost of obtaining the award must be negatively correlated with the quality of the signaler. That is, it should be easier, or less costly, for a high-quality actor to obtain the award than for a low-quality actor. The idea of signaling cost is paramount to Spence's (1970) signaling theory. Without it, low-quality actors will falsely signal. Misleading signals will become so prevalent that receivers would learn to ignore them. Thus, to remain credible, the cost of obtaining the signal must be structured in a way that makes false signaling prohibitively expensive.

The Signal Receiver. The final element of the signaling model is the receiver. Receivers are outsiders who have incomplete information about the signalers quality. Relevant receivers also are likely to change their behavior in some way that benefits the signaler in the presence of a credible signal. For example, an HR professional is more likely to select an applicant if that applicant can credibly signal their quality through the achievement of an award. Other receivers include financiers, shareholders, customers, and employees.

1.3 Awards as Incentive

Scholars have long been interested in the effects of incentives on individual behavior. Organizations use incentives to align the interests of agents, often employees, with those of the organization. Incentives are particularly useful in Agency Theory, which assumes two actors: a principal and an agent. The model begins with a risk-averse agent who is hired to produce some output that the principal owns. First, the agent and the principal sign a compensation contract. Next, the agent chooses his level of effort, which is unobservable by the principal. Because production is a noisy process, the agent's production is determined by his effort plus noise. Finally, the agent receives his compensation according to the contract.

The question of incentives asks: how should an organization structure the contract? A fixed contract that is not based on the level of output shields the risk-averse agent from random fluctuations in output caused by noise, but it provides no incentive for the agent to make output-producing investments. In the other extreme, a contract based solely on the level of output offers strong incentives but exposes the agent to high levels of risk. An efficient contract lies somewhere between these two extremes. Gibbons (2005) explores extensions to this model and Prendergast (1999) provides a broad review of the literature on monetary incentives and their use in solving agency problems. However, less attention has been given to the effect of non-monetary, positional, and symbolic incentives on the behavior of agents. Next, I discuss the benefits that awards may offer beyond those provided by strictly monetary incentives.

Status. People innately desire to distinguish themselves and to climb social hierarchies (Podolny, 1993; Frank, 1985). That is, they desire not just to be better than they were yesterday, but to be better than others too. Awards are one way in which individuals can distinguish themselves from their peers. Awards are likely better devices for providing status than monetary rewards because awards are easily observable and often even publicized. On the other hand, there are strong norms against discussing one's compensation and organizations are keen on keeping such information private.

One notable problem with using monetary rewards to solve agency problems is the envy and jealousy that they breed (Nickerson and Zenger, 2008). If individuals are more tolerant of status dispersion than they are of wage dispersion (Nickerson and Zenger, 2008) then the use of symbolic awards may come with fewer costs related to social comparison. On the other hand, it is possible that, because status is inherently comparative, awards lead to more social comparison between candidates. This is an important question remains open.

Feedback. Suvorov and van de Ven (2009), Neckermann and Yang (2017), and Bradler et al. (2016) argue that awards are also useful in providing valuable feedback. Because awards are public, they allow the granter to establish a relatively clear hierarchy at the top-end of the performance distribution. Thus, awards provide valuable feedback about one's *relative* position. Bradler et al. (2016) note that this feedback can have implications, not just for the winners, but for the non-winners as well. They find that non-winners increase their performance after an award is granted to a peer. Bradler et al. (2016) argue that by not being granted an award, the low performers receive valuable feedback to increase their effort.

Cost. From the granting organization's (principle's) point of view, monetary incentives have a notable downside: financial cost. For example, year-end bonuses may have significant effects on a firm's output, but to be profitable, these benefits must outweigh the financial burden that bonuses impose on the firm. Awards have the advantage of being relatively costless to the granting institution, and potentially very valuable for the winner. Thus, even if awards are less effective than monetary incentives, they may be more cost-effective.

1.4 Empirical Literature on Awards

The empirical literature on awards has found generally positive effects for the winners. One body of work looks at the impact of awards granted to firms and their CEOs. For example, Hendricks and Singhal (1996) find that firms given quality awards experience increased stock prices. Malmendier and Tate (2009) demonstrate, using a matched sample, that awards-winning CEOs receive higher compensation, but that winning also leads the CEOs to become overconfident and to focus on non-core tasks. Wade et al. (2006) also find that award-winning CEOs experience higher pay when the firm they are running experiences high returns, but lower pay than non-winning CEOs in bad times. They also see positive short-run stock market returns to CEO awards, but these are reversed in the long-run. Similarly, Siming (2016) similarly find that external awards (Swedish orders of merit) lead to increased CEO compensation, though he finds no significant effect on firm performance.

A separate, but related, literature assesses the effects of awards on employees and other agents. Studies have found that awards increase performance (Kosfeld and Neckermann, 2011), attendance (Markham et al., 2002), knowledge-sharing (Neckermann and Frey, 2013), and retention (Gallus, 2017). Restivo and van de Rijt (2012) demonstrates that even awards from peers, rather than from employers, can have positive effects. Neckermann et al. (2014) found that awards also have positive spillovers to other tasks. Though, recent work has demonstrated that the positive direct effects of awards may be accompanied by negative spillovers (Gubler et al., 2016).

Outside of corporate environments, scholars have looked at the role of awards in science and academia. Chan et al. (2014) find that, after receiving a prestigious award, academic researchers experience higher productivity and that their papers are cited more frequently. Azoulay et al. (2013) find similar effects for Howard Hughes Medical Institute (HHMI) Investigator winners, though the effects are strongest for winners who were previously low-status. In contrast, Borjas and Doran (2015) find that fields Medal recipients are less productive after winning. Reschke et al. (2017) provide one of the few investigations into award externalities, finding that the increased attention and status that goes to winners comes at the expense of non-winners.

Finally, there is a small literature on awards in creative industries, like art and technology. Ginsburgh (2003) shows that winners of prestigious award (e.g., Oscars, Golden Globes, Booker Prize) experience increased productivity in the period following an award. In Chapter 3 of this dissertation, I counter these findings by demonstrating a negative effect of awards on productivity after controlling for selection effects and omitted variables. Kovács and Sharkey (2014) find that book prize winners experience increased sales but decreased ratings due to a more diverse audience. Brunt et al. (2012) and Moser and Nicholas (2013) find that innovation awards induce competitive entry into technological sectors more effectively than monetary rewards. See Tables 1.2 and 1.3 for a review of the empirical literature on awards.

[Table 1.2 about here.]

[Table 1.3 about here.]

1.5 Future Research

Scholars have made significant progress in documenting some of the direct and indirect effects of awards. However, even the most basic questions, like "how do awards affect the behavior of winners" remain unresolved. Further, many other important questions have gone completely unanswered. Below, I have outlined opportunities for future research.

Winners. Previous studies tend to find that winners benefit from receiving awards, mainly because their signaling value increases others' perceptions of the winner (Chan et al., 2014; Azoulay et al., 2013; Ginsburgh, 2003). Yet, there are others that find negative effects (Kovács and Sharkey, 2014; Borjas and Doran, 2015). To reconcile these findings, we need more research on the underlying mechanisms and more robust and comprehensive theory of awards.

One mechanism that has received little attention in the literature is how awards affect the winner's perception of himself. Wade et al. (2006) suggest that awards may lead to overconfidence in CEOs. However, the effects on CEOs–an already overconfident group (Chatterjee and Hambrick, 2007)–cannot be generalized to other populations. It is possible that awards lead to feelings of anxiety and insecurity, especially if the winner does not feel deserving of the honor. Future research should consider the psychological effects of awards on the winner.

Competition, runners-up, and non-winners. The vast majority of work on awards has focused on the winners of awards or those perceiving the winners. But much less work has focused on the effects that awards have on those who do not win (Neckermann and Yang, 2017; Bradler et al., 2016). Work in psychology suggests that losing can have significant effects on emotional states and subsequent motivation (Medvec et al., 1995). To quantify the costs and benefits of awards competitions, organizations need to understand the effects of awards on winners, losers, and non-participants. If losing is found to have positive effects on subsequent motivation, then firms may enlarge the participant pool to increase the benefits of awards. On the other hand, if losing has negative effects on subsequent productivity and performance, then organizations ought to consider these costs before beginning a new awards program.

Another unanswered question is how losing an awards affects loyalty and attachment. It is possible that those who do not win awards feel unappreciated and are therefore less loyal to the organization. In any case, it is imperative to understand the effects of awards programs on non-winners to assess the costs and benefits of the programs.

Team Dynamics. Most models of awards and status signals consider a single signaler. In cases of team production, however, a single award may be sent on behalf of multiple parties. Whether the signal is produced by a group of individuals or by a firm and individuals, it is critical to understand the heterogeneous effects of signals. This especially true if the signal impacts the members of the production team differently or if the signal changes the structure of the relationship. Essay 2 of this dissertation demonstrates that a single signal, namely a patent, can cause employee inventors to leave their employers to join or start another firm. Future work should consider how an award granted to an individual member of a team may affect team dynamics. If one member of a team wins a prestigious award, the sudden status shift may cause team conflict (Overbeck et al., 2005; Bendersky and Hays, 2017). On the other hand, awards granted to entire teams may increase team cohesion, longevity, and productivity. A related, and unanswered question, is how award competitions that pit members of the same team against one another affect individual and team performance.

The granting organization. One party that is notably absent from most discussions of awards is the granting institution. Why do organizations give awards? Anecdotal evidence suggests that awards may be strategically given to benefit the awarding organization or individual. For example, Alfred Nobel, who read a draft of his obituary that condemned him for his invention of dynamite, established the Nobel prize to repair his legacy. We know little about how organizations can strategically grant awards to enhance their own status and reputation.

Scholars also know little about how the actions of winners reflect back onto the awarding organizations. Jean-Paul Sartre, who famously refused a Nobel Prize, realized that award giving and receiving creates an interdependence between the winner and the granter of the award. He said "The writer who accepts an honor of this kind involves as well as himself the association or institution which has honored him." He went on to explain that "[m]y sympathies for the Venezuelan revolutionists commit only myself, while if Jean-Paul Sartre the Nobel laureate champions the Venezuelan resistance, he also commits the entire Nobel Prize as an institution." Future studies should investigate how awards serve to intermingle the reputations of the award winner and granters and how scandals involving one party may reflect onto the other.

Another reason organizations may grant awards is to shape a field, or change the direction of an industry (Cattani et al., 2014). In a field or industry where quality is difficult to observe, organizations can define quality by creating awards programs. For example, the Oscars define what 'quality' movies are and therefore influence future movies to be more like previous Oscar winners. Future research should investigate how firms and organizations can strategically use awards to shape industries and to pick winners and losers. Researchers might gain traction on these questions by applying theories from neo-institutional theory, particularly institutional entrepreneurship (Greenwood and Suddaby, 2006). Similarly, if awarding institutions stand to benefit from granting awards, through increased status or by shaping a field or industry, then there should be competition between granting institutions. How do institutions compete to become the authority in a field?

Loyalty. Scholars interested in strategic human capital and HR might also consider how awards affect employee loyalty. Akerlof and Kranton (2005) argue that awards can increase employees identification with the granting organization. Awards granted to employees by employers may foster employee loyalty by showing the employee they are valued. On the other hand, employees may be able to leverage such awards on the labor market to attract more appealing and lucrative offers.

Furthermore, firms and scholars should consider the potentially negative effects on non-winner identification and loyalty.

Award Heterogeneity. Scholars have investigated the effect of attaching monetary rewards to symbolic awards (Neckermann and Frey, 2013). Yet, little research has examined the effect of non-monetary awards in the presence of monetary awards. We need more studies on the context in which the award is granted. For example, can organizations blunt the jealousy and envy (Nickerson and Zenger, 2008) felt by winners who are not given a monetary bonus with non-monetary recognition?

How does the perceived fairness of an award impact its effect? Wade et al. (2006) find that perceptions of unfair pay can have wide-ranging organization effects. Yet, we know little about how the perceived fairness of symbolic awards moderates their effects. This also has important implications for what scholars can learn from randomized experiments in this setting. If randomization causes the contestants to perceive that the award has been unfairly granted, then the effects of randomized experiments may not generalize to awards that are regarded as justly conferred (Restivo and van de Rijt, 2012; Angrist and Lavy, 2009).

Another dimension of heterogeneity that scholars should investigate is the relative prestige of the award. For example, I find in the third essay of this dissertation that winners of very prestigious awards decrease their productivity after the award has been granted. But these results are unlikely to generalize to less prestigious awards, like "Salesperson of the Month." Future theoretical and empirical work should consider how the relative prestige of an award moderates the effects that they have.

Receivers/Perceivers. The classic signaling model considers a single signaler and a single receiver. Yet, a single signal may be interpreted differently by different parties. For example, in the second essay of this dissertation, I demonstrate that patents, which are commonly used by firms to signal their quality to investors and other stakeholders (Conti et al., 2013; Hsu and Ziedonis, 2008), are also viewed by the firm's labor market competitors. I show that this leads to increased inventor mobility, entrepreneurship, and wages. Kim et al. (2018) also find that recognition by one group (traditional knitters) can cause rival audiences (avant-garde knitters) to devalue a product. Future research should consider how heterogeneous, and sometimes oppositional, audiences perceive a single award differently.

Table 1.1: Dimensions of the Literature on Awards

	Ex-ante	Ex-post
Perception of quality		Awards as Signal/Status *Essay 2*
Behavior	Awards as Incentive	*Essay 3*

Table 1.2: Empirical Literature on Awards

Authors	**Award Winner**	**Award**	**Direction of Effect**	**Ex-ante or ex post?**	**Effect of Award**	**Empirical Approach**
Hendricks and Singhal (1996)	Firm	Quality Award	positive	ex post	Increased stock prices	Event study
Wade et al. (2006)	CEOs	CEO of the year	positive/negative	ex post	Higher (lower) compensation when firm performed well (poorly). Positive (negative) short-run (long-run) stock returns.	Event study, controls
Malmendier and Tate (2009)	CEOs	Best CEO awards	positive/negative	ex post	Higher compensation, but lower firm performance	Matching on observables
Siming (2016)	CEO	Swedish orders of merit	positive	ex ante	Increase CEo compensation, no effect on firm performance	Diff-in-diff
Chan et al. (2014)	Academic Researcher	John Bates Clark Medal and the Fellowship of the Econometric Society	positive	ex post	Higher productivity and citations	Synthetic control
Azoulay et al. (2013)	Scientist	Howard Hughes Medical Institute (HHMI) Investigator	positive	ex post	Higher citations, especially for low-status researchers	Matching on observables
Reschke et al. (2017)	Scientist	Howard Hughes Medical Institute (HHMI) Investigator	negative	ex post	Lower citation rates/attention for other articles in field	Matched sample of articles in same journal
Borjas and Doran (2015)	Mathematicians	Fields Medal	negative	ex post	Winners produce fewer papers and explore more topics	Match winners to runners-up

Table 1.3: Empirical Literature on Awards (cont.)

Markham et al. (2002)	Manufacturing employees	Attendance Award	positive	ex ante	Awards increased attendance	Field experiment
Restivo and van de Rijt (2012)	Wikipedia contributors	Informal peer awards	positive	ex post	Increase in productivity	Field experiment
Gubler et al. (2016)	Employee	Attendance Award	positive/negative	ex ante/ex post	Positive effects on attendance in eligibility period, but decreased performance elsewhere	Randomized field experiment
Gallus (2017)	Wikipedia Editor	Symbolic editor award	positive	ex post	Editors are more likely to continue if awarded	Randomized field experiment
Neckermann and Frey (2013)	IBM employee	Employee award	positive	ex ante	Awards increase employees willingness to share knowledge with co-workers, and publicity positive moderates the effect.	Survey using hypothetical award
Kosfeld and Neckermann (2011)	Student employees	Congratulatory card	positive	ex ante	Symbolic award increased performance by 12 percent	Randomized field experiment
Brunt et al. (2012)	Inventions	Royal Agricultural Society of England Innovation awards	positive	ex ante	Increased competition	Panel data analysis
Kovács and Sharkey (2014)	Book	Book awards	positive/negative	ex post	Increased sales, decreased ratings	Match winners to runners-up
Moser and Nicholas (2013)	Technologies	Crystal Palace WorldâĂŹs Fair	positive	ex post	Increased patenting in winning technological fields	Match winners to other contestants
Ginsburgh (2003)	Art work	Oscars, Golden Globes, Booker Prize, etc.	positive	ex post	Increase economic performance and artistic evaluation	Match winners to other nominees

Chapter 2: Signals or Shackles? The Effect of Patents on Inventor Mobility and Entrepreneurship

2.1 Introduction

This paper investigates whether patents enable or constrain the mobility and entrepreneurship of employee inventors, or inventors whose patents are owned by their employers. Prior literature generally supports the notion that patents constrain inventors from leaving their employers because it makes the inventor's knowledge more firm-specific and reduces their ability to appropriate the value of the patented knowledge elsewhere (Hoisl, 2007; Marx et al., 2009; Palomeras and Melero, 2010; Ge et al., 2016; Melero et al., 2017). However, I argue that there are both theoretical and empirical reasons to doubt these findings. Specifically, I argue that patents increase opportunities for mobility and entrepreneurship by signaling the inventor's quality to potential employers, founding-team members, entrepreneurial financiers, and others. My results support the signaling mechanism by showing that, after addressing multiple sources of bias, patents do increase inventor mobility and entrepreneurship. The results challenge previous findings and have important implications for firms' intellectual property and human capital strategies.

Theoretically, scholars have argued that patents limit inventor mobility for several reasons. First, they argue that patents transfer the right to commercialize the inventor's ideas to their employer (Melero et al., 2017; Anton and Yao, 1995; Kim and Marschke, 2005). Thus, patents serve to diminish the stock of knowledge the inventor can profitably deploy at another firm. Further, the inventor's related tacit knowledge becomes more firm-specific after the patent is granted. Finally, patents increase the legal liability of poaching firms (Melero et al., 2017; Ganco et al., 2015; Agarwal et al., 2009). Given these theoretical arguments, it is perhaps unsurprising that both observational (Palomeras and Melero, 2010; Ge et al., 2016) and quasi-experimental studies (Hoisl, 2007; Melero et al., 2017) have found support for the notion that patents constrain employee inventors.

Despite arguments that patents constrain inventors (Melero et al., 2017; Ganco et al., 2015; Agarwal et al., 2009; Kim and Marschke, 2005), signaling theory predicts that patents will increase opportunities for inventor mobility. The signaling perspective begins with the observation that distinguishing high-quality inventors from low-quality inventors is difficult. Such information asymmetry leads to the well-known "lemons problem," which decreases opportunities for mobility and entrepreneurship (Akerlof, 1970; Greenwald, 1986). In such settings, patents may act as credible signals of inventor quality, increasing opportunities for mobility (Spence, 1973; Melero et al., 2017). Patent signals will also increase entrepreneurial opportunities by enhancing the inventor's ability to attract founding-team members, entrepreneurial finance, customers, and suppliers (Conti et al., 2013; Hsu and Ziedonis, 2008; Farre-Mensa et al., 2017; Ekinci, 2016). Therefore, the signaling perspective suggests that patents will increase, not decrease, inventor mobility and entrepreneurship.

There are also empirical reasons to question prior findings that patents negatively affect inventor mobility rates. First, most previous investigations of this question rely on patent-based measures of mobility (Hoisl, 2007; Marx et al., 2009; Palomeras and Melero, 2010; Melero et al., 2017),[1] which have recently come under criticism due to severe misclassification bias inherent in such measures (Ge et al., 2016). Second, patent-based measures of mobility also rely on samples of inventors with multiple patents, which leads to sampling on "star" inventors that are likely to behave differently than non-stars. Finally, the studies that do not rely on patent-based measures of mobility are unable to establish causality and focus on atypical samples, like university scientists (Crespi et al., 2007; Lenzi, 2009; Ge et al., 2016; Azoulay et al., 2017). Therefore, all prior empirical investigations of the effect that patents have on mobility suffer from misclassification, sampling, selection, or omitted-variable bias.

I improve on prior studies by matching hundreds of thousands of inventors' USPTO patent histories to confidential U.S. Census Longitudinal Employer-Household Dynamics (LEHD) data. These data allow me to observe the near-complete patenting, employer, and wage histories of most US inventors between 1995 and 2008. By measuring mobility using Census data, rather than patent data, I overcome the sampling and misclassification bias that has plagued prior studies. To identify the causal effect of patents, I implement an instrumental variables approach that leverages

[1] Marx et al. (2009) does not explicitly investigate the effect of patenting on mobility but uses patent productivity as a control variable.

the USPTO's quasi-random assignment of patent examiners to patent applications (Sampat and Williams, 2015; Farre-Mensa et al., 2017; Melero et al., 2017). My results challenge previous findings that patenting has a negative effect on inventor mobility (Hoisl, 2007; Marx et al., 2009; Palomeras and Melero, 2010; Melero et al., 2017; Ge et al., 2016). Rather, I find that patenting roughly doubles the short-term mobility and entrepreneurship rates of employee inventors after addressing sources of sampling, misclassification, and omitted-variable bias. I demonstrate that the results are not due to firms simply "discarding" inventors after they patent the inventor's idea by showing that inventor wages and patent productivity also increase after a patent grant.

This paper makes several meaningful contributions. First, I contribute to the literature on employee mobility and entrepreneurship. I challenge prior work that suggests patents constrain inventors (Hoisl, 2007; Marx et al., 2009; Palomeras and Melero, 2010; Melero et al., 2017; Ge et al., 2016) by showing that, after correcting for sources of bias, patents increase inventor mobility and entrepreneurship. For scholars interested in strategic human capital, it means that employee successes that are observable to outsiders may damage the employer's ability to realize informational rents (Campbell et al., 2012). I also contribute to the fields of innovation and entrepreneurship by being the first, to my knowledge, to empirically investigate the effect of patenting on employee-inventor entrepreneurship. For scholars interested in firm-level IP strategy, these findings introduce inventor mobility and entrepreneurship as an unintended consequence of patenting (Cohen et al., 2000), which may inflict significant costs on the firm (Coff, 1997). For scholars interested in the economic value of patents (Hall et al., 2005; Trajtenberg, 1990), this paper is one of the first to isolate the signal value of patents from the value of the property rights they confer by focusing on employee-inventors who do not own the rights to their inventions. Next, this study weighs in on the role of luck in determining career outcomes (Brookman and Thistle, 2013; Gompers et al., 2010). I demonstrate that a "lucky" patent-examiner draw has statistically and economically significant effects on inventor careers. This study also has significant policy implications. Scholars have long argued over whether patents are economically efficient. This study suggests that patents may increase economic productivity, even if the exclusivity rights are valueless, by allowing inventors to find more productive firm-matches (Jovanovic, 1979). Further, legal scholars have debated the need for "inventor compensation" laws, based on the assumption that inventors are not fairly rewarded for the patents granted to employers (Dratler, 1979; Manly, 1978; Noble, 1979; Merges, 1999). However, there has been little empirical evidence on how US labor markets reward inventors for their inventions. This paper provides evidence that inventors are rewarded by the market with increased opportunities for mobility and entrepreneurship as well as increased wages. Finally, this paper adds to the nascent literature that cautions against using patents to measure inventor mobility (Ge et al., 2016).

2.2 Related Literature and Theoretical Predictions

Employee mobility and entrepreneurship are, at the societal level, critical drivers of economic growth and productivity (Jovanovic, 1979; Schumpeter, 1934). However, for the source firm, mobility and entrepreneurship erode competitive advantage and deteriorate human-capital stocks (Coff, 1997; Campbell et al., 2012). This is especially true of employees with high levels of human capital, like inventors. For these reasons, scholars have investigated the many determinants of inventor mobility and entrepreneurship (Marx et al., 2009; Samila and Sorenson, 2011; Ganco, 2013; Palomeras and Melero, 2010; Agarwal et al., 2009; Ganco et al., 2015; Azoulay et al., 2017). Perhaps the most commonly investigated determinate of inventor mobility is patent productivity. This work suggests that patents constrain inventors from leaving their employers (Hoisl, 2007; Marx et al., 2009; Palomeras and Melero, 2010; Ge et al., 2016; Melero et al., 2017), though there are exceptions (Lenzi, 2009).[2]

2.2.1 Patents as Constraints

Hoisl (2007) was one of the first to investigate the effect of patents on inventor mobility. She finds, using an instrumental variables technique, that patents decrease the probability that the inventor will leave the firm by 18 percent. Hoisl (2007)

[2]I have omitted studies that focus on university-employed scientists from this review because their patenting behavior may be interpreted differently than industrial inventors. Briefly, Crespi et al. (2007) find patenting does not affect mobility rates of university inventors. Zucker et al. (2002) find that patenting increases the probability that university scientists will enter industry. Finally, Azoulay et al. (2017) find that prolific elite life scientists are more likely to move than those who are less prolific. I return to this literature, and the differences between industrial and academic inventors, later.

argues that this effect may be because patents are related to better inventor-firm matches or because the employer responds to outside offers with better counter-offers. Later, Marx et al. (2009) and Palomeras and Melero (2010) also found that patenting and mobility are negatively correlated, though the effect of patenting on mobility was not the primary motivation for their studies. As an exception, Lenzi (2009) finds that, in a sample of Italian pharmaceutical inventors, a single patent has no statistically significant effect on mobility, but that persistent patenting does have a positive effect.[3] More recently, Ge et al. (2016) returned to this question using an observational design and found, again, that patenting was negatively correlated with mobility. Finally, Melero et al. (2017) use an instrumental variables approach and find that patenting has a negative effect on rates of inventor mobility. Though the results are fairly consistent that patents decrease the rate of inventor mobility, I argue that there are both theoretical and empirical reasons to question these findings. Next, I briefly review the theoretical explanations that have been posited for the constraining effect of patents before presenting the alternative view.

The argument that patents constrain inventors from leaving their employer stem from theories of appropriability and firm-specificity (Melero et al., 2017). For example, Melero et al. (2017) point out that patents grant the employer the right to commercialize the inventor's knowledge that overlaps with the claims of the patent. Anton and Yao (1995) point out that in the absence of a valid patent, employee-inventors may appropriate the full value of their ideas by joining another firm or by

[3] This may suggest that the mobility is due to differences in the quality between prolific patenters and non-patenters, not because of the patent itself.

leaving to start their own firm. However, when an inventor's idea is patented, the inventor no longer has the right to "make, use or build upon patented technologies owned by their former employers" (Agarwal et al., 2009, p. 1353).

In addition to barring expropriation of the patented idea, patents serve to make the inventor's related, tacit knowledge more firm-specific. Though patents only protect a narrow set of claims, inventors often have a constellation of related knowledge that is helpful in extending the idea or bring the patented idea to market. This related knowledge that is not directly protected by the patent becomes more firm-specific after the core idea has been patented. Thus, patents may serve to increase the firm-specificity of the inventor's tacit knowledge, further tying them to their employer. Finally, in the case that poachers do hire inventors, patents will increase the legal liability of the poaching firm,[4] thus raising the cost of hiring the inventor (Ganco et al., 2015; Agarwal et al., 2009; Melero et al., 2017). Therefore, this line of reasoning posits that patents will diminish the inventor's outside options, thus reducing the probability that the inventor will exit the firm.

2.2.2 Patents as Signals

The above argument that patents will constrain employee inventors hinges on an implicit assumption that inventors are valued for the *stock* of commercializable knowledge they possess and that, by reducing the stock of commercializable knowledge, patents serve to make the inventors less valuable to others. On the other

[4]The assumption here is that it is easier to litigate patent infringement than trade secrecy violations.

hand, potential employers and entrepreneurial financiers may be more interested in the *ability* of the inventor to generate ideas than any specific idea in the inventor's mind. Along these lines, logic from signaling theory suggests that patents will increase the inventor's perceived ability or quality. This view begins with the assumption that information asymmetry plagues markets for labor and entrepreneurial talent (Stigler, 1962; Akerlof, 1970; Hall and Lerner, 2010). That is, the inventor and his employer will have better information about his quality than other market participants. Such markets suffer from the well-known "lemons problem," whereby market activity is suppressed (Akerlof, 1970). Patents will alleviate this problem by distinguishing high-quality inventors from low-quality inventors (Spence, 1973).

2.2.2.1 Patents Signals and Inventor Mobility

Importantly, patents meet the criteria for a Spencian signal. Patents are observable to those outside of the employer firm.[5] For example, it is common practice for inventors to list their patents prominently on their resumes and personal websites. Further, such claims are easily verifiable through online patent searches. Patents are also likely to be correlated with inventor quality since patenting is a direct output of the inventor's primary job responsibility. All else equal, an inventor with a patent should be considered higher quality than an inventor without one. Finally, the cost of obtaining a patent must be negatively correlated with the inventor's

[5]In few cases, patents are granted but not published. For example, governments may suppress the publication of patents in the interest of national security. In these circumstances, patents would not operate as signals.

ability to achieve a separating equilibrium.[6] (Spence, 1973). That is, it should be easier for a high-quality inventor to obtain a patent than for a low-quality inventor. This assumption is reasonable given that high-quality inventors generate more and better ideas that are able to meet the novel, non-obvious, and usefulness criteria for obtaining a patent.

Because patents are credible signals, outside observers will perceive inventors with patents as higher-quality than those without (Stole and Zwiebel, 1996; Spence, 1973). Thus, patents should cause the inventor to receive more and better outside employment offers, which will increase the probability of leaving. Assuming that patents do not dramatically decrease the probability that an inventor will accept an outside offer (conditional on receiving one), patent signals should increase rates of inventor mobility.[7]

2.2.2.2 Patents Signals and Inventor Entrepreneurship

Employee inventors assessing opportunities outside of their current employer may also consider entrepreneurship. Entrepreneurship provides several advantages over paid employment that may be particularly attractive to inventors. First, entrepreneurship offers independence to the employee inventor. Sauermann and Cohen (2010) find that scientists place more importance on independence than they do on

[6] A separating equilibrium, as defined by Spence (1973), is an equilibrium in which different types of people send different signals. In this case, a separating equilibrium is one in which high-quality inventors have patents (or more patents) than low-quality inventors.

[7] Banerjee and Gaston (2004) show that under certain reasonable assumptions of noisy signaling, switching costs, and imperfect counter-offering, signals will, in fact, result in increased mobility. The idea is that employers cannot perfectly respond to outside offers so some percentage of employees will leave even if their employer would like for them to stay.

salary, job security, or responsibility. Second, entrepreneurship may provide the largest potential returns to employee inventors because it allows them to capture more value from their innovations (Anton and Yao, 1995). For these reasons, entrepreneurship may be particularly attractive to employee inventors.

Despite its attractiveness, entrepreneurship is a costly and uncertain undertaking that requires the investment and trust of others. However, entrepreneurs have problems attracting investors, founding-team members, and customers if they cannot credibly signal their quality (Shane and Cable, 2002; Stuart et al., 1999; Hsu and Ziedonis, 2013). Scholars have investigated several ways entrepreneurs signal their quality, including industry experience (Dahl and Sorenson, 2013; Burton et al., 2002; Chatterji, 2008), eponymy (Belenzon et al., 2017), and social ties (Shane and Cable, 2002). Patents may, similarly, signal that inventors are high-quality.

Patents help aspiring entrepreneurs attract more and cheaper financial capital (Hsu and Ziedonis, 2008; Balasubramanian and Sivadasan, 2011; Farre-Mensa et al., 2017). It is difficult for investors, especially those who are technically unsophisticated, to differentiate between high- and low-quality entrepreneurs. For highly technical ventures, like those often founded by inventors, these information asymmetry problems are particularly pernicious. Patents should help inventors signal their ability to develop novel and useful ideas. In fact, previous studies suggest that entrepreneurial ventures that own patents are more successful (Balasubramanian and Sivadasan, 2011; Farre-Mensa et al., 2017). One reason is that signals help entrepreneurial firms signal their quality. However, entrepreneurial financiers care about the quality of the founders as well as the entrepreneurial idea. Thus, even patents not owned by the inventor may act as credible signals to investors, allowing the inventor to attract entrepreneurial capital.

Inventors with patent-signals should also attract high-quality founding-team members more easily. The quality of a founding team has vital consequences for the success of the entrepreneurial venture (Beckman, 2006; Phillips, 2002; Burton et al., 2002). Yet, the decision to join an entrepreneurial firm as an employee is a risky prospect, given their high failure rates. Therefore, entrepreneurial ventures with inventors who have successfully patented should be perceived by potential employees as having lower risk or higher potential. Thus, I predict that patenting will have a positive effect on an employee inventor's probability of founding a new firm.

2.3 Data and Empirical Design

2.3.1 Data Description

I combine several datasets to construct the patent and career histories of employee inventors. I begin with the Fung Institute's disambiguated USPTO patent dataset (Li et al., 2014). This dataset contains disambiguated, longitudinally stable inventor and firm (assignee) IDs for the United States Patent and Trademark Office (USPTO) and NBER patent datasets (Hall et al., 2001). The dataset also contains inventor names, assignee names, patent classes, and citation data for published patent applications.[8]

[8] Patent application data is available since 2001. The American Inventors Protection Act, which stipulated that patent applications be published, came into effect in 2001.

I augment the disambiguated patent data with the Patent Examination Research Dataset (Graham et al., 2015). This dataset, from the USPTO, contains 1.4 million issued or published patent applications that were filed through December 2014. Importantly these data include information on patent examiners and contain published patent applications that were not ultimately approved. The unapproved patent applications allow me to construct a counterfactual group of inventors, which I will discuss in more detail later.

To measure inventor wages, mobility, and entrepreneurship, I use the US Census Bureau's Longitudinal Employer Household Dynamics (LEHD) database. The LEHD Employment History Files (EHF) contain job records which link employees to employer establishments from 1990-2008. The EHF contain data sourced from the unemployment insurance wage records and contain nearly all salaried, private, non-farm wages except for self-employment wages. The EHF includes university employees but does not contain public sector employment in the federal government, state-elected officials, local government officials, or members of the armed forces. The data extract I use covers a total of 30 US states.[9]

The LEHD Employer Characteristics File (ECF) contains employer (SEIN) and establishment-level information including size, location, and industry. These data are also based on unemployment insurance records and are linked with the EHF files at the firm-quarter level. Finally, the individual characteristics file (ICF)

[9] In 1990, the LEHD extract I use only contains three states. Additional states are gradually added from 1990-2000. The states included in the LEHD extract are Arkansas, California, Colorado, Florida, Georgia, Hawaii, Iowa, Idaho, Illinois, Indiana, Louisiana, Maryland, Maine, Montana, North Carolina, New Jersey, New Mexico, Nevada, Oklahoma, Oregon, Rhode Island, South Carolina, Tennessee, Texas, Utah, Virginia, Vermont, Washington, Wisconsin, and West Virginia.

contains one record for every employee in a given state's unemployment insurance system. The ICF contains information on the employee's age, sex, residence location, education, and citizenship. See Abowd et al. (2005) for a detailed description of the LEHD data.

Finally, I use the Longitudinal Business Register Bridge, which contains all US establishments that have at least one employee (Abowd et al., 2005). This dataset links establishments to longitudinal firm IDs (alphas) and contain data on the establishment industry, corporate ownership, and total employment (including states that are not included in the 30-state LEHD extract). See Table 2.1 for summary statistics.

[Table 2.1 about here.]

2.3.2 Matching Procedure and Sample

The LEHD and disambiguated patent data provide longitudinally stable individual identifiers, which allows me to track individual career histories. Because these two datasets do not contain common identifiers, I match the two datasets using inventor names and locations (Graham et al., 2015). I leverage the Census Bureau's Person Identification System (PVS) to assign PIKs, or individual Census identifiers, to inventors. The PVS uses probabilistic algorithms to match personal data using many administrative and commercial datasets (see Wagner and Layne (2014) for further details on this process). Following a process similar to Graham et al. (2015), I begin with all patents that were granted from 2000 to 2011 and applied for after 1996. The original dataset included over 5.8 million patent-inventor pairs. About 47 percent of the observations are dropped because they do not have US addresses (foreign inventors). The sample also excludes records without inventor names, states, and at least 3-digit zip code. The PVS attempted to assign PIKs (individual census identifiers) to about 2.7 million non-unique inventors on over 1.2 million patents in three different passes:

1) fuzzy match on inventor name, same 3-digit zip code

2) fuzzy match on inventor name, same inventor state

3) fuzzy match on inventor name, same assignee state

I keep only the "best" matches – those matches at the lowest geographic area. For example, the algorithm prefers an inventor name match at the 3-digit zip code to a match at the inventor state-level. If there are multiple “best” matches at a given level, then I use middle initial matches to break ties. About 97 percent of US inventor records have at least one PIK match and about 80 percent have a unique “best” match. I exclude all records for which I cannot identify a “best” match.[10] Because the focus of this paper is employee inventors, I also exclude all patents that are not assigned to a firm at the time of invention.[11] Figure 2.1 demonstrates that employee inventors are responsible for approximately 90 percent of patents in 2010. I successfully match about 2.2 million non-unique inventors, which represents

[10]This results in a sample that is biased against inventors with popular names. It is possible to get a higher match rate by triangulating inventors using their employer/patent assignee. I did experiment with this approach using the Kerr and Fu (2008) crosswalk. However, this approach biases the sample towards inventors at large firms. The bias toward inventors that work at large firms seems, a priori, more consequential than a bias towards inventors with common names given that rates of mobility and entrepreneurship are demonstrably different for employees working in large and small firms. I, therefore, do not use employer-assignee information in the inventor match.

[11]Results are robust to the inclusion of patents assigned to inventors.

about an 80 percent match rate. The final sample, however, is significantly smaller because my instrumental variable is only available after 2001.[12]

[Figure 2.1 about here.]

2.3.3 Instrumental Variables Estimation

When an assignee submits a patent application, the Office of Initial Patent Examination assigns the patent to an art unit for review. Art units are based on the technology field, which is assigned through automated text analysis of the invention description contained in the application (Farre-Mensa et al., 2017). Each art unit contains a number of examiners that review patent applications for a narrowly defined set of technologies. There are about 900 art units and 13,000 patent examiners (Farre-Mensa et al., 2017). According to Farre-Mensa et al. (2017, p. 7), applications are assigned to examiners quasi-randomly with respect to invention or application quality. See Lemley and Sampat (2012) and Sampat and Lemley (2010) for further details of the patent examination process and the quasi-random nature of the assignment.

I follow Farre-Mensa et al. (2017) and Sampat and Williams (2015) in exploiting this quasi-random assignment of patent applications to examiners and the exogenous variation in examiners propensity to approve patents to identify the causal effect of patenting. Specifically, I instrument, using OLS two-stage least squares (2SLS), the $PatentGranted_{it}$ variable using the examiners' historical leniency. I calculate the examiner's historical leniency for each application as the cumulative

[12] I have not yet disclosed the number of unique inventors from the Census.

number of prior patents granted by the examiner divided by the cumulative number of patents reviewed by the examiner.[13] Figure 2.2 shows the distribution of examiner approval rates, which display a considerable level of variation.[14]

[Figure 2.2 about here.]

Following Farre-Mensa et al. (2017) and Sampat and Williams (2015), I include art-unit-by-application-year fixed effects because patent applications are quasi-randomly assigned within art units. Therefore, the first-stage specification of the two-stage model is as follows.

$$PatentGranted_{it} = \theta ExaminerApprovalRate_{it} + \kappa_{at} + \sigma X_{itj} + \mu_{itja} \tag{2.1}$$

and the second stage is:

$$InventorOutcome_{it} = Patent\widehat{Granted}_{it} + \kappa_{at} + \gamma X_{itj} + \epsilon_{itja} \tag{2.2}$$

were i indexes inventors, t indexes application years, j indexes examiners, and a art units.

Dependent Variables. The $InventorOutcome_{it}$ term takes several variables. First, I define *mobility* as a dummy variable equal to one in a year where an employee has at least one-quarter of zero wages from their previous dominant employer and non-zero wages from a different employer.

I also define $founder$ as a dummy variable equal to one if an inventor collects

[13]One concern is that this approach overweights decisions early in the examiner's career. Results are robust to only including the approval rate for the prior 200 patents, rather than the entire history of prior patents. Farre-Mensa et al. (2017) find that examiner rates are relatively stable over time.

[14]The distributions shown come from the full set of patent applications, not the set matched to US Census data. The matched distributions are very similar but are not disclosed due to Census restrictions on disclosing histograms.

wages from a firm in its first quarter of operation. Therefore, founders are not necessarily owners of the new firm, but founding team members.[15]

To test whether patents also increase inventors wages (further evidence of the signaling mechanism), I define $log(wages)$ as the logarithm of all inventor wages reported for a given year in the LEHD. I take the log because the distribution of inventor wages is highly skewed; even more than other professional services occupations like doctors and lawyers (Bell et al., 2016). Although my measure of wages does not capture other sources of income, like dividends and stock options, Bell et al. (2016) find that inventor income is "dominated" by salaries.[16] They also find that patent royalty income makes up a very small portion of inventor's overall income.

I measure productivity using *log(grants)*, defined as the logarithm of the number of US utility patent grants in an inventor-year.[17] I also measure $log(citations)$ as the logarithm number of US patent citation in the 5-year period after a patent is granted. Finally, I define $patentValue$ using the Kogan et al. (2017) measure of patent value, which measures abnormal stock market returns in the days following a patent grant.[18]

Independent Variables. The term $PatentGranted_{it}$ equals one if the inventor's first patent application in the period was approved, zero otherwise.[19] I include art-unit-application-year fixed effects, κ_{at}, and zero-mean error terms, ϵ_{itja} and μ_{itja}. The main specification does not include control variables, X_{itj}, but in robustness

[15]I define new firms as those with positive payroll and establishments with fewer than 50 employees in the first month in which they appear in the data. I enact this restriction to avoid counting divestitures as new firms. I also eliminate firms whose earliest appearance in the data coincides with the first year the LEHD has data available for the given state.

[16]For only 1 percent of inventors is non-wage income higher than wage income. These are likely cases of entrepreneurs that own firms.

[17]Results are robust to using a dummy variable equal to one if the inventor is granted any patents in the focal year and zero otherwise.

[18]https://iu.app.box.com/v/patents/file/66502400949

[19]Patent applications are not completely rejected by the USPTO. However, over time the probability that the assignee will appeal an examiner's decision declines. Therefore, I consider an application to be 'rejected 'if it is rejected by the examiner and not successfully appealed within five years. I also exclude all applications that are pending a decision as of 2014.

checks (not disclosed) I include inventor age, inventor age squared, inventor gender, inventor education, cumulative inventor patent applications, firm employment, total firm wages, and number of inventors employed.

For convincing casual identification, the instrument must be a strong predictor of $PatentGranted_{it}$. As reported in Table 2.2 and Table 2.3, first state F-statistics are all over 300.[20] The IV approach also relies on the exclusion restriction, which means that the examiner's propensity to approve a patent must only affect inventor outcomes through the $PatentGranted_{it}$ variable. This exclusion restriction holds in cases where the instrument is "as good as randomly assigned conditional on covariates" (Angrist and Pischke, 2008, p. 177). According to Farre-Mensa et al. (2017) and Sampat and Williams (2015), patent applications are assigned quasi-randomly, with respect to application and inventor quality, within art units. Therefore, after including art-unit-application-year fixed effects the instrument arguably satisfies the exclusion restriction. It is important to note that patent examiners are not assigned in a truly random fashion. Righi and Simcoe (2017) find evidence that, within art units, examiners do specialize in technologies. However, they find no evidence that examiners specialize in high- or low-quality applications. To address concerns that examiners specialize in subclasses, I run additional specifications that include patent class and subclass fixed effects.

2.3.4 Timing Considerations

As noted by Farre-Mensa et al. (2017), there are several points from which to begin measuring the effect of a patent. Inventors may list a patent application as "pending" as soon as the application is filed with the USPTO. However, the examiner's leniency has no effect at the time of filing, so using this date would bias my estimate towards zero. Alternatively, the first-action date (the date the examiner

[20] The rule of thumb is that F-statistics over 10 are sufficiently strong.

provides a preliminary decision) and the final decision date (the date at which the examiner provides their final decision) are reasonable candidates. However, both dates are endogenous. For example, it is possible that a given examiner may make an earlier decision for high-quality applications, leaving the marginal and more difficult applications for later. Therefore, patent quality may affect these dates. For these reasons, I use the patent publication date, or the date the USPTO publishes the contents of the application to the public, to begin measuring inventor outcomes. The American Inventors Protection Act stipulates that a patent application be published 18 months after filing. Therefore, this date is not influenced by the characteristics of the application.

2.4 Results

2.4.1 Main Findings

I begin by investigating the causal effect of patents on employee inventor mobility in Table 2.2. Model 1 uses OLS with art-unit-application-year, year, and patent class fixed effects. The coefficient is small, negative, and insignificant. This is similar to Melero et al. (2017) find using a comparable model. Model 2 uses an instrumental variables approach, described above, to find that inventors are more likely to leave their employer if the patent application is granted. The effect size is about 85 percent of the average mobility rate in this population (7.5 percent per year). Model 3 estimates a similar effect using patent-subclass fixed effects, rather than patent-class fixed effects.

[Table 2.2 about here.]

The finding that patents have a positive effect on inventor mobility challenges several prior findings that patents have a negative effect on inventor mobility (Hoisl, 2007; Palomeras and Melero, 2010; Melero et al., 2017). First, Palomeras and Melero (2010) find a negative correlation between patenting and mobility but do not identify the causal effect of patents. Therefore, it is possible that this analysis suffers from omitted-variable or selection bias. Hoisl (2007) studies the effect of patent productivity on inventor mobility and finds a negative causal effect. The study instruments patent productivity using "external sources of knowledge." Similarly, Melero et al. (2017) also find a negative effect of patenting on mobility using a similar independent variable (patent grant) and identification strategy (examiner leniency) to those used in this paper. Notably, all three papers use patent-based measures of mobility. Ge et al. (2016, p. 233) caution against patent-based measures of mobility, noting that the misclassification bias associated with such measures may "exaggerate, attenuate, or *even change the sign* of the estimates" (emphasis mine). Therefore, one interpretation of the seemingly contradictory findings between Palomeras and Melero (2010), Hoisl (2007), Melero et al. (2017) and this study is that the misclassification bias from patent-based measures of mobility does not merely attenuate the coefficients, but results in estimates with the wrong sign.

[Figure 2.3 about here.]

To corroborate that misclassification error is capable of biasing the results so dramatically as to reverse the sign of the coefficient, I simulate 100 datasets with measurement error similar to that of patent data (Ge et al., 2016). Specifically, I generate two independent variables, x_1 and x_2 from a normal distribution with variance equal to one. The dependent variable (mobility) is generated from a Probit model where $y^T = 1\{a + 0.25x_1 + 0.25x_2 + \geq 0\}$ where e is drawn from a standard normal distribution and is set so the mean of y^T is 0.1. That is, I assume an average annual mobility rate of 10 percent. I set the misclassification, m, on the dependent variable, y^T, to 70 percent (Ge et al. (2016) find even higher rates of misclassification). I vary the correlation between m, the misclassification error, and

x_1 between -0.5 and 0.5. Similar to Meyer and Mittag (2017), I draw 100 samples of 10,000 observations and run a Probit model on y^T to predict $\widehat{\beta}$ and on the data with misclassification error to get $\widehat{\beta}^M$. I record the difference ($\widehat{\beta}$ - $\widehat{\beta}^M$) as the bias.

Figure 2.3 demonstrates that if the measurement error is correlated with x_1 by more than about -0.1 the regression will estimate a coefficient with the wrong sign. Thus, even if there is no correlation between the misclassification error and x_1 Probit regressions estimate coefficients with the wrong sign. These results suggest that misclassification bias, alone, is powerful enough to cause the differences in results between my study and prior studies (Hoisl, 2007; Palomeras and Melero, 2010; Melero et al., 2017) based on patent-measures of mobility.

Table 2.3 explores the effect of patenting on an inventor's propensity to become a founding team member. Model 1 uses OLS to estimate a moderately sized, but statistically significant, negative effect on an inventor's probability of becoming a founding member of a new venture. However, Model 2 uses an instrumental variables approach to estimate a positive effect. The reversal in signs between Models 1 and 2 implies that selection effects are negatively biasing the coefficient. One explanation for this is that employee inventors wishing to become entrepreneurs are more likely to leave before revealing their ideas to their employer (Anton and Yao, 1995). Another explanation is that inventors who have found high-quality firm matches are more likely to patent, but less likely to leave to start their own firm. When I include patent subclass fixed effects, the coefficient becomes statistically insignificant (Model 3). However, because entrepreneurship is a relatively rare event, this may be due to a lack of statistical power. In either case, the effect of patenting on entrepreneurship should be interpreted with care.

[Table 2.3 about here.]

2.4.2 Alternative Explanations and Mechanism Tests

The above results demonstrate that patents have a positive causal effect on inventor mobility and entrepreneurship. Previously, I argued that the operant mechanism was signaling. However, there are other mechanisms that may drive these results. One explanation is that patents, by granting the employer the right to the inventor's idea, decrease the value of the inventor to external firms *and* their current employer. Once the current employer has patented the inventor's idea, they may simply "dispose" of them by reducing their pay, reducing the rate of pay increases, mistreating them, or by simply terminating them. If inventors are less valuable to their current and potential employers after a patent, then patenting should have a negative effect on inventor wages. On the other hand, if patents act as signals, then patents should have a positive effect on inventor wages. Models 1 and 2 of Table 2.4, demonstrate that patents cause inventors to receive a roughly 15 percent increase in their wages, supporting the conjecture that patents act as credible signals of inventor quality.

[Table 2.4 about here.]

To further isolate signaling as a mechanism for enabling mobility and entrepreneurship, I investigate the effect of patenting on inventors' future productivity. If patents act as signals of inventor quality, then they should allow inventors to attract more resources and better collaborators; leading to increased patent productivity. Table 2.5, Model 1, reveals that inventors whose patent application is approved are about 27 percent more likely to submit a successful patent in the next five-years.[21] Model 2 suggests those patents receive around 57 percent more citations than patents by inventors whose application was not approved. This implies

[21]These results are based on the full sample of inventors, not the sample matched the LEHD data.

that a patent grant leads to higher quality patents in the future. Model 3 uses the Kogan et al. (2017) measure of patent value, which depends on the firm's abnormal returns in the days following the patent grant. Model 3 estimates that the subsequent patents of inventors whose application is approved are worth approximately 28 percent more than those whose first patent application was denied. I interpret this as evidence that patents act as signals of inventor quality, allowing them to attract more resources and better collaborators.

[Table 2.5 about here.]

2.5 Discussion and Conclusion

Many studies have investigated the effects that patents have on firms (Farre-Mensa et al., 2017; Trajtenberg, 1990; Gambardella et al., 2008; Hall et al., 2005; Geroski et al., 1993; Balasubramanian and Sivadasan, 2011). However, fewer have explored how inventors, themselves, are affected by patenting. Of those that do study the effect of patenting on the careers of employee inventors, most find that patents have a constraining effect – reducing the probability that the inventor will leave their employer. In contrast, I have proposed and demonstrated that patents act as valuable signals of inventor quality. I argue that patent signals allow inventors to attract better outside employment options, entrepreneurial finance, and founding-team members. These results challenge several other studies that have found a negative relationship between patenting and inventor mobility (Hoisl, 2007; Palomeras and Melero, 2010; Melero et al., 2017). I further find that patenting has a positive effect on the inventor's probability of leaving for entrepreneurship. I rule out involuntary mobility and entrepreneurship as an operant mechanism by demonstrating that inventor wages and productivity also increase as a result of patenting.

The results present an interesting paradox for innovative firms. By capturing the rights to an inventor's idea, patents significantly increase the probability of the inventor leaving for a competitor firm or starting a new firm. This is strategically important given that prior studies have demonstrated that employee mobility and entrepreneurship has deleterious effects on a firm's competitive advantage by increasing knowledge spillovers (Møen, 2005; Campbell et al., 2012). These results suggest that firms may be overlooking employee mobility and entrepreneurship as a cost to patenting. Thus, firms may realize informational rents by using other sources of IP protection, like trade secrecy, that do not send signals of inventor quality to the firm's labor market competitors.

This paper also contributes to the field of entrepreneurship. Prior studies have demonstrated that patents help young firms acquire funding and increase their probability of success (Farre-Mensa et al., 2017; Long, 2002; Conti et al., 2013; Galasso and Schankerman, 2015). However, no studies have yet explored the effect of patenting at incumbent firms on an inventor's likelihood of founding a firm. Further, by focusing on patents that are owned by young firms, previous studies confound the signal value of patents with the valuable monopoly rights they confer. By focusing on employee inventors, who do not own the monopoly rights to their inventions, this study is one of the first to isolate the signal value of patents from their exclusivity rights.

Next, this study adds empirical evidence to the debate on the role of luck in determining career outcomes (Brookman and Thistle, 2013; Gompers et al., 2010; Bertrand and Mullainathan, 2001). This study demonstrates that a "lucky" draw from a pool of patent-examiners has a statistically and economically significant effect on career outcomes of employee inventors.

The results also add to an important policy discussion on the need for "inventor compensation" laws. Many industrialized countries, including Germany and Japan, have implemented laws requiring firms to compensate employee inventors for patents. These laws are presumably based on the assumption that market mechanisms will not lead to "fair" outcomes for employee inventors (Dratler, 1979; Manly, 1978; Noble, 1979; Merges, 1999). However, there has been little empirical evidence brought to bear on this important question (Toivanen and Väänänen, 2012; Depalo and Di Addario, 2015). This paper provides evidence that, even in the absence of inventor compensation laws, inventors are rewarded by increased opportunities for mobility and entrepreneurship as well higher wages and patent productivity.[22]

Finally, this paper has several important empirical contributions. Prior studies on the relationship between patenting and mobility suffer from a number of empirical challenges. First, they rely on patent data to measure mobility (Hoisl, 2007; Palomeras and Melero, 2010; Melero et al., 2017). The fundamental challenge of this approach is that mobility can only be observed if an inventor patents at least twice and at two different firms (Ge et al., 2016). Unfortunately, most inventors only patent once in their career.[23] Therefore, prior studies have implicitly sampled on "stars," or inventors who are more productive than the average. Perhaps more importantly, using patent data to measure mobility introduces misclassification bias that is correlated with the independent variable (patenting). Such measurement error can amplify, attenuate, or even estimate coefficients with the wrong sign (Meyer and Mittag, 2017; Ge et al., 2016). Finally, prior studies have suffered from omitted variable bias. Patent productivity and mobility are likely both driven by inventor quality, firm characteristics, and technological life cycles. By using patent examiner leniency as an instrument, this study is one of the first to demonstrate the causal effect of patents on inventor mobility and entrepreneurship. This study shows that, after correcting for these important sources of bias (sampling, misclassification, and omitted variable), regressions estimate a positive, rather than negative, effect of

[22]The United States has no laws mandating that inventors be compensated for their inventions.

[23]Calculated by the author. The median number of lifetime patents, conditional on having a patent, is one.

patenting on mobility and entrepreneurship. The results should caution scholars against using patent-based measures of mobility and opens up an agenda to revisit prior findings based on patent measures of mobility.

Figure 2.1: Rise of Employee Inventors from 1980-2010.

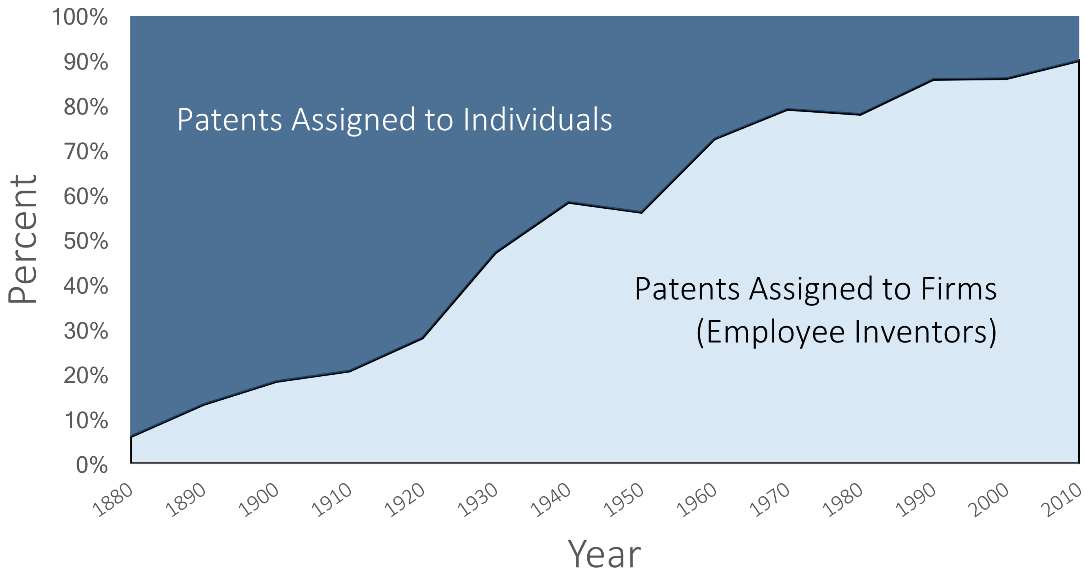

Figure 2.2: Distribution of Patent Examiner Approval Rates.

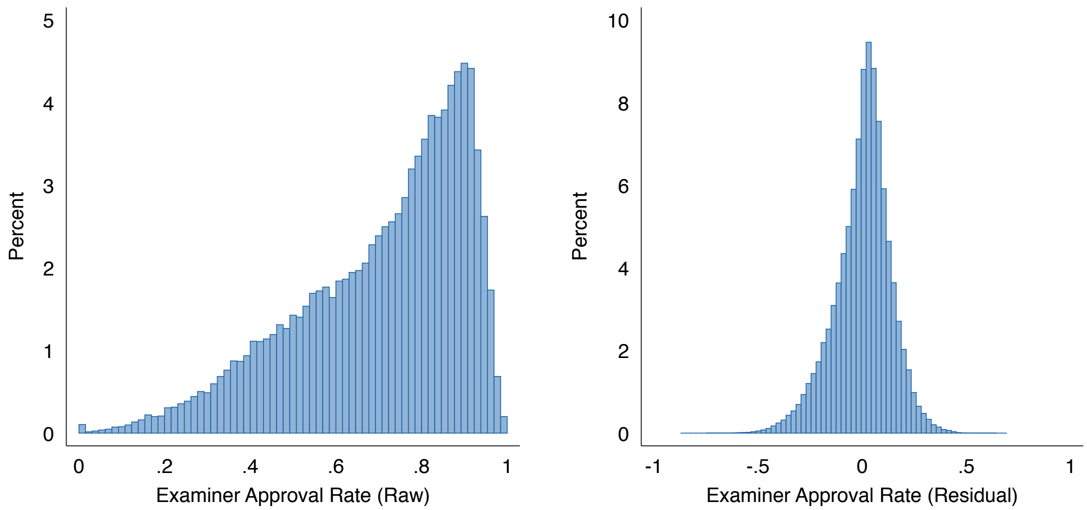

Figure 2.3: Simulated Misclassification Error Correlated With x_1.

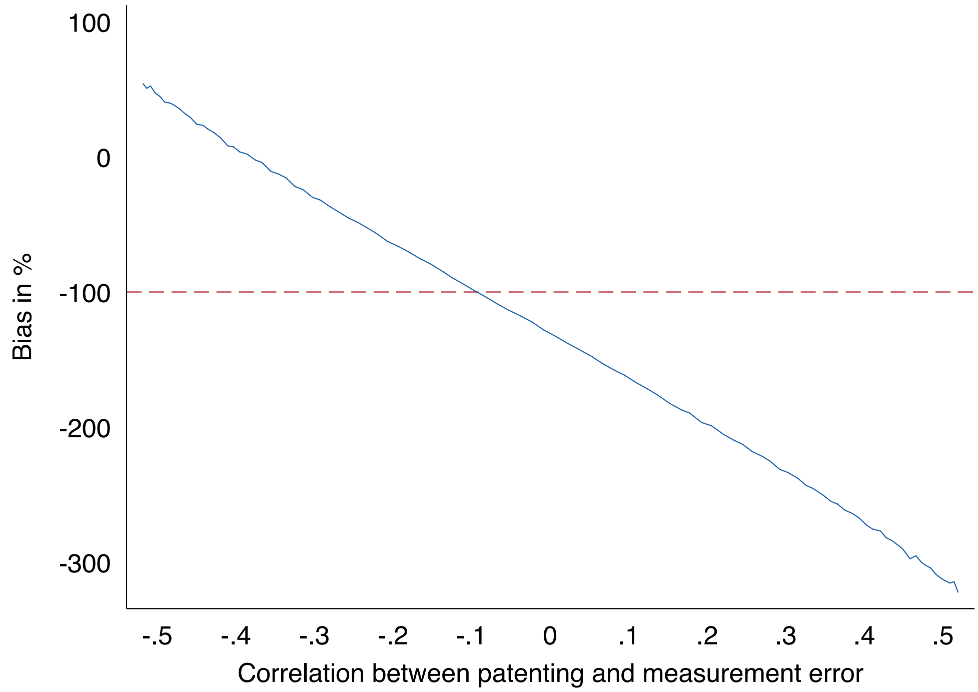

Table 2.1: Summary Statistics

Variable	Observations	Mean	SD
Mobility	~794,000	0.07545	0.2641
Wages	~794,000	137800	131400
Founding Member	~794,000	0.01154	0.1068
Patent Granted	~794,000	0.933	0.25
Examiner Approval Rate	~794,000	0.7717	0.1494
Sequence	~794,000	1.743	1.997
Cumulative Patent Applications	~794,000	1.06	0.4454
Patent Co-applicants	~794,000	4.001	2.792
Observation Year	~794,000	2004	2.567
Application Year	~794,000	2002	1.849
First Action Year	~794,000	2004	2.155

Table 2.2: The Effect of Patenting on Inventor Mobility.

	1	2	3
	Mobility (OLS)	Mobility (2SLS)	Mobility (2SLS)
Patent Granted	-0.002	0.063***	0.053***
	(0.001)	(0.016)	(0.015)
Art-Unit-App-Year FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Class FE	Yes	Yes	No
Subclass FE	No	No	Yes
Mean of DV	0.075	0.075	0.075
Kleibergen-Paap F-stat	-	354	369
Observations (Person-Years)	~794,000	~794,000	~794,000
r-squared	0.015	0.012	0.022

* p<0.05, ** p<0.01, *** p<0.001

Robust standard errors clustered by art-unit. The unit of observation is the inventor-year. The dependent variable is a dummy variable equal to one if the inventor changed jobs in the current year and is equal to zero otherwise. Models 1 is an OLS regression of mobility on whether the inventor's first patent in the focal timer period was granted. Model 2 uses 2SLS to instrument for whether the patent was granted using the examiner's historical leniency. Models 1 and 2 include art-unit-application-year fixed effects, year fixed effects, and patent class fixed effects. Model 3 is identical to Model 2, except I include patent sub-class fixed effects rather than patent-class fixed effects. Results are robust to the inclusion of controls for inventor age, inventor age squared, inventor gender, inventor education, inventor order, the cumulative number of previous inventor patents, patenting-firm age, patenting-firm employment (headcount), total patenting-firm wages, and the number of inventors

Table 2.3: The Effect of Patenting on Whether an Inventor Becomes a Founding-Team Member.

	1	2	3
	Founder (OLS)	Founder (2SLS)	Founder (2SLS)
Patent Granted	-0.002**	0.014*	0.01
	(0.000)	(0.007)	(0.007)
Art-Unit-App-Year FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Class FE	Yes	Yes	No
Subclass FE	No	No	Yes
Mean of DV	0.012	0.012	0.012
Kleibergen-Paap F-stat	-	354	369
Observations (Person-Years)	~794,000	~794,000	~794,000
r-squared	0.012	0.011	0.019

* p<0.05, ** p<0.01, *** p<0.001

Robust standard errors clustered by art-unit. The unit of observation is the inventor-year. The dependent variable is a dummy variable equal to one if the inventor was a founding member of a new firm in the current year and is equal to zero otherwise. Models 1 is an OLS regression of founder on whether the inventor's first patent in the focal timer period was granted. Model 2 uses 2SLS to instrument for whether the patent was granted using the examiner's historical leniency. Models 1 and 2 include art-unit-application-year fixed effects, year fixed effects, and patent class fixed effects. Model 3 is identical to Model 2, except it includes patent sub-class fixed effects rather than patent-class fixed effects. Results are robust to the inclusion of controls for inventor age, inventor age squared, inventor gender, inventor education, inventor order, the cumulative number of previous inventor patents, patenting-firm age, patenting-firm employment (headcount), total patenting-firm wages, and the number of inventors employed.

Table 2.4: The Effect of Patenting on Inventor Wages.

	1	2
	ln(Wages) (2SLS)	ln(Wages) (2SLS)
Patent Granted	0.163***	0.156***
	(0.035)	(0.033)
Art-Unit-App-Year FE	Yes	Yes
Year FE	Yes	Yes
Class FE	Yes	No
Subclass FE	No	Yes
Mean of DV	11.6	11.6
Kleibergen-Paap F-stat	353	369
Observations (Person-Years)	~794,000	~794,000
r-squared	0.616	0.624

* p<0.05, ** p<0.01, *** p<0.001

Robust standard errors clustered by art-unit. The unit of observation is the inventor-year. The dependent variable is the logarithm of all annual wages. Models 1 uses 2SLS to instrument for whether the patent was granted using the examiner's historical leniency. Both models include art-unit-application-year fixed effects and year fixed effects. Model 3 is identical to Model 2, except Model 2 includes patent-class fixed effects while Model 3 includes patent sub-class fixed effects instead. Results are robust to the inclusion of controls for inventor age, inventor age squared, inventor gender, inventor education, inventor order, the cumulative number of previous inventor patents, patenting-firm age, patenting-firm employment (headcount), total patenting-firm wages, and the number of inventors employed.

Table 2.5: The Effect of Patenting on Subsequent Productivity.

	(1)	(2)	(3)
	Granted Patent	ln(Cites)	ln(Abn. Returns)
Patent Application Approved	0.019***	0.571***	0.281***
	(0.00)	(0.05)	(0.05)
Art-Unit-App-Year FE	Yes	Yes	Yes
Mean of DV	0.070	0.797	0.489
First-Stage F-Stat	3,847	1,221	1,221
Clusters (Art-unit-app-year)	6,616	5,217	5,217
Observations (Person-Years)	1.24e+06	1.27e+05	1.27e+05

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Robust standard errors clustered by art-unit-application-year. The unit of observation is the inventor-year. The sample includes all observations five years after an inventor's first patent application is approved. The dependent variable in Model 1 is the number of patents granted. In Model 2, the dependent variable is the log number of citations. The dependent variable in Model 3 uses the measure of patent value based on market returns developed by (Kogan et al., 2017). Models 2 and 3 have fewer observations than Model 1 because Kogan et al. (2017) is missing some patents included in my larger sample.

Chapter 3: The Effects of Prestigious Awards on Artistic Careers

3.1 Introduction

This paper investigates the effects of winning prestigious awards on the winner's subsequent productivity and performance. The impacts of awards have been studied from two distinct lenses. The first perspective approaches awards as incentive devices that organizations can use to encourage productivity and performance. This literature has focused on the ex ante consequences of awards, finding generally positive effects on productivity and performance before the awards are granted (Frey and Neckermann, 2008; Chan et al., 2014; Gallus and Frey, 2015; Gallus, 2017; Restivo and van de Rijt, 2012), with some negative effects also noted (Gubler et al., 2016). However, scholars in this stream have paid little attention to the consequences of awards in the periods after they are bestowed.

Other scholars have studied awards as a means of climbing status hierarchies (Azoulay et al., 2013; Reschke et al., 2017). This literature suggests that awards have positive effects on productivity because they boost the award-winners' status, access to resources, perceived competence, and self-determination (Azoulay et al., 2013; Reschke et al., 2017; Ertug and Castellucci, 2013; Bothner et al., 2012; Wade et al., 2006). In comparison to the "awards as incentive" literature, status scholars do generally focus on the ex post effects of award-winning. Yet, this literature has paid little attention to the downsides of award-winning.

This paper bridges these two literatures by investigating the downside effects of awards in the period after the award has been granted. I argue that winning awards can decrease subsequent productivity and performance because winners feel more complacent and are sheltered from the risks of failure associated with exploration and experimentation.

I empirically test these conjectures in the US film industry. I measure the post-award productivity and ratings of winners and nominees of the Academy and Golden Globe Awards. I use prediction markets to measure an actor's ex ante probability of winning an award. I then condition on these probabilities using a propensity score design to estimate the effect of winning an Oscar or Golden Globe award on the winner's future productivity. This design estimates a causal effect of winning the award, assuming that winning the award is not correlated with future productivity, conditional on the probability of winning. This is a reasonable assumption if all of the information observable to the market is factored into the prediction market. My results suggest that winning does lead to a decrease in the actor's future productivity. Other results indicate that winning an award leads the winner to take on other roles. For example, actors that win an Academy Award are more likely to become directors than non-winners. I also find that winners take less important roles (are listed lower in the billing order), participate in movies that are rated more highly, but perform worse in the box-office. I find no effect on the number of screens the movies are released on or the budget size of the movies.

3.2 Theory

3.2.1 Awards, Productivity, and Performance

3.2.1.1 The Positive Effects of Awards

There is a considerable body of literature that has investigated how organizations can use monetary rewards to increase productivity and performance (See

Prendergast (1999) for a review). More recently, however, scholars have begun investigating how non-monetary rewards act to promote employees and other agents (Markham et al., 2002; Neckermann and Frey, 2013; Kosfeld and Neckermann, 2011; Brunt et al., 2012). A common finding of this literature is that non-monetary awards motivate productivity similarly to financial rewards, with fewer direct financial costs (Gallus and Frey, 2015; Frey and Neckermann, 2008). Specifically, non-monetary rewards bolster the recipient's autonomy and self-confidence, have few direct monetary costs, are less likely to crowd-out intrinsic motivation, and have fewer negative externalities on non-award winners (Gallus and Frey, 2015).

While most of the "awards as incentive" literature has focused on the ex ante effects, recent work has begun to investigate the consequences of awards on ex post productivity. For example, Chan et al. (2014) find that winners of the John Bates Clark Medal and the Fellowship of the Econometric Society are subsequently more productive and receive more citations than a synthetic control group of non-recipients. Gallus (2017) shows, using a randomized field experiment, that awards have positive effects on the retention of volunteer editors at Wikipedia. Finally, Restivo and van de Rijt (2012) demonstrate, in a laboratory experiment, that non-monetary awards increase subsequent productivity by 60%. Although there is limited evidence from the field, these studies suggest that the award-winner's productivity and performance are boosted in the period after awards are granted.

A separate body of literature on awards comes primarily from organizational theorists and sociologists who tend to view awards as a means increasing ones position on a status hierarchy (Azoulay et al., 2013; Reschke et al., 2017; Kovács and Sharkey, 2014; Ertug and Castellucci, 2013; Bothner et al., 2012; Wade et al., 2006). This stream has focused much more, relative to the "awards as incentive" literature, on the ex post effects of awards. However, status scholars generally pay less attention to the behavioral consequences of status and awards; focusing instead on the effects that awards have on others' perception of the winner. These studies also find that award-winning leads to positive outcomes. [1]

The sources of status advantage are two-fold. Awards cause winners to be perceived as higher status, which leads to access to better resources at lower costs. Merton (1968) recognized that low-status scientists were constrained in their ability to access the physical and social capital necessary for successful careers while high-status scientists were less constrained. Since then, numerous studies have confirmed the proposition that high-status actors have better access to resources (Stuart et al., 1999; Phillips, 2001; Stuart and Ding, 2006; Podolny, 1993). Second, high status actors are perceived more favorably and attract more attention than their low-status counterparts (Malter, 2014; Azoulay et al., 2013; Simcoe and Waguespack, 2011; Kovács and Sharkey, 2014). Kovács and Sharkey (2014), for example, find that books that win prestigious awards receive significantly more attention than runners-up. In sum, the bulk of evidence on awards find positive effects on winner productivity and performance.

3.2.1.2 The Negative Effects of Awards

Recently, scholars have begun to recognize that awards may not have universally positive effects. Several studies have identified significant downsides of award-winning Kovács and Sharkey (2014); Borjas and Doran (2015); Wade et al. (2006). These downsides stem, primarily, from feelings of self-satisfaction and complacency that status and awards may foster[2]. Pareto (1991), Veblen (1899), and Burt (2010) all cautioned that increased social status may cause individuals may become complacent and lazy. Recent empirical evidence suggests that, at least in some circumstances, this may be true. Wade et al. (2006) found that company

[1] See Reschke et al. (2017), Wade et al. (2006), and Malmendier and Tate (2009) for negative spillovers and unintended consequences.

[2] One exception is Kovács and Sharkey (2014), who find evidence of demand-side discounts to status.

stocks increased immediately after a company's CEO won an award (due to positive perceptual effects that the award had on investors) but suffered in the long run (likely due to the negative behavioral effects on the CEO). Malmendier and Tate (2009) similarly find the ex post effects of CEO awards on stock returns to be negative, though CEOs are positively affected. Finally, Borjas and Doran (2015) find that Fields Medal recipients are less productive than similar scientists who did not win the award.

This seemingly contradictory evidence on the effect of awards on ex post performance and productivity is yet to be reconciled. The key may lie in the prestige associated with the award. In surveying the findings, it is only for very prestigious awards like CEO awards (Wade et al., 2006; Malmendier and Tate, 2009) and the Fields Medal (Borjas and Doran, 2015) that negative effects were observed. For less prestigious awards, the positive effects of awards dominate (Chan et al., 2014; Restivo and van de Rijt, 2012; Gallus, 2017). Bothner et al. (2012) similarly argues that positive effects of status may dominate at low levels of status, while high levels of status "encourage unproductive behaviors" (p. 417).

High-status actors are also shielded from the deleterious consequences of poor performance and non-conformity (Malter, 2014; Phillips and Zuckerman, 2001). This will give high-status actors the freedom to attempt activities outside of their core expertise. For example, Borjas and Doran (2015) argue that status may allow winners to explore more widely, rather than focus on their expertise. Thus, in the case of very prestigious awards, the mechanisms that lead to positive productivity, like increased status and access to resources, will be overcome by the negative mechanisms that lead to lethargy and exploration. Therefore, I predict that winners of prestigious movie awards will produce fewer movies in the future. I also predict that winners will be more likely to explore alternative careers. For example, I predict that actors who win awards will be more likely to become directors or producers.

These forays into areas for which they have little experience will, on average, take longer and produce lower quality results. Therefore, I predict:

Hypothesis 1: Winning a prestigious award will have a negative effect on subsequent productivity.

Hypothesis 2: Winning a prestigious award will have a negative effect on subsequent performance.

Hypothesis 3: Winning a prestigious award will increase the probability of exploring alternative careers.

3.3 Data and Empirical Design

3.3.1 Empirical Setting and the Problem of Identification

I test the above hypotheses in a sample of Hollywood actors and directors who were nominated for an Academy Award (Oscar Award) or Golden Globe Award. These are the most prestigious awards available to members of this field, with Academy Awards being somewhat more prestigious than Golden Globes.

I use data from IMDB.com to construct the careers of Hollywood actors, and directors.[3] IMDB is the most comprehensive dataset for movies and TV shows available and has been used in previous research on the industry (Rossman and Schilke, 2014; Cattani et al., 2014; Hsu, 2006; Sorenson and Waguespack, 2006). IMDB contains information on movies and television shows, including year of production, release date, and production studio. It also contains data on actors, producers, directors, and other crew members. It is possible that very small budget projects do not get listed on IMDB. But because I limit the sample to nominees of very prestigious awards, it is unlikely that the careers are significantly misrepresented by IMDB. To construct the careers of actors and directors, I include all non-adult,

[3] I downloaded data from http://www.imdb.com/interfaces in March 2018.

full-length films released in the US between 2006 and 2018.

I also use Betfair, an online prediction market, to construct the probability of a nominee winning an award. Betfair allows users to bet on the outcomes of events, including sports games, presidential elections, and prestigious awards. I exclude any award categories where fewer than 100 bets were placed. I also include budget data from Boxofficemojo.com. The final sample include 163 nominees, and 2,040 movies. See Table 3.1 for summary statistics.

[Table 3.1 about here.]

3.3.2 Identification Strategy

An ideal experiment to test the effect of an Oscar or Golden Globe award on subsequent productivity and performance would be to randomly assign these awards to nominees and observe the behavior of winners and losers afterward.[4] In contrast, a naive comparison of winners to the non-winning nominees would likely suffer from omitted variable bias that stems from unobservable differences in quality and effort. For example, winners of Academy Awards are likely to be more skilled, on average, than non-winners.

A common solution to this problem is to control for observed variables or to construct a matched sample of non-award winners that have similar observable traits (Azoulay et al., 2013; Wade et al., 2006). Another is to compare winners to runners-up, under the assumption that nominees had *nearly* the same chance of winning as the winners. For instance, Kovács and Sharkey (2014) compare award-winning books with "short-listed" books to identify the causal effect of winning a prestigious book award. The identifying assumption of these designs is, conditional on observable

[4]Note that even this "ideal" experiment may not be ideal. To test the real effects, the awards need to be legitimate. It is likely given the betting odds discussed below, that a random assignment, even amongst the nominees, would be perceived as unfair. Thus, the ideal experiment would need random assignment and a perception of fairness by the contestants and the audience.

traits or on being short-listed, awards are “as good as randomly assigned” (Angrist and Pischke, 2008, p. 177). However, it is difficult to test this assumption because the prior probabilities of winning awards are typically unobserved. Researchers are usually left to control for observable characteristics, in the hope that they adequately captured the relevant selection mechanisms. However, in cultural goods like books, music, and movies the important characteristics that drive award-winning are often difficult for the researcher to observe. For example, two movies may be identical in their genre and thematic elements, but vary significantly in the quality of production, plot development, character development, originality, and style – all of which are important to winning but difficult for the researcher to measure. In addition to quality, there are other characteristics that may affect the probability of winning an award. Rossman and Schilke (2014) observe that some movies are strategically made with hopes of winning an Oscar award. They note that “Oscar appeal” is often easy for informed movie-goers to observe, but is difficult for the researcher to estimate. The task of the researcher, then, is to account for theoretically observable characteristics, like “Oscar appeal” that are unmeasured. To do this, I turn to prediction markets.

3.3.2.1 Prediction Markets and Propensity Scores

Prediction markets are “markets where participants trade contracts whose payoffs are tied to a future event, thereby yielding prices that can be interpreted as market-aggregated forecasts” (Wolfers and Zitzewitz, 2006, p. 1). Wolfers and Zitzewitz (2006) review the evidence on prediction markets, noting that they are quite efficient, respond quickly to new information, are very difficult to manipulate, and provide forecasts that generally outperform alternative prediction tools.

Importantly, prediction markets incorporate the observable, but difficult to measure, information that affects an individual’s chance of winning an Oscar or

Golden Globe award. For example, industry analysts have observed that Academy Award voters tend to appreciate when actors lose or gain large amounts of weight for a role.[5] Pre-production weight changes are difficult for a researcher to systematically measure, but are easily observed by the market and are, therefore, priced into prediction markets. Furthermore, the market decides how much an actor's weight loss will contribute to the probability of winning an award. Thus, predictions markets for Academy and Golden Globe awards should incorporate all observable information including characteristics about the movie, actors, studio, advertising, etc. that has an effect on the probability of winning. Any significant systematic biases in prediction markets represent profit opportunities and will quickly be traded away in a reasonably efficient market. Pennock et al. (2001) find that prices of "securities in Oscar, Emmy, and Grammy awards correlate well with actual award outcome frequencies, and prices of movie stocks accurately predict real box office results" even in "play-money" markets.

I use a Betfair, the largest prediction market in the world (Vellacott, 2010) to harvest market predictions of Academy Award and Golden Globe Award outcomes. Betfair reports the odds that any given nominee will win at a given time. Because these odds vary over time, I use the reported odds immediately before a winner is announced because this is the time at which the market has the most information. I convert the reported odds ratios to probabilities of winning. I then use the probabilities as propensity scores. Figure 3.1 plots the average predicted probability of winning an award compared with the actual probability of winning. The regression line is a second degree polynomial, though it looks linear. The near 45 degree angle of the line and the proximity of the plotted points to this line, suggest that Betfair markets are quite accurate, on average.

[Figure 3.1 about here.]

[5] Examples include Robert De Niro in Raging Bull, Hilary Swank for Million Dollar Baby, George Clooney in Syriana, Natalie Portman in Black Swan.

To test the assumptions of previous studies that use nominees as a control group, I plot the average predicted probability of a winner versus non-winning nominees in Figure 3.2. The graph shows that the assumption that non-winners have a similar probability of winning, or that awards are as good as randomly assigned conditional on being nominated, are not supported. Rather, winners are several times more likely to win than non-winning nominees across all categories.

[Figure 3.2 about here.]

Rather than assume the probability of winning is the same conditional on being nominated, I am able to condition on the probability of actually winning. Anderson (2017) demonstrates that in the case of a binary treatment variable, conditioning on the probability of winning using a propensity score design allows the researcher to estimate the causal effect. A standard critique of propensity score matching is that it can only account for observable and *observed* covariates. Therefore, when a researcher uses observed variables to construct a propensity score, he does not solve the problem of omitted variable bias (Shadish et al., 2002). I overcome this problem by using the predicted probabilities from prediction markets. My approach is not subject to the standard critique because the propensity score is constructed using covariates observed by the market participants, not by the researcher. Again, there are good reasons to believe that the online bettors observe all or most important covariates because if there were some observable characteristic that predicted winning and was not accounted for in the betting odds, this would represent an arbitrage opportunity. Wolfers and Zitzewitz (2006) note that "betting strategies based on publicly available information appear to yield no profit opportunities" and that arbitrage opportunities are "few" and "fleeting". Therefore, with the assumption that prediction markets reflect all observed and observable covariates that predict winning, using the predicted probabilities as propensity scores will yield causal estimates of award winning. In other words, conditional on the probability of winning, awards are randomly assigned. See Anderson (2017) for a formal treatment of prediction markets and propensity scores to estimate causal effects.

I use only the most recent odds because, assuming that information is revealed over time, the most recent odds should reflect the prices that incorporate the most information. The most recent odds generally reflect the market just moments before the award is announced. I convert the odds to probabilities as follows.

$$WinProbability_{ij} = \frac{1}{odds_{ij}} \tag{3.1}$$

where $WinProbability_{ij}$ is the predicted probability of individual i winning award j and $odds_{ij}$ are the odds of individual i winning award j. In some cases, several individuals may win an award. For example, some movies are directed by multiple directors. In my sample, I include all Oscar and Golden Globe awards from 2006-2012 because Betfair data are not available before 2006. I include only the most prestigious awards given to individuals: Best Director, Best Actor, Best Actress, Best Supporting Actor, and Best Supporting Actress.

3.3.2.2 Independent Variable and Propensity Score Matching

To test the effect of winning, I define a variable $AwardWinner$ equal to one if an individual won an award and zero if they were nominated but not awarded. Any individuals that were not nominated for an Oscar or Golden Globe award are not included in my data. I construct a propensity score estimator based on the predicted probability of winning. I use the nearest neighbor propensity estimator from the "teffects psmatch" Stata command and estimate robust Abadie-Imbens standard errors. The propensity score estimator assumes conditional independence. That is, I assume that the probability of winning is based solely on the *predicted* probability of winning as measured by Betfair. Thus, I assume that there are no other factors that lead to an individual winning that are unobserved by the market. Again, this is a reasonable assumption because any information not factored into the betting odds represent a profitable arbitrage opportunity. One noteworthy exception is private information, possibly held by only a small number of voters, that is not traded on. For example, in the extreme case that a nominee successfully bribed a sufficient number of awards voters to win, this information may not be captured by the prediction markets.[6]

[Figure 3.3 about here.]

The propensity score design also assumes common support, which means that people with the same predicted probability of winning (according to Betfair) must have a positive probability of winning and of losing. To test this assumption, I plot in Figure 3.3 the kernel densities of the predicted probability of winning for those who eventually won and for those who did not. The figure shows that there is considerable common support between 0.2 and 0.7. However, the winners with over a 70 percent predicted probability of winning have no losers with similar probabilities to match to. Thus, I am only able to estimate the mean differences in outcomes for individuals within this range. The estimates produced below should not, therefore, be generalized to those with very high or low probabilities of winning.

3.3.2.3 Dependent Variables

I use data from IMDB.com, Betfair.com, and boxofficemojo.com to construct a number of variables. The first is *movies per year*, which is a measure of productivity. This variable is a count of the number of movies the nominee was billed on in a given

[6]Even such privately held information may, however, be incorporated into prediction markets because those with the information that bribes are occurring can legally, and profitably, trade on such information. Such trading would be legal because prediction markets are not governed by the same 'insider trading' regulations as financial markets.

year.[7] This is the only variable constructed that individual-year level. All others are constructed at the individual-movie level.

I define *new role* as a binary variable equal to one of the role in the focal movie was different than the focal award. For example, if an actor won an award for "Best Actor" and later directed a movie, then I would count this as a changed role. The variable *billing order* is a continuous variable equal to the order the person was billed on the movie. Higher values mean less important roles. I set $log(Budget)$ equal to the logarithm of the estimated movie budget (in millions) according to BoxofficeMojo.com. I do not have budget estimates for all movies. The variable *rating* is the average rating according to IMDB.com. The term $log(votes)$ is the logarithm of people who rated the focal movie on IMDB.com and represents a measure of popularity. *Wide release* is a binary variable equal to one if the focal movie was released on more than 600 screens in the opening weekend, and zero otherwise. Finally, *log(total gross)* is defined as the logarithm of the total gross receipts for the movie as reported by BoxofficeMojo.com. Again, I am not able to observe the box office returns for all movies in the sample.

3.4 Results

I test the effect of winning awards on an individual's future productivity in Table 3.2. Model 1 replicates the method commonly used in empirical investigations into the effects on awards. Specifically, I use a difference-in-differences design to measure the change in productivity before and after the award is granted between winners and non-winning nominees (Kovács and Sharkey, 2014). The negative coefficient on *Award Winner* in Model 1 implies that award winners are less productive than non-winners in the pre-award period. The positive coefficient on *Post* means

[7] This includes actors, directors, producers, etc. Results are robust to limiting the movies to only those where the nominee was billed in the top 4 or top 10 positions.

that non-winners are significantly more productive after an award has been granted. Finally, the positive and significant coefficient on *Post * Award Winner* suggests that, according to the difference-in-differences model, the causal effect of winning an award is to boost productivity by 0.25 movies per year. That is, according to this estimate winning an award causes the winners to be involved in an additional movie every 4 years. However, the difference-in-differences relies on the "parallel trends assumption," which is that the trends of the treatment and control would be parallel in the absence of a treatment. However, 3.4 demonstrates that this assumption is unreasonable in this case; the trends are not parallel. Thus, the estimates in Model 1 are likely biased.

[Table 3.2 about here.]

[Figure 3.4 about here.]

Model 2 and 3 use a propensity score design to estimate the effect of winning an award. The propensity score design conditions on the individual's probability of winning. Specifically, Model 2 uses a propensity score design to match winners with non-winners that had the same predicted probability of winning, as estimated by Betfair. The estimated coefficient suggests that winners participate in about 0.57 *fewer* movies per year, or about one fewer movie every two years. This effect falls to -0.33 movies per year, or one fewer movie per three years, when I trim the sample to the common support. Finally, in Model 4 I use an instrumental variables technique similar to that used in Anderson (2017). The intuition is that the predicted probability of winning should have no effect on conditional outcomes, except through actually winning the award. Thus, the predicted probability of winning (from Betfair) meets the exclusion restriction of a valid instrument. The coefficient is similar in size, direction, and statistical significance to that in Model 3.

The results support the hypothesis that very prestigious awards lead to decreased productivity. Comparing the coefficient in Model 1 to those in Models 2-4 cautions against specifications that rely on the assumption that winners and nominees are identical or have identical trends. Instead, I show that failing to condition on the probability of winning leads to estimates that are biased and, in this case, biased in the wrong direction.

Interestingly, Table 3.3 demonstrates that the negative effects of awards on productivity are driven by males. Model 1 implies a positive, but statistically insignificant effect of awards on female's future productivity. Model 2, however, demonstrates that awards have a significantly negative effect on males. There are several potential reasons for these findings. Males are much more likely to win movie awards in the later years of their life. The average female in my sample is approximately ten years younger than the average male. However, controlling for age does affect the result. Another explanation is that the psychological effects of awards are different for men and women. Yet another explanation is that audiences perceptions of award winners are moderated by gender. I leave this to future researchers.

[Table 3.3 about here.]

As described above, there are several explanations for why winning a prestigious award may cause a decrease in future productivity. One explanation is that winning a very prestigious award frees the winners up to try new roles without fear of being punished (Phillips and Zuckerman, 2001). Table 3.4, Model 1 provides some evidence for this explanation. According to Model 1, winners are about 40 percentage points more likely to join a movie in a role different than the role for which they won an award. Note that by role here, I mean the role they played in the crew. For example, if someone won an award for an acting role, but later joined a movie as a director, then this is a changed role.

Another explanation is that, after winning a prestigious award, winners take on more important roles in fewer movies. Model 2 of Table 3.2 suggests this is not what is driving the results. Conditional on joining a movies project, winners are billed 1.6 positions lower than non-winners (higher billing numbers represent less important positions), perhaps because they are entering different roles, as found in Model 1. Model 3 estimates a positive but statistically insignificant effect of winning on the budget of the movie joined. However, because the number of observation for which I am able to observe budgets is small, this result is inconclusive.

Model 4 suggest that winners are more likely to join movies that get higher ratings on IMDB. This may be because winners join higher-quality movie teams, because winning causes actors and directors to perform better in the future, and/or because audiences perceive movies with award-winners to be higher quality. Unfortunately, I cannot empirically distinguish between these explanations. The coefficient in Model 5 implies that movies joined by winners get fewer ratings, which suggests that they are less popular. This interpretation is supported by Model 7, which estimates that winners join movies that end up making fewer dollars the box office, even though they are not significantly less likely to be widely released (Model 6). Overall these results present a picture that winners are more likely to diversify into different roles and to to perform in higher quality (in terms of ratings), but less commercially appealing movies.

[Table 3.4 about here.]

3.5 Discussion and Conclusion

This paper investigates the effect of winning prestigious awards on future productivity and performance. The results suggest that winners of prestigious awards are less productive than non-winners with similar probabilities of winning. I demonstrate that the decline in productivity is not due simply to complacency. Rather, I show that winners are more likely to explore new careers, take less important roles, in less popular movies. I also find that the movies winners go on to make movies that are perceived to be more artistic, but perform worse in the box office.

The weaknesses of this paper deserve discussion. First, I study a very high-status group—Hollywood actors and directors that have been nominated for prestigious awards. The negative effects of awards likely do not generalize to less prestigious awards granted to lower-status individuals. In fact, the mounting evidence suggests that low and middle prestige awards have generally positive effects in the ex ante and ex post periods. Another question that remains is why some prestigious awards have positive effects (Chan et al., 2014; Azoulay et al., 2013; Ginsburgh, 2003), while others have negative effects (Borjas and Doran, 2015). Another weakness of this paper is relatively few observations. The results presented above on box office returns and movie budgets, in particular, should be interpreted with caution due to the limited sample size.

This paper offers a unique empirical design, using prediction markets, for addressing selection and omitted variable bias. By using the predicted probability of winning an award from prediction markets, researchers can condition on all variables that observed and observable to the market, not just the researcher. This design could be used in a number of research settings like elections, sports, etc. As prediction markets gain popularity, so too does the applicability of this design.

I contribute to the robust literature that examines awards as incentives. Though awards may boost productivity before the award is granted, scholars and practitioners should be aware that there may be significant declines in productivity for the winners in the post-award period (Gubler et al., 2016). This is noteworthy because awards may be hurting the productivity of the best producers. Awards designers should be aware that awards have the potential to destroy value if the negative ex post effects outweigh the ex ante effects.

These findings may also be of interest to status scholars (Podolny, 2010; Sauder et al., 2012b; Malter, 2014). Previous findings have supported the idea that status hierarchies are self-reinforcing – whereby high-status actors are able to produce more and better offerings, which in turn increase status. The results of this paper imply that there may be behavioral counter-forces that, over time, erode social standing.

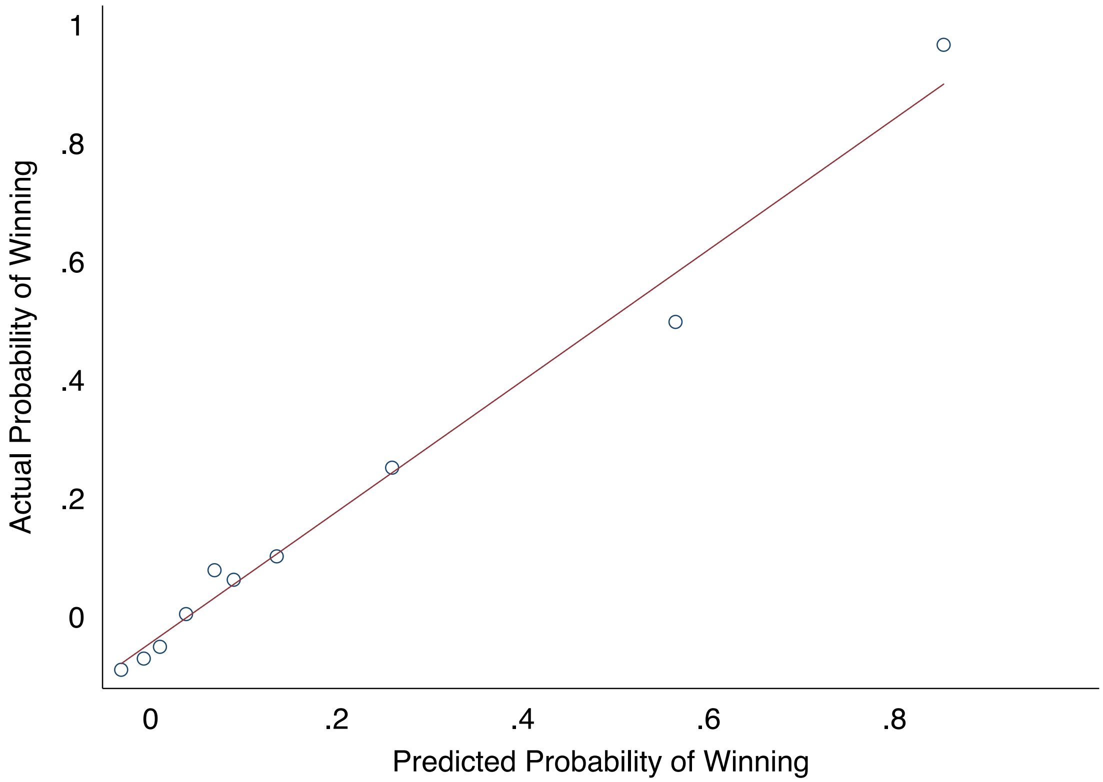

Figure 3.1: Predicted vs. Actual Probability of Winning

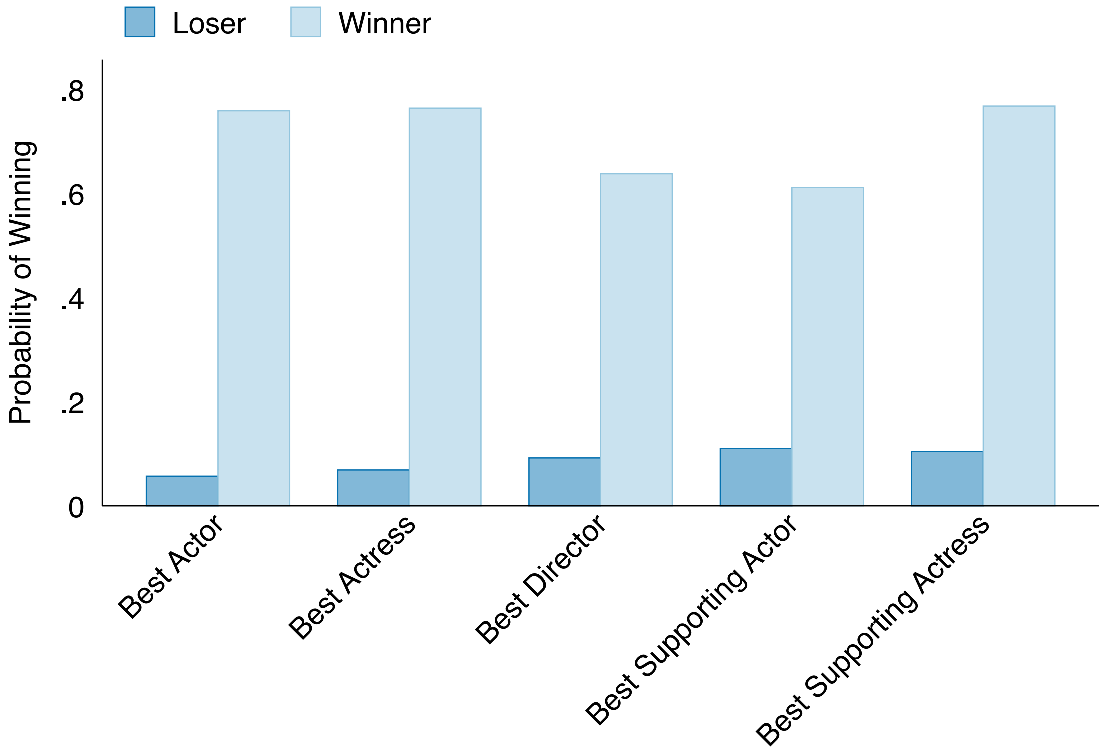

Figure 3.2: Predicted Probability for Winners and Non-Winners, by Award Type

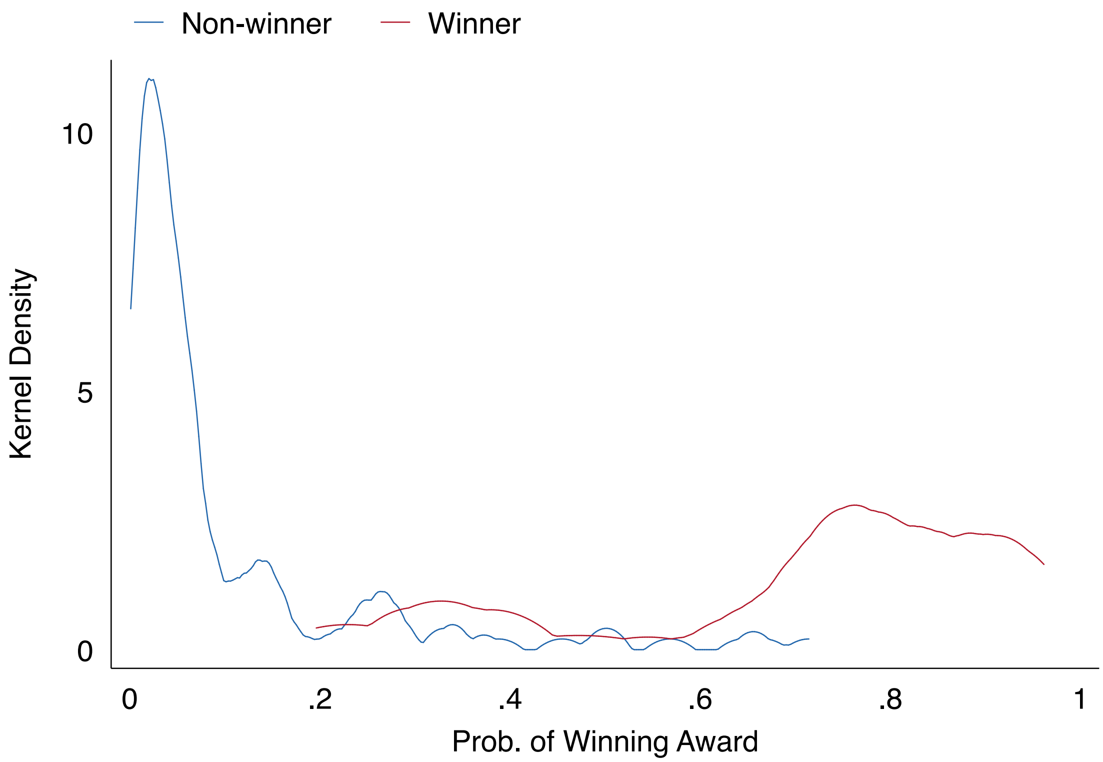

Figure 3.3: Kernel Density Plots of the Probability of winning, by Winners and Losers

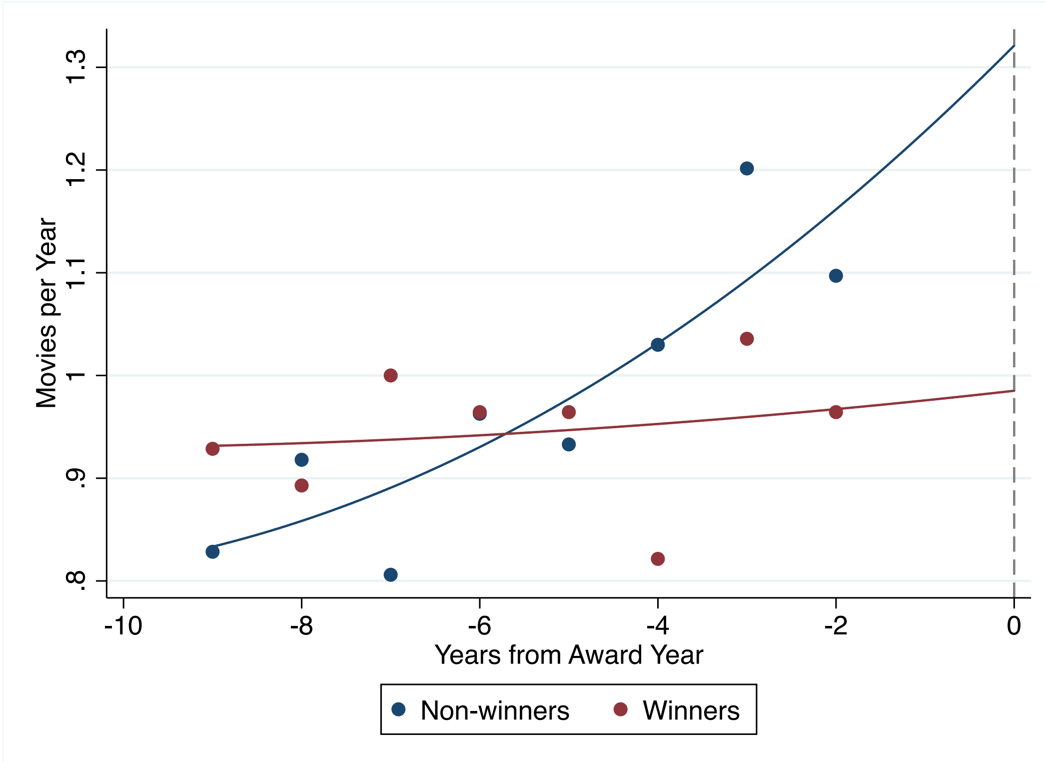

Figure 3.4: Pre-treatment trend

Table 3.1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Award Winner	0.165	0.371	0	1	2040
Probability of Winning	0.186	0.275	0.001	0.962	2040
Movies per Year	2.653	1.836	1	13	2040
New Role	0.167	0.373	0	1	2040
Billing Order	2.515	1.84	1	10	2040
log(Budget) (in millions)	3.812	0.945	0.693	5.707	379
Wide Release	0.832	0.374	0	1	2040
log(Opening Gross)	14.38	3.123	6.447	19.29	661
log(Total Gross)	15.835	3.025	7.37	20.095	672
log(Votes)	9.345	3.045	1.792	14.462	1798
Rating	6.632	0.907	2.8	9.300	1798

Table 3.2: The Effect of Winning Award on Future Productivity.

	(1)	(2)	(3)	(4)
	Movies per Year	Movies per Year	Movies per Year	Movies per Year
Award Winner	-0.392*	-0.569***	-0.329*	-0.299**
	(0.17)	(0.16)	(0.15)	(0.11)
Post	0.150*			
	(0.07)			
Post × Award Winner	0.244*			
	(0.10)			
Observations	2122.000	1474.000	764.000	1474.000
Model	DID	PS	PS, Trimmed	2SLS
Matched Vars.	-	Prob of Win	Prob. of Win, Award, Win Year	-
Year FE	Yes	No	No	No
Award FE	Yes	No	No	No

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 1 and 4 list Huber White robust standard errors in parentheses. Models 2 and 3 list Abadie-Imbens robust standard errors in parentheses. The unit of observation is the individual-year. The sample period for Model 1 is ten years before and after the award date and for Models 2-4 it is ten years after winning. The dependent variable is the number of movies an individual acted in, directed, or produced. Model 1 uses a simple differences-in-differences OLS estimator. Models 2 and 3 use propensity score matches, with the propensity score based on Betfair's estimated probability of winning. Model 2 uses the full sample to find matches. Model 3 replicates Model 2 but uses a sample trimmed to common support and matches on the award type and year in addition to the probability of winning. Model 4 instruments whether an individual won an award based with Betfair's estimated probability of winning an award.

Table 3.3: The Effect of Winning Award on Future Productivity, by Gender.

	(1)	(2)
	Female Sample	Male Sample
	Movies per Year	Movies per Year
Award Winner	0.277	-0.537**
	(0.34)	(0.17)
Observations	593	881
Model	PS	PS
Matched Vars.	Prob of Win	Prob of Win
Year FE	No	No
Award FE	No	No

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abadie-Imbens robust standard errors in parentheses. The unit of observation is the individual-year and the sample period is ten years after winning. The dependent variable is the number of movies an individual acted in, directed, or produced. Both models use propensity score matches, with the propensity score based on Betfair's estimated probability of winning.

Table 3.4: The Effect of Winning Award on Project Quality and Type.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	New Role	Billing Order	log(Budget)	Rating	log(Votes)	Wide Release	log(Total Gross)
Award Winner	0.410**	1.697*	0.138	0.531*	-3.466**	-0.086	-2.598***
	(0.13)	(0.69)	(0.19)	(0.25)	(1.15)	(0.13)	(0.27)
Observations	913	913	176	807	807	913	318
Model	PS, Trimmed	PS, Trimmed	PS, Trimmed	PS, Trimmed	PS, Trimmed	PS, Trimmed	PS, Trimmed
Matched Vars.	Prob of Win	Prob of Win	Prob of Win	Prob of Win	Prob of Win	Prob of Win	Prob of Win

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abadie-Imbens robust standard errors in parentheses. The unit of observation is the individual-movie and the sample period is ten years after being nominated for an Oscar or Golden Globe award. All models use a propensity score design, similar to model 3 of Table 3.4, with the propensity score based on Betfair's estimated probability of winning. The sample has trimmed to common support and matches were based on the probability of winning, award type, and award year. The dependent variable in Model 1 is a dummy equal to one if the individual was a different role (actor, director, producer, etc.) than the award-nominated role, zero otherwise. The dependent variable in Model 2 is the billing order (order of importance) of the individual in the movie. The dependent variable in Model 3 is the logarithm of the movies budget, as estimated by boxofficemojo.com. For Models 4 and 5, the dependent variables are the the average rating (1-10) and number of ratings, respectively, the movie was given on IMDB.com. The dependent variable in Model 6 is a dummy equal to one if the movie was released in 600 or more theater in its opening week. For Model 7, the dependent variable is logarithm of the total gross receipts of the movie.

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