Carnegie Mellon University

CARNEGIE INSTITUTE OF TECHNOLOGY

THESIS

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF Doctor of Philosophy

TITLE **Following the Light: Opportunities for Technology and Innovation in the Optoelectronics Industry Across Multiple Business Cycles (1955-2010)**

PRESENTED BY **Eyiwunmi Oluyinka Akinsanmi**

ACCEPTED BY THE DEPARTMENT OF

Engineering and Public Policy

Erica Fuchs	May 05, 2014
ADVISOR, MAJOR PROFESSOR	DATE
M. Granger Morgan	May 07, 2014
DEPARTMENT HEAD	DATE

APPROVED BY THE COLLEGE COUNCIL

Vijayakumar Bhagavatula	May 16, 2014
DEAN	DATE

Following the Light:
Changing Opportunities for Technology and Innovation in the Optoelectronics Industry across Multiple Business Cycles (1955 – 2010)

Submitted in partial fulfilment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering and Public Policy

Eyiwunmi Oluyinka Akinsanmi

B.Sc., Electrical Engineering, Howard University
M.Sc., Engineering and Public Policy, Carnegie Mellon University

Carnegie Mellon University

Pittsburgh, PA

May, 2014

Acknowledgements

My deep appreciation goes to my advisor, Dr. Erica Fuchs, for her mentorship, amazing insights into the optoelectronics industry, and unrelenting encouragement. My extreme gratitude goes to the other distinguished members of my dissertation committee, Drs. Jeffrey Furman, David Hounshell, and Granger Morgan for their careful guidance, astonishing wealth of knowledge and thought-provoking questions.

I am incredibly grateful to the Schlumberger Foundation for investing in women from developing countries by creating the Faculty for the Future Fellowship which has supported my doctoral studies. I also thank the National Science Foundation Science of Science and Innovation Policy Program for their financial support.

I would like to thank Dr. Eugene Arthurs, Krisinda Plenkovich and SPIE for providing inventor contact information. I also thank the Optical Society of America and IEEE’s Photonics Society for extending access to the societies’ member databases.

I would like to acknowledge Dr. Rebecca Nugent and Sam Ventura for their work in developing the disambiguated USPTO optoelectronics patent database and the associated disambiguation algorithms as well as their statistical insights. I could not have collected my data without the undergraduate research assistants with whom I worked to call, email and web-stalk inventors: Willis Chang, Carl Glazer, Farjad Zaim, Sabrina Larkin, Neha Nandakumar and my MVP, Angela Ng.

Thanks to Dr. Ray Reagans for his advising and support in implementing the research design early-on; to Drs. Shane Greenstein, Scott Stern and Michael Piore for sharing their insight through multiple conversations; and to Drs. Lee Branstetter, Brian Kovak, and Fiona Murray for their time and insights. I thank the faculty attendees of the EPP doctoral qualifying exam for their feedback. I also thank Drs. Carliss Baldwin, James Utterback, and other participants of INFORMS, Industry Studies Association, Production and Operations Management, Atlanta Conference on Science and Innovation Policy, Consortium for Co-operation and Competition doctoral consortium, and the Wharton Technology and Innovation Conference for their insights.

To my incredibly supportive friends, adoptive siblings and mentors, from Queen's College, through The Rock Foundation Mission and University of Lagos, Howard University and RCCG New Wine Assembly, Shoreline Christian Center, Berean Fellowship, and my Pittsburgh support system: Thank you for being true friends, and thank you for your prayers. May you always find encouragement in your time of need. Thanks also to Mofe Grage for pushing me to challenge the status quo so many years ago and Barbara Blazick for her insights and calming influence.

To my siblings: growing up with you was the best experience. Thank you for being my rocks. To my siblings-in-law, nieces and nephews: you all inspire me every day, and I hope to make you proud. To my mom, Dr. Bosede Akinsanmi, and my dad, Dr. Eniola Akinsanmi (1939 – 2011): thank you for supporting my dream of college in the US over a decade ago. Thank you, mom, for all the times you stayed up while I finished my assignments, for helping me figure out how to pay for the SATs, for not losing hope while we waited for the right scholarship, and for all your intercession. Thank you, dad, for getting on board and for letting me know how proud you were of me even before I was done. *Işę ti ę ran mi ni mo ti şe.*

Abstract

Economic downturns have been shown to have disparate effects on the productivity of individuals and firms. However, not much is known about their influence, if any, on technology trajectories. This dissertation explores the relationship between the burst of the telecommunications bubble and the rate and direction of innovation of United States (U.S.) inventors in optoelectronics, a technology pivotal to the telecommunications industry.

Leveraging a hand-built dataset of 790 inventor CVs, we analyze optoelectronics' inventor market shifts and associated innovation outcomes before, during, and after the burst of the telecommunications bubble. We find that the burst of the bubble disproportionately reduced inventor innovation in the rest of the field compared to the emerging general purpose technology (GPT) enabler. An increase in the emerging GPT-enabler post-burst is driven by Super Star inventors (top 1.5% both by cumulative patents and annual patenting pre-bubble) that switch markets applications post-burst out of diversified firms with telecommunications divisions and into firms focused exclusively on telecommunications. These Super Stars continue an increase in integration patenting that was driven during the bubble by Non Stars who left a period of unemployment, other markets and academia and went into firms focused on telecommunications and diversified firms with telecommunications divisions.

These superstars do not act in an institutional vacuum, however. There were several factors that influenced the growth of innovation in optoelectronics. This dissertation explores the ways

that the location of research in different kinds of organizations, government funding and government regulation have combined to influence innovation worldwide in optoelectronics.

Analyzing patenting patterns in optoelectronics between 1955 and 2010, we identify the most influential firms, government agencies and individuals responsible for leading innovation in this field. We use archival data on firms' decisions, firms' market applications and collect oral histories on key individuals. We find evidence for co-operation and competition between academia and industry in the early years. We also find that the most prolific firms are not the most influential. In addition, government regulation influenced innovation in at least two unexpected ways: by limiting U.S. permanent residents from defense applications of the technology and by inspiring new ventures when mergers were delayed by Department of Justice investigations.

This dissertation contributes to research on innovation and mobility, and to academic discourse on the relationship between business cycles and technology trajectories. Previous research in the field of mobility and innovation that has used patent data to estimate mobility is limited by inventors only showing up in patent data if they patent after they move, thus biasing the observed sample. CV data disentangles the relationship between mobility and patenting. With respect to business cycles, our results suggest that both non-stars and super-stars may have important roles in pushing innovation frontiers during different parts of the business cycle. While super-stars advance the emerging GPT enabler during resource-constrained parts of the business cycle, they continue the efforts of non-stars during less constrained times. This suggests there may be a role for government in supporting emerging-GPT-enabler innovations during economic downturns.

Table of Contents

List of Figures

List of Tables

List of Exhibits

List of Appendices

I

Seeing Rainbows While Others Flee: How Innovation in the Most Advanced Optoelectronic Technology grew after the Burst of the Telecommunications Bubble

1.1 Abstract

This paper explores the relationship between the burst of the telecommunications bubble and the rate and direction of innovation of inventors in optoelectronics, a technology pivotal to the telecommunications industry. Leveraging a dataset of 790 inventor CVs including the inventors' institutional and associated patenting histories, we use a two-stage difference-in-difference regression model to analyze optoelectronics' inventor market shifts and associated innovation outcomes from 1962 to 2007 (specifically, before, during, and after the burst of the telecommunications bubble).

We find that the burst of the bubble disproportionately reduced inventor innovation in the rest of the field compared to the emerging general purpose technology (GPT) enabler. An increase in the emerging GPT-enabler post-burst is driven by Super Star inventors (top 1.5% both by cumulative patents and annual patenting pre-bubble) who switch markets applications post-burst out of diversified firms with telecommunications divisions and into firms focused exclusively on telecommunications. These Super Stars continue an increase in integration

patenting that was driven during the bubble by Non Stars who left a period of unemployment, other markets and academia and went into firms focused on telecommunications and diversified firms with telecommunications.

We make contributions in the area of innovation and mobility as well as to the relationship between business cycles and technology directions. Previous research in the field of mobility and innovation that has used patent data to estimate mobility is limited by the fact that inventors only show up in patent data if they patent after they move, thus biasing the observed sample. CV data allows us to disentangle the relationship between mobility and patenting. With respect to business cycles, our results suggest that both non-stars and super-stars may have important roles in pushing innovation frontiers during different parts of the business cycle. While super-stars advance the emerging technology during resource-constrained parts of the business cycle, their efforts build on the innovation efforts on non-stars during less constrained times.

1.2 Introduction

Economic downturns have been shown to have disparate effects on the productivity of individuals (Mowery and Rosenberg, 1989, Bowlus, 1993, Davis et al, 1996, Gittel and Sohl, 2005) and firms (Bresnahan and Raff, 1991, Geroski & Gregg, 1997, Goldfarb et al, 2006, Brunello, 2009, Paik & Woo, 2013). However, very little is known about the influence of economic downturns, if any, on technology trajectories. This paper investigates whether the burst of the telecommunications bubble and the resulting economic downturn following the NASDAQ's peak on March 10, 2000, influenced the rate and direction of innovation of a representative set of inventors with different patenting portfolios and productivity profiles in the

US optoelectronics industry through changes made by inventors in their research, and the firms and market applications in which they conducted those projects.

We analyze patenting patterns from 1962 to 2007 across optoelectronics' many market applications: telecommunications, energy, computing, imaging, manufacturing, defense and aerospace, in both the public and private sectors, and academia. We specifically examine relationships between inventor backgrounds and career decisions in terms of mobility between firms and market application, and changes in patenting rate and direction between the emerging optoelectronic technology, integration, and the rest of the field technology, referred to as general optoelectronics.

We leverage USPTO patent data on all patents filed by US inventors in optoelectronics and inventor contact information provided by the top three professional societies in the field to collect 790 inventor CV and biographies in the optoelectronics industry. In contrast to papers that use patent data to estimate both productivity and mobility, we collect and use inventor CVs. CVs have the advantage of (1) eliminating the forced correlation between career length, mobility and patenting, as we can now see inventors who work for a company for several years before they first patent, as well as inventors who move but do not patent after they do. Being able to see inventors even after they move even if they don't patent has particular value, especially in contexts such as economic downturns, where we may expect people to lose their jobs. Furthermore, (2) hand-matched CV to patent data eliminates several errors that disambiguation algorithms overlook in matching inventors to their patents. Finally, (3), patent data tells us nothing about the background characteristics of the inventors, while CVs do.

The CVs we collect represent four subsections of the full USPTO inventor population at before the telecom burst: the top 1.5% by cumulative patents, the top 1.5% by rate of patenting, all inventors with patents in the emerging technology that reduces the size of optoelectronic components and thereby opens up opportunities for inventors to apply their knowledge to applications outside of telecommunications, and a random sample of all inventors without a patenting history in the emerging technology. We hand-code each year of the histories of the 2100 firms represented in the CVs into one or more of 20 possible market applications. We account for the propensity of an inventor to change firms and change market applications, and estimate the effect of each kind of mobility on their patenting outcomes. We probe that mobility effect for how it differs depending on what market applications the inventors are entering and exiting out of, the period of the move, the patenting portfolio of the moving inventor, and the productivity profile of the moving inventor.

We find that the burst of the bubble disproportionately reduced inventor innovation in the rest of the field compared to the emerging general purpose technology (GPT) enabler. An increase in the emerging GPT-enabler post-burst is driven by Super Star inventors (top 1.5% both by cumulative patents and annual patenting pre-bubble) who switch markets applications post-burst out of diversified firms with telecommunications divisions and into firms focused exclusively on telecommunications. These Super Stars continue an increase in integration patenting that was driven during the bubble by Non Stars who left a period of unemployment, other markets and academia and went into firms focused on telecommunications and diversified firms with telecommunications.

We make contributions in the area of innovation and mobility as well as to the relationship between business cycles and technology directions. Previous research in the field of mobility and innovation that has used patent data to estimate mobility is limited by the fact that inventors only show up in patent data if they patent after they move, thus biasing the observed sample. CV data allows us to disentangle the relationship between mobility and patenting. With respect to business cycles, our results suggest that both non-stars and super-stars may have important roles in pushing innovation frontiers during different parts of the business cycle. While super-stars advance the emerging technology during resource-constrained parts of the business cycle, their efforts build on the innovation efforts on non-stars during less constrained times.

1.3 Economic Downturns, Mobility and Productivity

The National Bureau of Economic Research (NBER) defines a recession as a period between a peak and a trough in economic activity in the chronology of the U.S. business cycle, using measures such as real Gross Domestic Product (GDP), employment, and real income (NBER, 2010). The NASDAQ's peak on March 10, 2000, the benchmark for the burst of the telecommunication bubble, preceded a period of decline in economic activity. According to the NBER, the U.S. economy was in recession from March 2001 to November 2001 (NBER, 2001). Productivity, however, does not always decline during an economic downturn. Furthermore, not all firms, people and technologies are affected the same way during or after a downturn.

Existing literature points to multiple factors which may contribute to a firm's survival during an economic downturn. First, firm survival during an economic downturn is often dependent on a firm's pre-downturn characteristics. In the case of the Great Depression, Bresnahan and Raff find that survival in the automotive industry was dependent on a firm's pre-downturn productivity, as the Great Depression caused inefficient automobile manufacturing firms to fail, while high-productivity firms later expanded (Bresnahan and Raff, 1991). In the case of the telecommunications bubble, scholars have found that survival was dependent on a firm's pre-downturn growth strategy: those that adopted a "Get Big Fast" strategy were more likely to fail, while those who followed a more traditional trajectory were more likely to be successful (Goldfarb et al, 2006). In addition, size plays a role in the probability of a firm's survival. Start-ups are more likely to fail during a recession than larger firms (Geroski & Gregg, 1997) and new firms are less likely to get venture capital funding during downturns associated with the real sector (Paik & Woo, 2013).

With regards to people, previous literature suggests the Great Depression and the burst of the telecommunications bubble may have had opposite effects on employment in scientific and technological fields. Employment of research scientists grew during the Great Depression (Mowery and Rosenberg, 1989). On the other hand, after the burst of the telecommunications bubble, technology centers had the highest unemployment rates (Gittel and Sohl, 2005). Some economists have also argued that jobs created during recessions are likely to be low paying and temporary (Bowlus, 1993, Davis et al, 1996) and firms are more likely to train incumbents during a downturn while simultaneously reducing the recruitment and training of new employees (Brunello, 2009).

When it comes to technology advancement, economic downturns have likewise not always had negative effects. Caballero and Hammour argue that recessions can have a "cleansing effect", as production units that embody the newest process and product innovations continue to be created while outdated units are destroyed (Caballero and Hammour, 1994) and firms may invest in product innovation rather than process innovation (Breschicci et al, 2013). Along the same vein, leveraging data on industries ranging from petrochemicals to automobiles, Field argues that the Great Depression was the most technologically progressive decade of the century, despite the troubles of the larger economy (Field, 2003, 2010). Indeed, college graduates during economic booms produce significantly fewer patents over the subsequent two decades than those graduating during economic downturns (Shu, 2012). In contrast, Greenstein argued that the financial meltdown of 2008 would have a negative effect on US high technology markets, as demand for high technology products and services would decline (Greenstein, 2008). Importantly, not all technologies may be affected equally. Nicholas and Nabar argue that during the Great Depression, uncertainty concerning payoffs to technological development changed the timing of early stage R&D in some sectors but not in others, and therefore affected the technology's trajectory, depending on the underlying sector-level advances in technology (Nicholas and Nabar, 2000). What remains unclear is what the impact of a sector-specific shock such as the burst of the telecommunications bubble may have had on technology development and trajectories.

Economic downturns can be associated with both job losses and changes in employment. Past academic literature offers significant insights into the impact of inventor mobility on inventors' own productivity and creativity, the hiring firms' productivity and social capital, and the knowledge base of the firms they leave.

Past literature suggests that mobile inventors can be more productive than non-mobile inventors (Hoisl 2007). Within the same firm, mobility from an outward office to the headquarters leads to higher patenting (Choudhury, 2010). Further, Singh shows a positive effect of cross-regional knowledge integration (specifically, having an inventor who recently moved from a different region) on not just productivity but also innovation quality (Singh, 2007). One explanation for a positive relationship between mobility and productivity might be that being in a new environment with different colleagues and ideas may increase an inventor's output: corporate R&D teams with heterogeneous networks have been found to achieve higher level of productivity than teams with homogenous networks (Reagans and Zuckerman, 2001). However, the majority of these studies rely only on patent data to estimate mobility. They thus only observe moves of inventors who patent after moving. As a consequence, these studies may be underestimating the extent of mobility in their population, and misestimating the relationship between mobility and productivity.

Mobility may not only influence productivity, but also knowledge flows, and thus technology directions. An individual's mobility is associated with knowledge flows across firms (Singh & Agrawal, 2011), regions (Almeida & Kogut, 1999, Fleming & Marx, 2006) and countries (Song, Almeida & Wu, 2001, Oettl & Agarwal, 2008) as well as firms' increased 'knowledge brokering[1]' capability (Hsu & Lim, 2009). The positive influence of that mobility on knowledge flows increases with technological distance (Rosenkopf & Almeida, 2003, Song, Almeida & Wu, 2003, Hsu & Lim, 2009, Palomeras & Melero, 2010). Although, at least in the case of acquisitions, higher productivity may be achieved when there is a high overlap in routines and moderate overlap in skills (Kapoor & Lim, 2007) as well as prior communication (Agarwal et al, 2012). As for the locations they leave behind, research has found that knowledge flows can be bidirectional (Agrawal, Cockburn & McHale, 2006, Oettl & Agarwal, 2008, Corredoira & Rosenkopf, 2010, Godart, Shiplov & Claes, 2013).

There are, of course, regulatory, institution, and personal limits to an individual's mobility. A firm's litigiousness significantly reduces spillovers anticipated from employee inventors (Agarwal, Ganco & Ziedonis, 2009) and firms with potential employee departures are less desirable candidates for acquisitions (Younge et al, 2012, Younge, 2012). The enforcement of non-competes likewise can attenuate mobility (Marx et al, 2009), leading to some ex-employees subject to non-competes taking career detours (Marx, 2011). In addition to regulatory and

[1] Knowledge brokering capability is the ability of firms to profitably transfer ideas from where they are known to where they represent more innovative possibilities (Hargadon, 1998).

institutional limits on mobility, personal situations and the business climate can also influence an inventor's propensity to move. Higher unemployment can create more uncertainty among individuals about future income and place of employment. In these uncertain times, individuals with significant moving costs are more likely to consider delaying a physical move to a new geographic location (Hacker, 2000). Indeed, during economic downturns, even more mobile researchers may not be likely to relocate in space (Breschi & Lissoni, 2008). In contrast, when mobility is not hindered by an economic downturn, regions with high enforcement of non-compete agreements end up driving away inventors with greater human and social capital (Marx et al, 2012).

When considering the individual differences in the context of mobility and innovation, star inventors can be a particularly important group to study, given to their disproportionate contribution to overall innovative output. Past research also suggests that stars can be expected to behave differently than non-stars. On the one hand, employees with higher performance and higher earnings (aka stars) are less likely to leave their firms (Campbell et al, 2011, Carnahan et al, 2012). Research shows, however, that higher performing inventors who do move draw level with or overtake in productivity non-movers in the post-move period (Hoisl, 2009). The mobility of a star and the location where a star works can also have impacts on productivity beyond the stars themselves. In the private sector, close, bench-level working ties between academic stars and firm scientists were needed to accomplish commercialization of their breakthroughs (Zucker & Darby, 1998). In academia, department-level productivity increases by over 38% after the arrival of a star, after accounting for the direct contribution of the star and controlling for department size (Agarwal et al). There is likewise evidence that the departure of a star can have consequences for those left behind. Following the death of a superstar, collaborators experience a lasting decline in their quality-adjusted publication rates (Azoulay et al, 2010). Here, the characteristics of the star may matter: coauthors of helpful scientists that die may experience a decrease in output quality but not output quantity, while the deaths of high productivity scientists that are not highly helpful may not influence their coauthors' output (Oettl, 2012).

Building on this past literature, this paper seeks to understand how a sector-specific downturn – specifically the burst of the telecommunications bubble may affect the quantity and direction of innovation in optoelectronics, a technology whose advance is central to the field of telecommunications. We seek to shed insights into aggregate national trends through the activities of individual inventors: In particular, we explore whether inventor innovation outcomes can in part be explained by the inventor's mobility into and out of telecom during (for the former) and after the burst of (for the latter) the bubble. We likewise explore the extent to which inventors with different underlying characteristics (and in particular stars vs non-stars) respond differently during the business cycle

1.4 The Optoelectronics Industry Context

Optoelectronics is one of the more fundamental technologies driving recent advances in communications and with them the information economy (NRC, 2013). In 1999, the market for optical components in the telecommunications sector was worth 6.4 billion dollars (Henbury, 2007). It had $400B global revenues in 2011 (Lin, 2011) and is forecasted to be a $1T industry by 2016 in terms of both components and enabled products (Lebby, 2006). Optoelectronics sits at the intersection of electronics and photonics. As a field, optoelectronics is concerned with the study, design, application and manufacture of components that source, detect and control visible and invisible light for the purpose of transmitting and receiving data. Optoelectronics, in harnessing the power of photons, enables the design of devices that lack the cross-talk complications of electrons while also enabling higher bandwidths and lower power consumption. Due to these benefits, over time, optoelectronic devices are increasingly replacing electronic ones in information technology applications.

An important emerging technology in the field of optoelectronics is integration. Integration is concerned with the combination of multiple optoelectronic functions such as lasers and modulators onto a single chip, thus enabling the design of devices with smaller form factors. This is typically done using semiconductor fabrication techniques, These smaller form factors enable optoelectronics to move from more conventional applications in tele- and data-communications and sensing, to applications in computing (e.g. core to memory or even between cores on a microprocessor), biology (such as transmitting, receiving, and sensing technologies inside contact lenses or inside the body), and energy. In computing for example, computer optical buses requiring the integration of seven functions may be needed in microprocessors to continue Moore's Law (Moore, 1965) and there with higher memory capacity and processing speeds (Eng, 2010). Such high speeds are especially crucial for internet data center operators' cloud-computing services (Vusirikala, 2010).

Figure 1.1: Optoelectronic Integration transforms design of Dense Wavelength Division Multiplexers (Ferry, 2010)

Innovation in optoelectronics was in the 80s and 90s driven by the telecommunications industry. However, as noted above, as component size is reduced, optoelectronics has opportunities for application in markets including but not limited to computing, biomedical, energy and defense. Due to its "general applicability" in a vast array of markets and "innovative complementarities" such that "technical advances in the GPT make it more profitable for users to innovate in their own technologies" (Rosenberg and Trajtenberg 2004), optoelectronics could be considered to fit the definition of a general purpose technology (NRC 2013): "extremely pervasive and used as inputs by a wide range of sectors" (Helpman, 1998). Integration, by reducing the size of optoelectronics, is in turn key to enabling optoelectronics to access to this broader set of markets beyond telecommunications. In this context, inventors who have or can develop this integration capability may have a unique opportunity to switch market applications while leveraging their same technical competency. As integration is both an emerging technology in the field of optoelectronic and also a key enabler of optoelectronics reaching a broader set of market applications and fulfilling its GPT potential, we call integration an "emerging GPT-enabler."

According to the OECD, the increase in spending in the telecom sector in the late 1990s can be attributed to a combination of factors including new firm entrants into the sector and the introduction of marketable new technologies, most notably mobile phones and Internet access services. These factors led to high levels of venture capital investment, and telecom companies planned large scale investment projects based on speculation that demand for their services was about to skyrocket [OECD, 2003].

When the telecommunication bubble burst leading to US fiber-optic market revenues by 2002 being less than 20% of what had previously been projected (Fuchs, 2010) the telecom industry faced financial challenges. Some firms reduced overall investment in R&D (OECD, 2003) and several moved the manufacturing (assembly, and in some cases also fabrication) of their active optical components off-shore (Fuchs, 2010). While optoelectronic firms that move component manufacturing overseas have reduced incentives to invest in integration (Fuchs), individual researchers need not necessarily stay at or follow the same research trajectory as the offshoring firms or even of optoelectronic component manufacturers for telecom more broadly. To understand the progress of innovation in optoelectronics as a field (general OE) versus optoelectronics integration before, during and after the telecommunications bubble, we show in Figure 1.2 below, on normalized axes, the number of patents filed in each year in the US in general OE and OE integration between 1976 and 2007.

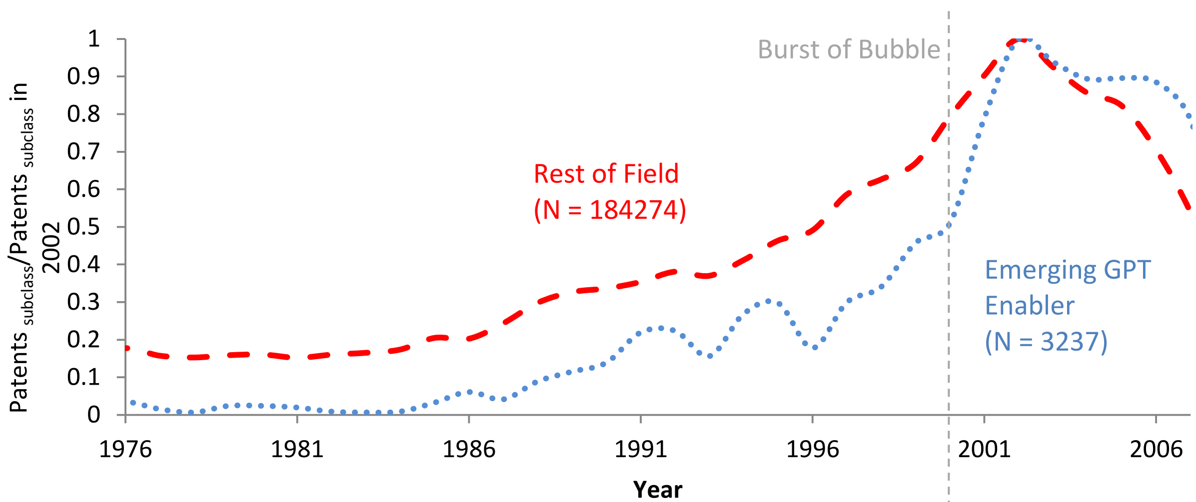


Figure 1.2: USPTO Patents in general OE and in integration over time by file date

From this plot, we see that, patenting in general optoelectronics (OE) and in integration increase at approximately similar rates in the pre-bubble period (1991 – 1996). During the bubble (1996 – 2002, when allowing a 1-year lag for patents to be filed after completing research) patenting in general OE and in integration continue to increase but patenting in integration increases at a faster rate than patenting in general OE. Both general OE and OE integration peak in 2002. After the burst of the bubble (2002 – 2007, allowing again a 1-year lag for patents to be filed after completing research), patenting in general OE declines, while patenting in integration holds steady close to 2002 levels.

The burst of the telecommunications bubble is apparent across different sources of data, as shown in the table 1.1 below:

Data Source	Description	Pre-burst period	Bubble Burst	Post-Burst Period
NBER	the telecom bubble burst in March 2001, and the resulting decline in economic activity lasts until November 2001 (business cycles based on trends in GDP, employment and real income)	1991 – 2001	March 2001	2001 – 2007 Next recession start: Dec 2007
Full USPTO: OE Patent Data	patenting in both general OE and integration reach their peak in 2002	pre-bubble: 1991 - 1998 bubble: 1998 – 2002	2002	2002 - 2007
CV Sample: Patent Data	Patenting in both general OE and integration reach their peak in 1999 (suggests bias in sample, likely due to disproportionate number of stars)	1991 - 1999	1999	2000-2010
CV Sample: Market Changes	mobility into telecom drops off to infinitesimally small levels after 2002	bubble: 1998 – 2002	2002	2002 - 2007

Table 1.1: The telecom bubble burst: evidence in different sources of data

One might expect the burst of the telecommunications bubble and the subsequent economic downturn and offshoring of many optoelectronic component firms' manufacturing to translate to less innovation in the emerging technology, which is harder to research and implement. Instead, patenting in the emerging technology (integration) stays high while general OE declines after the burst. Can inventor mobility and research trajectories help explain this trend? Is the burst of the telecommunications bubble perhaps leading certain inventors to leave telecommunications, and once they do, to patent in the emerging (integration) technology for applications outside telecom?

1.5 The Conceptual Framework and Hypotheses

1.5.1 Research Question

How do sector-specific business cycles (during bubble and post-burst) affect the

(1) quantity (patents) and

(2) direction (emerging general purpose technology enabler versus rest of the field)

of innovation?

Are inventor innovation outcomes in part explained by the inventor's mobility into and out of telecom?

Do star inventors respond in a different way from non-stars?

In answering the above questions, we hope to shed insights, through the individual inventor-based trends, into possible mechanisms behind national trends in the rate and direction of optoelectronics innovation during the bubble and after the bubble burst.

1.5.2 Hypotheses

H1. Inventors who move into telecom during the bubble increase their patenting in both the rest of field optoelectronic technology and the emerging GPT enabler (integration). (e.g. Hall 1992; Hao and Jaffe 1993; Himmelberg and Peterson 1994; Goldfarb, et al, 2007)

H2. Inventors who move out of telecom post-burst increase their patenting in the emerging GPT enabler (integration) but not in the rest of field optoelectronic technology (e.g. Caballero and Hammour, 1994; Nicholas and Nabar, 2000; Field 2003, 2010)

- STAR inventors who move out of telecom post-burst disproportionately increase their patenting in the emerging GPT enabler (integration) but not in rest of field optoelectronic technology (Hoisl, 2009)

1.6 Methods

1.6.1 Research Design

To answer the research question and investigate our hypotheses, we use a combination of descriptive analyses and a 2-stage difference in difference regression analysis. In our descriptive analyses, we use graphical methods to help shed light on underlying trends in the data set. Then using regressions, we first estimate the probability that an inventor will change firms or market applications and then accounting for that probability, we estimate the effect of mobility on inventor accounts. We probe this mobility effect for changes depending on the time on the new job or market application, the period of the move, and the origin and destination markets.

Past research has used publicly available patent data to measure productivity and performance (Mowery et al, 2001, Kapoor & Lim, 2007, Fleming, 2007, Singh &Fleming, 2009, Oettl, 2012, Subramanian, et al, 2012), inventor mobility (Song et al, 2001, Song et al, 2003, Oettl & Agarwal, 2008, Rosenkopf and Correidora, 2009, Marx, et al, 2009, Palomeras & Melero, 2010, Marx et al, 2012), transfer of knowledge (Almeida & Kogut, 1999, Song et al, 2003, Rosenkopf & Almeida, 2003, Singh, 2005, Singh, 2007, Rosenkopf & Correidora, 2009, Singh & Agrawal, 2011, Agrawal et al, 2011, Azoulay et al 2012), and research direction and technological change (Azoulay et al, 2009, Strumsky et al, 2012).

In contrast to these papers that use patent data to estimate productivity and mobility, we collect and use inventor CVs. CVs have the advantage of (1) eliminating the forced correlation between career length, mobility and patenting, as we can now see inventors who work for a company for several years before they first patent, as well as inventors who move but do not patent after they do. Being able to see inventors even after they move even if they don't patent has particular value, especially in contexts such as economic downturns, where we may expect people to lose their jobs. (2) Furthermore, hand-matched CV to patent data eliminates several errors that disambiguation algorithms overlook in matching inventors to their patents. Finally, (3), patent data tells us nothing about the background characteristics of the inventors.

In order to estimate the causal effects of the telecom bubble burst on inventor patenting in general optoelectronics and in integration, we use difference in difference methods. Difference-in-difference models mimic random assignment with treatment and comparison samples, and can be applied in situations where the data arise from a natural experiment, or a quasi experiment (Wooldridge, 2009, Furman et al, 2012). These experiments often result from an external shock, most often in the form of a policy change.

This paper employs a non-traditional difference in difference method, as it does not include a control sample of inventors that was wholly unaffected by the burst of the telecommunications bubble. Instead, the differences occur within the optoelectronics industry, with the different kinds of technology being innovated upon: general optoelectronics versus integration. We also compare differences between the stars in the industry (first defined as those in the top 1.5% by patenting pattern, and then with sensitivity analyses to that number) and the non-stars. We do have CVs of inventors in academia as well as ‘other markets’ which includes defense, which are regarded as being less susceptible to the burst of the telecommunications bubble than telecom and diversified-with-telecom firms, and we therefore compares these too. However the opportunity cost of getting a comprehensive sample of CVs of inventors in the optoelectronics industry was not having an equally sized control sample that was unaffected by the burst of the telecom bubble.

1.6.2 Data

1.6.2.1 USPTO Patent Data

Using the US Patent and Trademark Office (USPTO) database, we identified all inventors who have been granted a patent in optoelectronics classes between 1976 and 2007. An overview of the data is shown in Table 1.2 below. These patents are defined as being within a pre-determined set of classes and subclasses (shown in Appendix 1.1).

Total Number of US Inventors active pre-burst	49,744
Number of Inventors with patents only in integration	189
Number of inventors with patents in both integration and General OE	1255
Number of inventors with patents only in General OE	48300
Total Number of patents by US inventors	150, 358
Number of integration patents	2821
Number of general OE patents	147,537
Number of forward citations	479,094

Table 1.2: USPTO optoelectronics patent data overview

From these data, we gleaned, for each inventor, his number of general OE patents, number of integration patents, earliest patenting date from which we estimated a career length, and number of assignees. This is shown in table 1.3 below.

Variable	Minimum	Mean	Maximum
Number of integration patents per inventor	0	3	158
Number of general OE patents per inventor	0	0.06	46

Table 1.3: USPTO patent data descriptive statistics

We also were able to tell if the inventor was patenting from a US location, thereby designating him a US inventor.

1.6.2.2 CV Data

Although past research has used publicly available patent data to measure productivity (Kapoor and Lim, 2007, Fleming 2007), inventor mobility (Song et al, 2003 Rosenkopf and Correidora, 2009, Marx et al 2009), and transfer of knowledge (Almeida Kogut, 1999, Song et al, 2003, Rosenkopf and Correidora, 2009), these analyses suffer from many challenges. The lack of individual inventor IDs in the USPTO database mean that the accuracy of one's data is based on one's disambiguation algorithm. One of the first efforts was made by Trajtenberg et al, in 2006. Even more importantly, patent data will not identify inventors as having moved if they do not patent after they move, nor the career length of inventors who stay with a firm but do not patent. Furthermore, patent data tells us nothing about the background characteristics of the inventors.

To help correct for these limitations, we identified and collected CVs for four sub-populations of inventors, based on inventors patenting histories before the bubble. We discovered from plots that the top 1.5% of all inventors were responsible for 15% of all patents in the industry pre-burst, and after this threshold the cumulative plot drops. We therefore collect CVs for the top 1.5% of inventors by total number of patents (MOST), top 1.5% of inventors by patents/year (RATE), all inventors with at least one patent in the emerging GPT-enabling technology (integration) (INT), and a random sample of the general OE inventors in the USPTO population (RAND-NI).

For each of these groups, we liased with the three largest societies in photonics: the Optical Society of America, SPIE, and IEEE's Photonics Society to collect inventor contact information (phone, email, and address). Using this contact information, we made calls, sent emails and searched the web for additional contact information to find inventors and collect their CVs. Over the course of the dissertation we collected 900 inventor CVs. We then audited these CVs to ensure that they were the right ones for the sample, and that they reflected the same history as the inventor who they were supposed to be. Next, we hand-matched these inventors' patents based on their CVs to have a complete view of their patenting history without the problems associated with the USPTO database of not having individual inventor IDs.

Inventors	Target Population	CV Sample	Response Rate
Top 1.5% by Total Patents (MOST)	760	237	30%; 73% of those reached
Top 1.5% by Patents/Year (RATE)	680	233	34%; 82% of those reached
All Inventors in Integration (INT)	900	247	27%; 95% of those reached
Random Sample of Gen OE (RAND-NI)	1250	180	15%; 83% of those reached

Table 1.4: CV collection and response rates
Note that there are overlaps between the samples, which are detailed in Appendix 1.2.

The largest challenge we faced in collecting CVs was inventors for whom we could not find contact information. As we can see from table 1.4 above, the response rates of inventors that we reached range from 73% to 95%. For the MOST sample, the response rate was 73%. Being in the top 1.5% by total number of patents is correlated with having had a long career. Many inventors in this category may be retired or even deceased, and thus may have been more difficult to find contact information for or otherwise reach. In the RATE sample, our response rate was 82%. Although we had hypothesized that these inventors may have had short but productive careers in optoelectronics and may have since moved out of the industry, we were able to find slightly more of these inventors than the MOST inventors (34% vs 30%) and the inventors we reached were amenable to sharing their CVs. The INT sample had the highest response rate of 95%. It may be that having the skills in integration takes extra investment of time and effort, which may be more correlated with a greater interest in research surrounding the industry in general, thereby explaining the high response rates. Finally, and perhaps most surprisingly, we had an 83% response rate for the RAND-NI sample.

1.6.2.3 Sample Bias Investigations

In order to check the extent to which our samples reflected the overall USPTO optoelectronics (OE) inventor population, we ran logit regressions between ~49000 inventors' pre-burst characteristics based on the USPTO patent data a 1/0 variable indicating that we have the inventor's CV for the inventor for each of the four samples. These are presented in table 1.5.

VARIABLES	Dependent variable: Do We have their CV?			
	MOST	RATE	INT	RAND-NI
# OE Patents Pre	0.0192**	0.0246*	0.0162*	0.0499
	(0.00796)	(0.0145)	(0.00936)	(0.0535)
# INT Patents Pre	0.146***	0.151**	-0.00454	
	(0.0534)	(0.0745)	(0.0611)	
# Assignees Pre	0.0747*	0.174**	0.0103	0.113
	(0.0440)	(0.0797)	(0.0691)	(0.202)
# Career Years Pre	-0.0224*	-0.0619	0.0320**	-0.00865
	(0.0134)	(0.0456)	(0.0137)	(0.0249)
Constant	-1.213***	-1.101***	-1.250***	-2.111***
	(0.255)	(0.145)	(0.162)	(0.218)

Table 1.5: Logit regressions between whether or not we have a CV and pre-burst patent characteristics

In the MOST sample, we are more likely to have a CV for inventors who have more integrated patents, and to a lesser extent, those who have more OE patents and who are more mobile, where mobility here is measured by the number of assignees pre-burst. Interestingly, we are less likely to have a CV for inventors with longer careers pre-burst. This may be because they have either been retired for a longer time, or in a few cases, now deceased. In the RATE sample, we are more likely to have a CV for inventors who are more mobile pre-burst, as well as those who have more integrated patents, and to a lesser extent, more general OE patents pre-burst. In the INT sample, we are more likely to have a CV for inventors who had long patenting careers pre-burst. There is no evidence of sample bias in the RAND sample.

There were overlaps between the these samples, of course. After collection, we re-classified all 790 inventors into four categories depending on how they overlap. MOST and RATE overlap inventors are our Super Stars, as they have both high total productivity and high annual productivity. MOST-alone inventors are our Sustaining Stars: they have high total productivity and also a high career length. RATE alone inventors are our Evanescent Stars, who have high annual productivity and shorter career length on average. Finally, those inventors who are neither MOST nor RATE are simply our Non Stars.

1.6.2.4 Descriptive Statistics

After deleting CV files that were the wrong person, we were left with 723 files. From those, we glean inventor CV and biographical data, we were able to collect useful information on inventor background characteristics as shown in table 1.6 below:

Variable	
Educational information	
Number of inventors whose highest level of education is a doctoral degree	517
Number of inventors with a masters' degree	109
Number of inventors with a BSc	71
Number of inventors with other degree	26
University which the highest number of inventors attended	Stanford U
Firm which the highest number of inventors were at one time or the other	AT&T Bell Labs
University which the highest number of inventors worked at	MIT
Number of inventors who report have also founded a company	108
Number of inventors who report have also been a director of a company	117

Table 1.6: CV biographical data overview

Based on our CV data, we also were able to update the inventor information that normally would have been based on patent data as shown in table 1.7 below:

	Based on Patent Data			Based on hand-matched CV Data		
Variable	**Minimum**	**Mean**	**Maximum**	**Minimum**	**Mean**	**Maximum**
Number of integration patents for each inventor	0	0.66	22	0	1.01	50
Number of general OE patents for each inventor	0	11.51	126	0	16.3	163
Career length	1	8.15	35	1	15.5	48
Number of assignees/jobs	1	2.16	10	1	2.24	15
Number of market applications	NA	NA	NA	1	1.98	9
Age	NA	NA	NA	24	54	81

Table 1.7: CV inventor sample descriptive statistics

To help answer our research question, we leveraged the International Directory of Corporate histories, Mergent Webreports, LexisNexis Corporate Affiliations, Hoover's and online news archives to assign to each firm in the inventors' CV file one or more market application codes for each year that the inventor was in that firm. We hand-code each year of the histories of the 2100 firms represented in the CVs into one or more of approximately 20 possible market applications. The number of inventors in various market applications over time, and how these trends vary with inventor's pre-burst patenting characteristics can be observed in figures 1.4 and 1.5. The full set of market application codes that we developed in conjunction with the 2013 NRC write-up on the field, and subsequently assigned to firms are shown Table 3.3.

1.7 Results

1.7.1 Descriptive Analyses

In order to understand the underlying relationships in our data set, we use graphical methods. We first examine to the trends in patenting from hand-matched patent data for the set of inventors for whom we have CVs over time, by file dates as shown in figure 1.3 below:

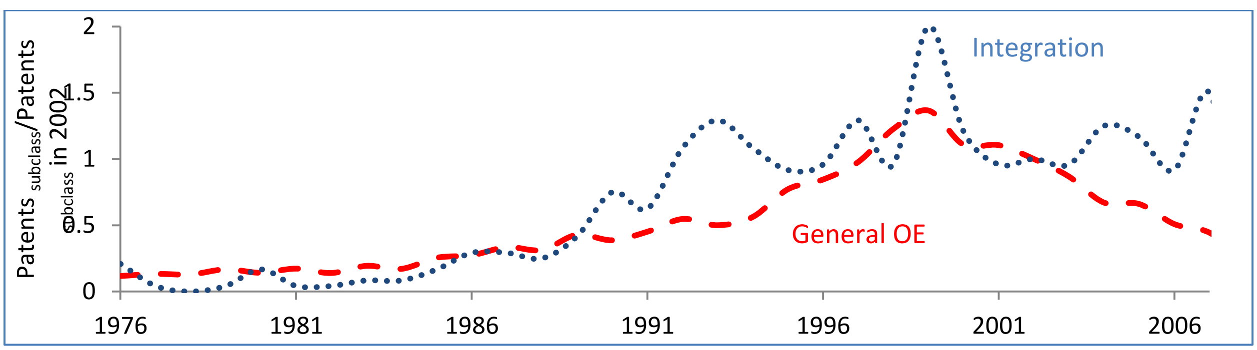


Figure 1.3 Patents filed over time in general OE and in integration compared, pooled CV sample

We observe that whereas in the USPTO patent data, patenting in both general optoelectronics and integration peaked in 2002 (figure 1.1), in the CV sample, patenting peaks in 1999. As suggested subsequently in Figure 1.4, we suspect this shifted peak is due to the disproportionate number of “stars” in our CV data. In addition, as can be see in Figure 1.3, there is greater variability in the integration patenting, likely due to the smaller sample size when using just the CVs rather than the full USPTO OE data. Unsurprisingly, again due to the disproportionate number of “stars”, the CV sample has on average higher levels of patenting both in general OE and in integration than the full USPTO OE data.

To understand how these trends may differ across the different types of inventors in our CV data, we extend the analyses to examine patenting trends by sub-sample. As explained before, we account for overlaps between our four samples by re-organizing them into top 1.5% according to cumulative patenting (but not in the top 1.5% by rate of patenting) leading into the bubble (Sustaining Stars, or MOST alone), top 1.5% according to rate of patenting (but not in the top 1.5% by cumulative patenting) leading into the bubble (Evanescent Stats, or RATE alone), the top 1.5% according to both their cumulative patenting and their rate of patenting leading into the bubble (Super Stars, or MOST and RATE overlap), and from either our INT group or our RAND-NI group, but in none of the above categories (Non Stars, or non-MOST and non-RATE). In Figure 1.4 below, we observe that inventors that belong to inventors in the top 1.5% by average number of patents pre-burst (but not in the top 1.5% by cumulative patenting) (RATE alone) increase patenting in general OE as well as in integration during the bubble (1996 to 2002) and then decline patenting in both fields after the burst of the bubble (2002 – 2007).

We also observe that Super Star inventors, i.e., those that belong both to the top 1.5% by total number of patents and top 1.5% by average number of patents (MOST & RATE overlap) increase patenting in integration after the burst of the bubble (2002 – 2007). Sustaining Star inventors, i.e., those that belong to the top 1.5% by cumulative number of patents pre-burst but not in the 1.5% by rate of patenting (MOST alone) continue patenting at approximately the same rates over time in both general OE and integration. Finally, Non-Star inventors increase patenting in integration starting in the late 1980s but rapidly drop off after 1999.

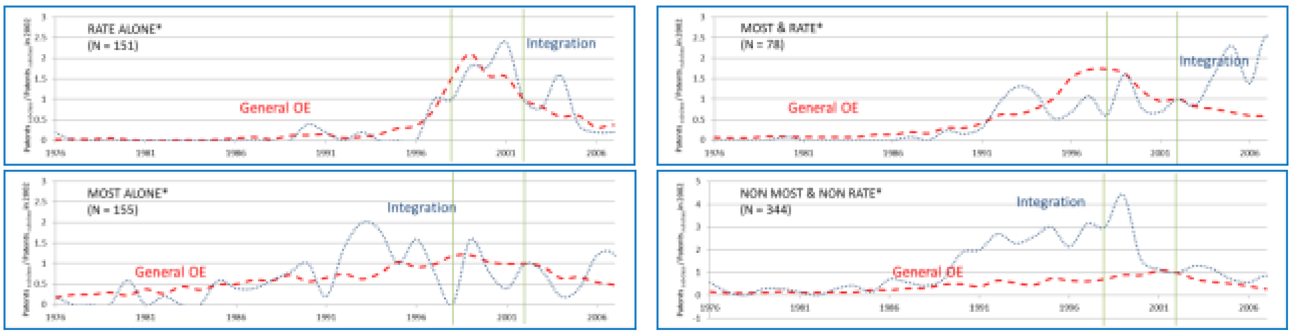


Figure 1.4: Patents filed over time in general OE and in integration compared to 2002 levels, individual CV samples

We next observe the markets applications over time to which the inventors belong. First, we observe the pooled CV sample in figure 1.5. There are a number of observations to be made from figure 1.5. First, the number of inventors in each market application is growing over time, which is consistent with the upward trend in active inventors at any given point of time in our sample. However, there are very different trends across market applications.

Prior to the burst of the bubble (pre-2002), the number of inventors in firms selling to telecommunications markets increases dramatically. Inventors also increase entry into "diversified firms" (firms selling to multiple market applications) engaged in telecom activities until approximately 1998 after which this number starts to decline. The number of inventors in defense grows until 1996, then generally declines until the burst of the bubble (2001). Inventors are found in academia at increasing rates over time until 1994, after which entry flattens until the burst of the bubble (2001). Entry into consulting, and the life sciences also grow but at low rates during the pre-bubble and bubble periods.

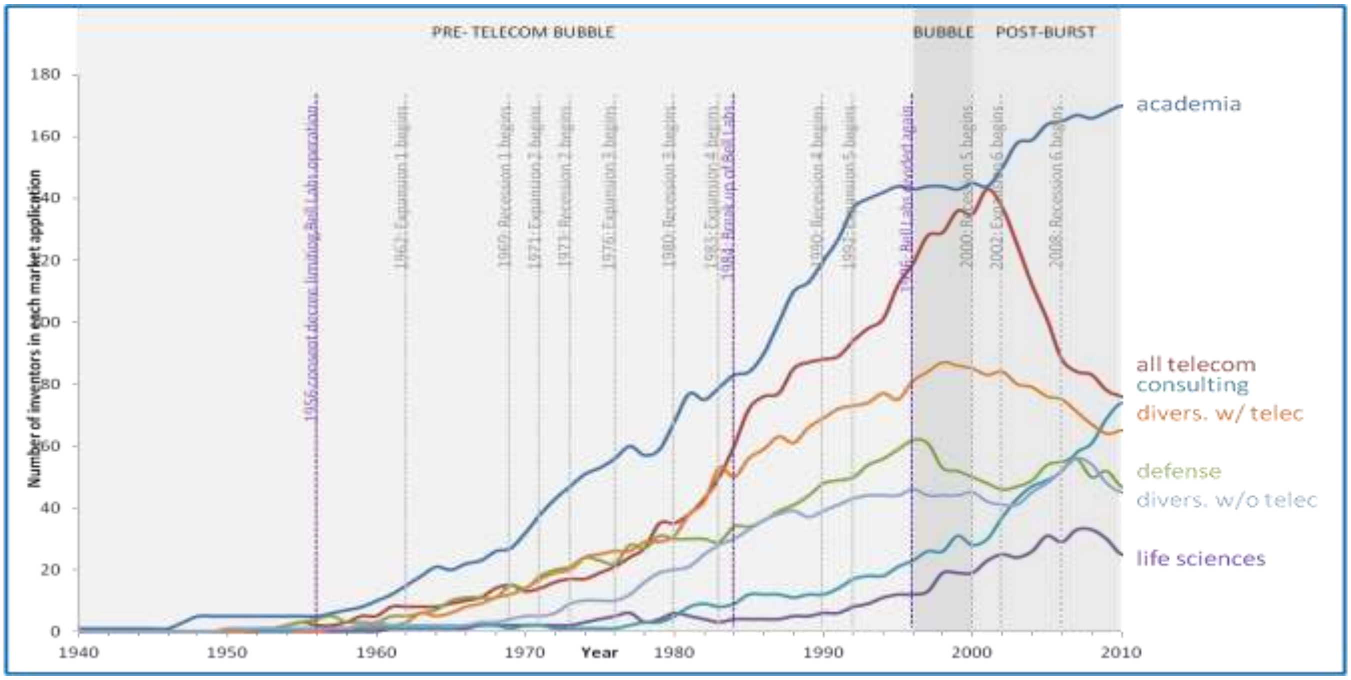


Figure 1.5: Number of inventors in each market application, pooled CV sample

After the burst of the bubble, entry into academia rises again sharply starting in 2001. Inventors in “consulting” also rises at an increased rate (starting in 2000), as does the number of inventors in diversified firms without market applications in telecommunications (starting in 2002). Inventors in life sciences continue its pre-burst increase . The number of inventors in defense also starts increasing in 2001, after its previous pre-burst decline. On the other hand, the number of inventors in firms selling to telecommunications markets declines sharply starting in 2001, and entry into diversified firms selling to telecommunications market continues the decline that had started in 1998.

To understand how these trends may differ across the different types of inventors in our CV data, we extend our analyses to examine inventor market application trends by pre-burst patenting history sub-sample. As can be seen in Figure 1.5, across all four samples, we see an increase in inventors' entry into telecom up through 2001, followed by a sharp decline in the number of inventors in telecommunications. These trends give weight to the argument that there was a shock to the field of optoelectronics that impacted inventors and firms involved in telecommunications more than it did other industries.

We had previously seen that the Evanescent Star (RATE Alone) sample increased patenting in both integration and in general OE during the bubble. Here the plot shows that during the bubble the greatest number of RATE inventors exists in telecom – the proportion of the sample in telecom starts to increase in 1994 and does so until 2001, after which it declines sharply, leveling off again by 2006. A similar pattern occurs for Evanescent Star inventors in diversified firms selling to telecom markets: the number of Evanescent Star inventors in these firms starts to rise in 1996, and then declines starting in 2002. On the other hand, the proportion of the RATE alone sample entering academia increases until 1992, then somewhat plateaus until 2001, when it starts to increase again. The number of Evanescent Star inventors in "consulting" starts to increase in 2001, and the number of Evanescent Star inventors in diversified firms that do not sell to telecom markets and in life sciences likewise increase starting in 2003.

Leading up to the burst of the bubble, the proportion of inventors in the Super Star (MOST-and-RATE overlap**)** sample in telecom increases starting in 1978 and continues increasing until 2001 as seen in Figure 1.5 above. Similarly, the number of inventors in diversified firms selling to telecommunications market applications starts increasing in 1978, and continues to do so through 2001. Entry into academia declines between 1992 and 2001. Post-burst, inventors in "consulting", defense, academia and diversified firms not selling to telecommunications markets all increase. In contrast, inventors in firms selling to telecommunications markets declines sharply while entry into firms in the life sciences and diversified firms not selling to telecommunications markets plateaus.

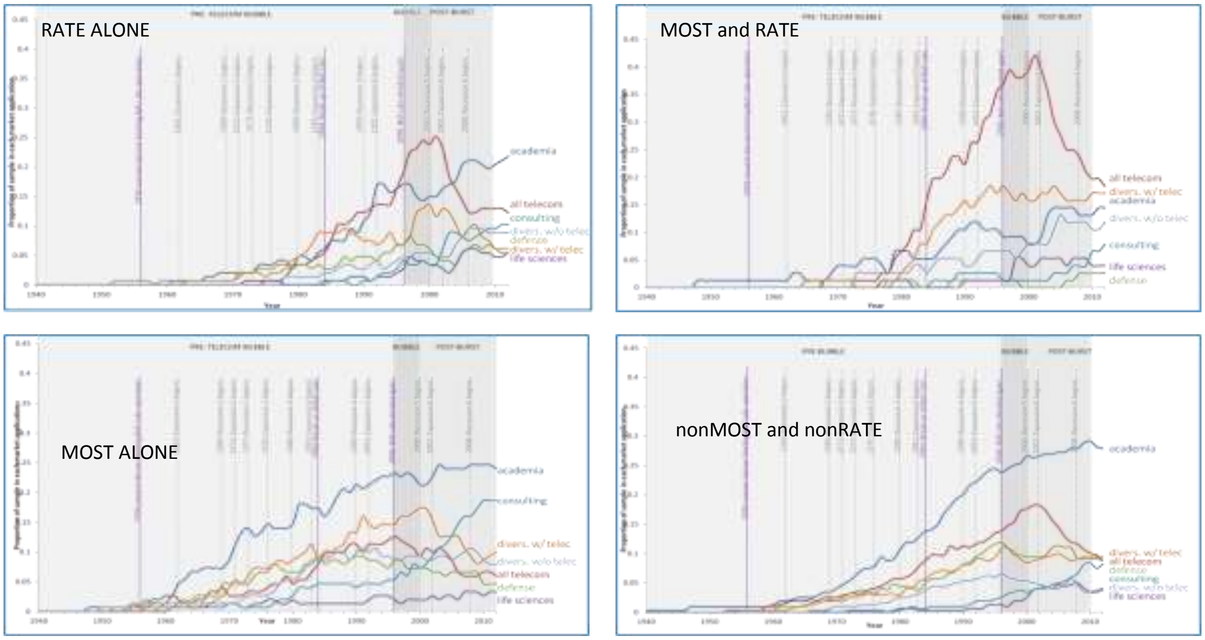


Figure 1.6: Number of inventors in each market application, individual CV sample

Leading up to the burst of the bubble, the Sustaining Star (MOST-alone) sample does not have one market application where there is a dramatic increase in the number of inventors in contrast to what we see in the Evanescent Star and Super Star samples. The proportion of inventors in diversified firms selling to telecommunications markets and firms selling exclusively to telecommunications markets does increase until 1996 and 2001, respectively. Interestingly, the proportion of inventors in consulting starts to rise after the 1996 breakup of Bell Labs. After the burst of the bubble, the number of inventors in diversified firms selling to telecommunications markets and firms selling exclusively to telecommunications markets decline while the number of inventors in “consulting” continues its pre-burst rise.

The Non Star (non-MOST-and-non-RATE) sample can perhaps be thought of as representing inventors most similar to the average inventor in this industry. Pre-burst, we observe that the number of inventors in firms selling to telecommunications markets increases until 2002 and entry into diversified firms also selling to telecommunications markets increases until 1996 and then plateaus. The number of inventors in the sample in academia increases over time, but at a slower rate after 1996. The number of inventors in "consulting" also starts to increase staring in 1996. After the burst of the bubble, the number of inventors in telecom declines (starting in 2002). The number of inventors in academia, life sciences and consulting, continue their pre-burst upward trend. The number of inventors in defense and diversified firms selling to telecommunications markets remains flat.

1.7.2 Two Stage Regression Analysis: Firm Mobility and Future Patenting

We collected 790 raw CVS of USPTO inventors who had filed patents in optoelectronics before the burst of the bubble. for this portion of the analyses. We parsed this CV data, cleaned it and removed inventors whose CVs were missing employment institution name or date, leaving us with a set of 692 inventors. To further ensure the integrity of these analyses, we excluded inventors whose earliest hand-matched patenting dates pre-dated their first CV employment date, suggesting that we had incomplete CV information. This led us to 501 inventors.

Finally, we limited this section of the analyses to inventors whose earliest employment dates pre-dates the bubble, that is, they were already working in this industry by Dec 31, 1995. We also re-categorized everyone into MOST_96 or RATE_96 based on their patenting patterns before the bubble. With this set of 14220 inventor-year observations we will now explore the relationship between mobility, in terms of firm changes and market application changes, and patenting in general OE and in integration.

1.7.2.1 Estimating Propensity to Change Firms

First, we estimate the probability that an inventor will change firms. The variables we use are the inventor's career length or tenure, his technological focus up until that year, and the number of co-authors he has had up until that year (Trajtenberg, 2006).

$$probit(p(firm\_change_{it} = 1) = \beta_{0i} + \beta_1 tech\_focus_{i(t-1)} + \beta_2 num\_co\text{-}authors_{i(t-1)} + \beta_3 tenure_{i(t-1)} + \varepsilon_{it}$$

Parameter	Interpretation
Firm Change$_{it}$	Whether or not an inventor i changes firms in year t
Tech Focus$_{it-1}$	Whether an inventor i has focused on just general OE or has had an emerging GPT enabler patent by year t-1
Num co-authors$_{it-1}$	The number of co-authors an inventor i has had by year t-1
Tenure$_{it-1}$	How long an inventor i has been in employment by year t-1
$\boldsymbol{\varepsilon_{it}}$	Error term

Table 1.8: Estimation equation for propensity to change firms and variables definitions

As seen in table 1.8 above, the inventor's career length or tenure is how long he has been working at a firm. This variable is calculated based on information from CV data, and is expected to be more accurate than estimations made from patent data. Age and tenure are highly correlated so we only include one of them at a time. In the model shown below, we show the results for using tenure. We think the longer an inventor has been at a firm, the less likely he is to change firms.

The inventor's technological focus is a 0 for every year that he has a patent in general OE, and then it switches to 1 and stays at 1 once he has filed his first integration patent. A more accurate measure of technological focus may be to calculate for each year what proportion of his patents are integration patents. We think the more an inventor gets into integration patenting, (tech_focus = 1) the more likely he is to change firms since his skills will now be in demand in many different kinds of firms.

The inventor's number of co-authors is how many co-authors he has had on his patents up until the current year. We think the more co-authors he has had up until that year, the less likely he is to change firms, since this indicates that he probably has a support system around him at his existing firm, assuming that inventors are more likely to co-author patents with other inventors in their same firms.

After running the probit regressions shown in table 1.9 below, the model shows that our hypothesis for tenure is corroborated: inventors with longer tenures are less likely to change firms. Also, having at least one patent in integration is associated with an inventor being more likely to change firms. However, contrary to what we expected, the more co-authors an inventor has, the more likely he is to change firms.

VARIABLES	firm_change
Tenure	-0.038***
	(0.002)
1.tech_focus	0.076*
	(0.045)
num_coauthor	0.002***
	(0.000)
Constant	-0.809***
	(0.027)
Observations	14,220
Number of cvid	473
lnsig2u	-2.884***
	(0.184)

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

Table 1.9: Estimating Inventor's Propensity to Change Firms in Each Year

We save the predicted propensity for each inventor to change firms from this model.

1.7.2.2 Effect of firm change on an inventor's general OE and integration patenting

We include the predicted likelihoods that an inventor will change firms (fitted values, y_hats) from the previous model in this second stage model that estimates the inventors' general OE and integration patenting after he has changed firms. First we estimate the basic firm mobility effect on an inventor's general OE and integration outcomes, while controlling for the inventor's previous general OE and integration patents, first with year effects (Appendix 1.3, Table A2 Model 1 & Table A3 Model 1), and then including period effects (Appendix 1.3 Table A2 Model 2 & Table A3 Model 2): period 0 includes the years before the telecom bubble (1962 – 1995); period 1,the years during the telecom bubble (1996 – 1999); and period 3, the years after the burst of the telecom bubble (2000 – 2010). Next we tease out more accurately how the period in which an inventor moves modifies the basic firm mobility effect by adding in an interaction between the two (Appendix 1.3 Table A2 Model 3 & Table A3 Model 3). Then we examine how the firm mobility effect is modified by the inventor's previous general OE and integration patent levels by adding in an interaction between those three terms (Appendix 1.3 Table A2 Model 4 & Table A3 Model 4). Finally, we examine how this firm mobility in each period effect differs for each inventor type based on their patenting pattern pre-burst (Appendix 1.3 Table A2 Model 5 & Table A3 Model 5). In this 5^{th} model, we estimate simple slopes using margins (Aiken, 1991).

A. Inventors Changing Firms and Future Patenting

From the coefficients in Model 5, we find that an inventor changing firms is associated with a 5.8% reduction in his future general OE patenting (as opposed to the 8.3% reduction estimated by the incomplete Model 1) and a 1.3% decrease in his integration patenting. This makes sense not only because it takes time to re-establish a line of research after an inventor has changed firms, but also because there are internal legal and regulatory hurdles to cross before a patent can be filed. The fact that the reduction in integration patenting is reduced may be explained by the fact that integration is the enabling GPT technology, and that fact helps mitigate some of the negative effects of switching firms. Still, does not explain the increase in integration patenting that we observed in figure 1.1.

In order to tease out the relationships between firm change, period, patent portfolios and productivity profiles, we estimate simple slopes using the margins command in Stata.

B. Inventors Changing Firms During Different Periods and Future Patenting

The time period during which an inventor changes firms could also modify the basic firm mobility effect. The three time periods being examined here are: before the burst of the bubble (up until end of 1995), during the burst of the bubble (between 1996 and 1999 inclusive), and after the burst of the bubble (from 2000 onwards). We estimate simple slopes on the interaction between firm mobility and period in Model 5 using margins in Stata 11 (Aiken).

We find that on average, inventors who change firms during the bubble experience an increase in integration patenting. Inventors who change firms at all time periods experience a decrease in general OE patenting. This is shown in Figure 1.7 below.

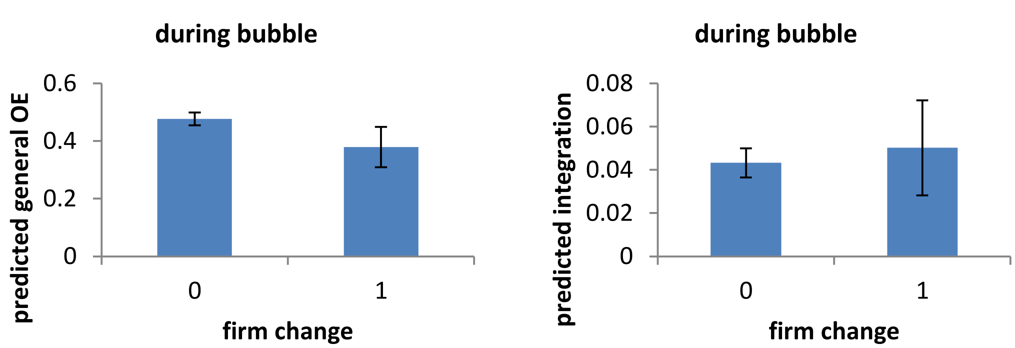


Figure 1.7: Average general OE and integration outcomes after a firm change during the bubble

This result begins to suggest that the continued increase and stability of in innovation patenting post-burst started to occur during the bubble; same with the decline in general OE patenting post-burst.

C. Inventor with Different Patent Portfolios Changing Firms and Future Patenting

First, we examine the effects of firm change on future patenting of inventors with different patent portfolios: several general OE patents with several integration patents, several general OE patents with few integration patents, few general OE patents with several integration patents, and few general OE patents with few integration patents.

After estimating simple slopes, we observe that on average, none of these combinations who changed firms had any changes in their future integration patenting. For future general OE patenting, inventors with several general OE patents with few integration patents had a 5% reduction, while those who had few patents in both had a 9% reduction.

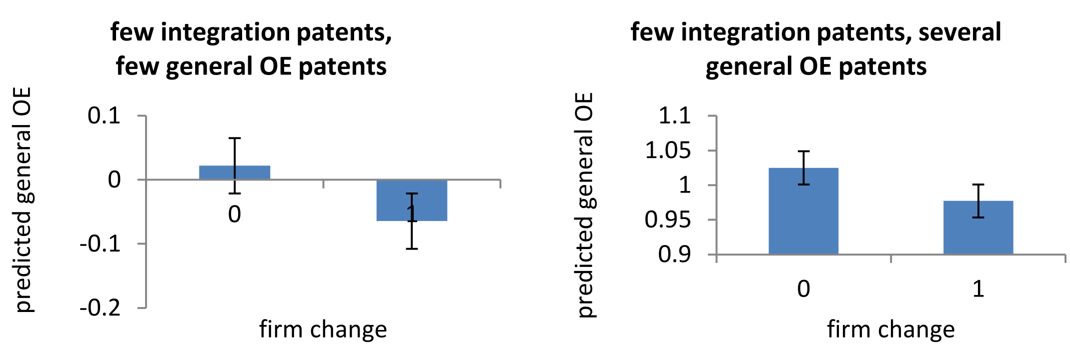


Figure 1.8: Average general OE outcomes after a firm change for inventors with different patent portfolios

Changing firms with few integration patents in one's portfolio therefore decreases one's future general OE patents without an accompanying increasing one's integration patents.

D. Inventors with Different Productivity Profiles Changing Firms in Different Time Periods and Future Patenting

Inventors with different productivity profiles could also have different outcomes from changing firms, and these outcomes could also change depending on the period of the change. The productivity profiles being examined are: Super Star inventors (MOST and RATE overlap), Sustaining Star inventors (MOST alone), Evanescent Star inventors (RATE alone) and Non-Star inventors (NonMOST and NonRATE). We examine these relationships using margins on the interaction between firm mobility, period and inventor type in Model 5.

We find that changing firms is associated with a reduction in future general OE patenting for almost all inventor productivity profiles during all time periods. The exception is Sustaining Star inventors that change firms after the burst of the bubble and increase general OE patenting. These inventors may be the reason general OE patenting does not decline even more post-burst.

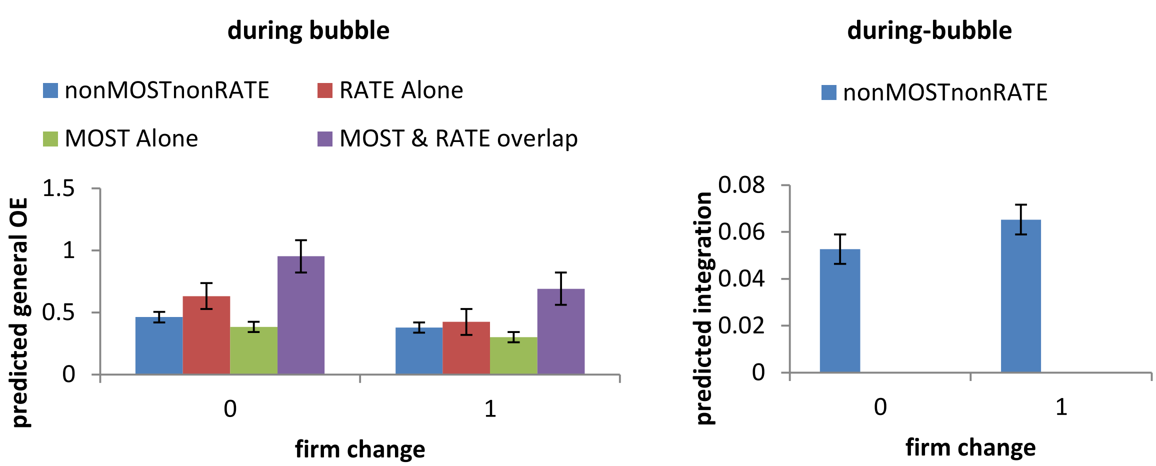


Figure 1.9: Average general OE and integration outcomes after a firm change for inventors with different productivity profiles during the bubble

Changing firms is associated with changes in integration patenting only for firm changes made during the bubble, and by one inventor productivity profiles: Non-STAR inventors who change firms during the bubble increase integration patenting by 1% as seen in figure 1.9 above

Current academic literature that measures only firm mobility would be likely to stop here and conclude that mobility has a positive effect on integration patenting during the bubble but not post-burst. However, we extend these existing boundaries by measuring mobility across market applications. We will therefore continue the analysis using market change information.

1.7.3 Two Stage Regression Analysis: Market Mobility and Future Patenting

First we estimate the probability that an inventor will change market applications, and then see how changing markets influences an inventor's integration and general OE patenting outcomes.

1.7.3.1 Estimating Propensity to Change Markets

We estimate the probability that an inventor will change market applications, including here cases where the inventor changes to a firm in a different market application as well as cases where an inventor's firm changes market applications. Again, we use an inventor's career length or tenure, his technological focus up until that year, and the number of co-authors he has had up until that year (Trajtenberg, 2006). We think the longer an inventor has been at a firm, the less likely he is to change market applications. We also think the more an inventor gets into integration patenting, (tech_focus = 1) the more likely he is to change market applications. Finally, we expect that the more co-authors an inventor has had, the less likely he is to change.

VARIABLES	market_change
Tenure	-0.042***
	(0.002)
tech_focus	0.039
	(0.046)
num_coauthor	0.002***
	(0.001)
Constant	-0.876***
	(0.026)
Observations	14,220
Number of cvid	473
lnsig2u	-3.950***
	(0.455)

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

Table 1.10: Estimating Inventor's Propensity to Change Market Applications in Each Year

From the probit regressions shown in Table 1.10 above, we see that our hypothesis for tenure is corroborated: inventors with longer tenures are less likely to change markets. Technological focus, on the other hand, again does not have a significant relationship with changing markets. Interestingly, the higher the number of co-authors an inventors has had, the more likely he is to change markets, perhaps as a result of the ties he has created over time.

Again, we save the predicted fitted values that indicate the propensity for each inventor to change market applications from this model.

1.7.3.2 Effect Of Market Change On An Inventor's General OE and Integration Patenting

We include the predicted likelihoods that an inventor will change market applications (fitted values, y_hats) from the previous model in this second stage model that estimates the inventors' general OE and integration patenting after he has changed markets. First we identify the basic market mobility effect on an inventor's general optoelectronics or integration outcomes using year effects (Appendix 1.3, Table A4 Model 1 & Table A6 Model 1) and then using period effects instead (Appendix 1.3, Table A4 Model 2 & Table A6 Model 2). Next we investigate the interaction of market change and period (Appendix 1.3, Table A4 Model 3 & Table A6 Model 3). Next, we examine how the market mobility effect in each period is modified depending on the inventor's previous general OE and integration patent levels (Appendix 1.3, Table A4 Model 4 & Table A6 Model 4). Then we include how different inventor types fare when they switch market applications (Appendix 1.3, Table A4 Model 5 & Table A6 Model 5). We are also interested in what happens when inventors leave specific market applications (Appendix 1.3, Table A5 Model 6 & Table A7 Model 6) and switch into specific market applications (Appendix 1.3, Table A5 Model 7 & Table A7 Model 7). We show the equation for inventors with different characteristics switching into new markets at different periods below.

$$
\begin{aligned}
ln(integ) = \quad & \beta_0 + \beta_1 p(market\_change)_{it} + \beta_2 (market_{i(t-1)} * market\_change_{it} * period_i * sample_i) + \\
& \beta_3 (market\_change_{it} * \; previous\_integration_{i(t-1)} * previous\_general\ Oe_{i(t-1)} + \varepsilon_{it}
\end{aligned}
$$

On this model, we estimate simple slopes for the modifying effects of period, previous patenting levels and inventor types in market mobility using margins (Aiken, 1991).

E. Inventors Changing Market Applications and Future Patenting

From the coefficients of Appendix 1.3 Models 5, we find that on average, changing market applications is associated with a 7.1% decrease in future OE patenting. However, there is no change to his integration patenting in the next year. Therefore, if several inventors are changing market applications post-burst, it would explain why integration patenting stays at its high levels while general OE patenting begins to decline. Fortunately, we do not have to speculate. In order to tease out the relationships between market change, period, patent portfolio and productivity profile, we estimate simple slopes using the margins command in Stata.

F. Inventors Changing Markets Applications During Different Economic Periods and Future Patenting

The time period during which an inventor changes firms could also modify the basic firm mobility effect. The three time periods being examined here are: before the burst of the bubble (up until end of 1995), during the burst of the bubble (between 1996 and 1999 inclusive), and after the burst of the bubble (from 2000 onwards). We estimate simple slopes on the interaction between firm mobility and period in Model 5 using margins in Stata 11 (Aiken).

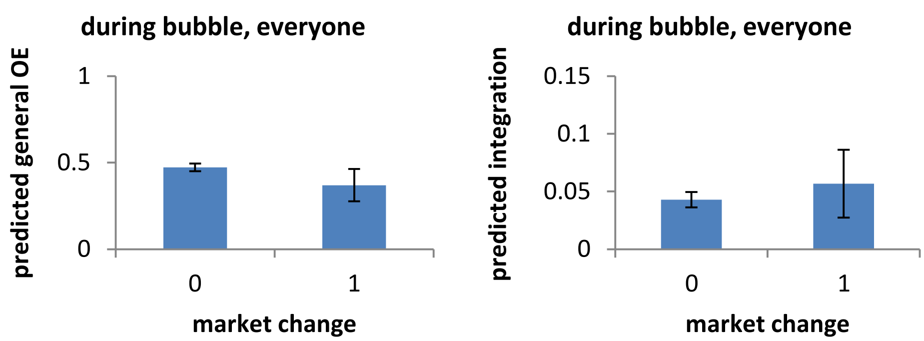


Figure 1.10: Average general OE and integration outcomes after a market change for inventors during the bubble

From figure 1.10 above, we see that on average, inventors who change markets reduce their future general OE patenting at all times. On the other hand, inventors who change markets during the bubble increase their future integration patenting.

Who are these inventors changing markets during the bubble and increasing integration patenting? To answer, we examine outcomes of inventor with different patent portfolios.

G. Inventors with Different Patent Portfolios Changing Market Applications and Future Patenting

First, we examine the effects of a market application change on future patenting of inventors with different patent portfolios: several general OE patents with several integration patents, several general OE patents with few integration patents, few general OE patents with several integration patents, and few general OE patents with few integration patents.

After estimating simple slopes, we observe that on average, inventors who had patented prolifically in integration but not in general OE increased their general OE patenting after a market change; other combinations reduced their future general OE patenting. On the other hand, inventors who had patented prolifically in general OE but not in integration increased their future integration patenting after a market change. This is shown in figure 1.11 below.

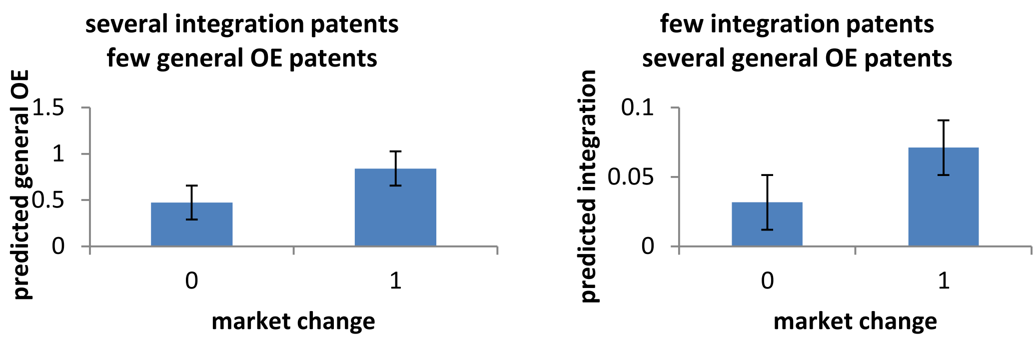


Figure 1.11: Average general OE and integration outcomes after a market change for inventors with different patent portfolios

This suggest that while firm changes seem to have at best no effect and at worst a negative effect for general OE patenting without an accompanying positive effect for integration patenting, changing markets could be a way for an inventor to get into a new specialization, that is from general OE to integration and from integration to general OE, within optoelectronics.

H. Inventors with Different Productivity Profiles Changing Market Applications in Different Time Periods and Future Patenting

Inventors with different productivity profiles could also have different outcomes from changing market applications, and these outcomes could also change depending on the period of the change. The productivity profiles being examined are: Super Star inventors (MOST and RATE overlap), Sustaining Star inventors (MOST alone), Evanescent Star inventors (RATE alone) and Non-Star inventors (NonMOST and NonRATE). We examine these again using margins on the interaction between firm mobility, period and inventor type in Model 5.

We find that Non Stars who change market applications during the bubble increase integration patenting by 3%; while Super Stars who change markets post-burst increase in integration patenting by 8%. This is shown in figure 1.12 below.

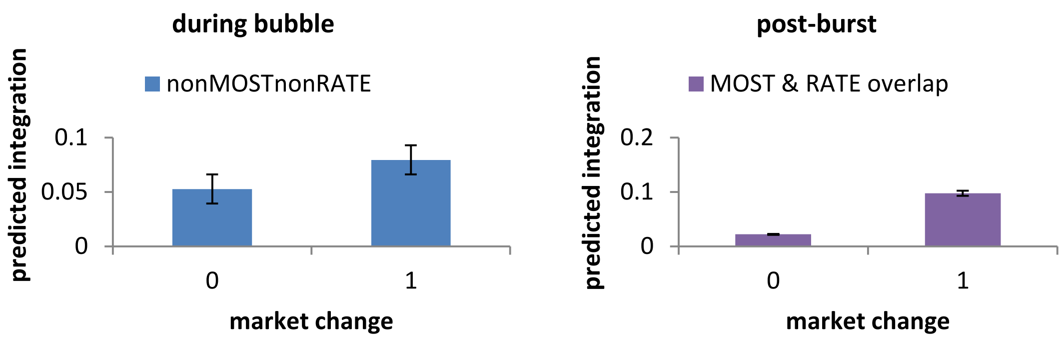


Figure 1.12: Integration outcomes after a market change for inventors with different productivity profiles during the bubble and post-burst

For changing markets during the bubble, almost all inventor profiles have reduced general OE patenting; the exception is Evanescent Stars who show no difference in future general OE patenting. However, Sustaining Stars and Super Stars who change markets post-burst increase general OE patenting by 6% and 15% respectively. This is illustrated in figure 1.13 below:

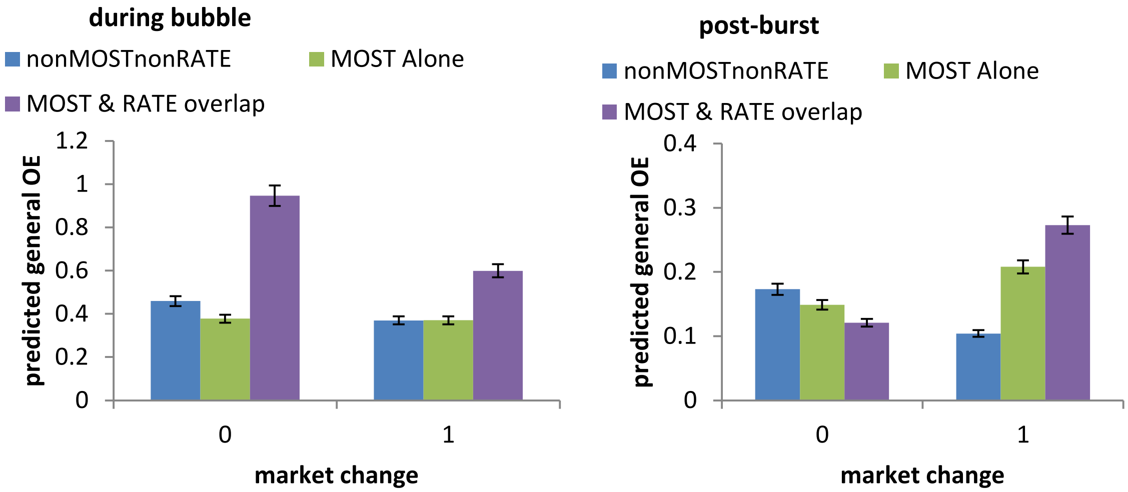


Figure 1.13: General OE outcomes after a market change for inventors with different productivity profiles during the bubble and post-burst

After this, we examine how the basic market mobility effect on future patenting is modified for different inventor types by first switching out of (Appendix 1.3 Models 6) and switching into (Appendix 1.3 Models 7) six different market applications in different time periods. Once again we use margins to estimate simple slopes. In Models 9, 12, and 15, we perform sensitivity analyses of models 6 to our definition of who is a top inventor pre-bubble, using instead of the top 1.5%, the top 0.5%, top 3% and top 5% in each of the models respectively. In models 10, 13 and 16, we perform sensitive analyses to model 7.

I. Inventors Changing Market Applications Out of Specific Markets and Future Patenting

First we compare simple slopes for <u>all inventors switching out</u> of market applications grouped into five groups: telecom, diversified with telecom, diversified without telecom, academia and all other markets. We identify and classify separately inventors leaving a period of unemployment.

As shown in figure 1.14 below, switching out of diversified with telecom, diversified without telecom and to a much lesser extent, other markets, are all associated with increases in integration patenting on average. On the other hand, switching out of all market applications is associated with a reduction in future general OE patenting – this is the same negative average effect of changing market applications on future general OE patenting that we had seen earlier.

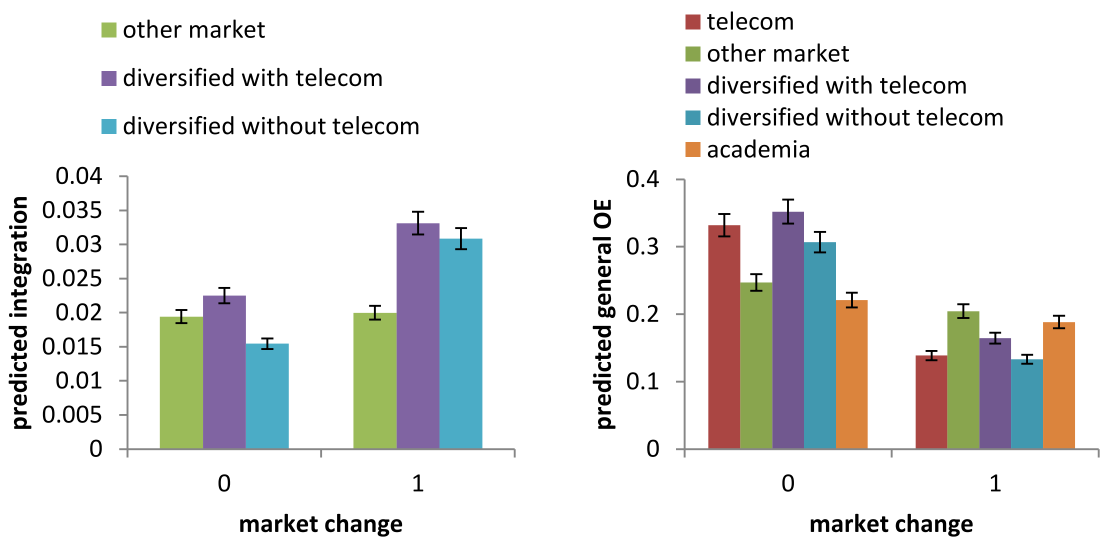


Figure 1.14: Integration and General OE outcomes after a market change for inventors switching out of specific market applications

Next we examine the effects of switching out of these markets at <u>different periods</u>. Inventors who left 'other' markets and academia during the bubble increased integration patenting. Inventors who left other markets during the bubble reduced general OE patenting while those who left academia increased general OE patenting. This is shown in figure 1.15 below.

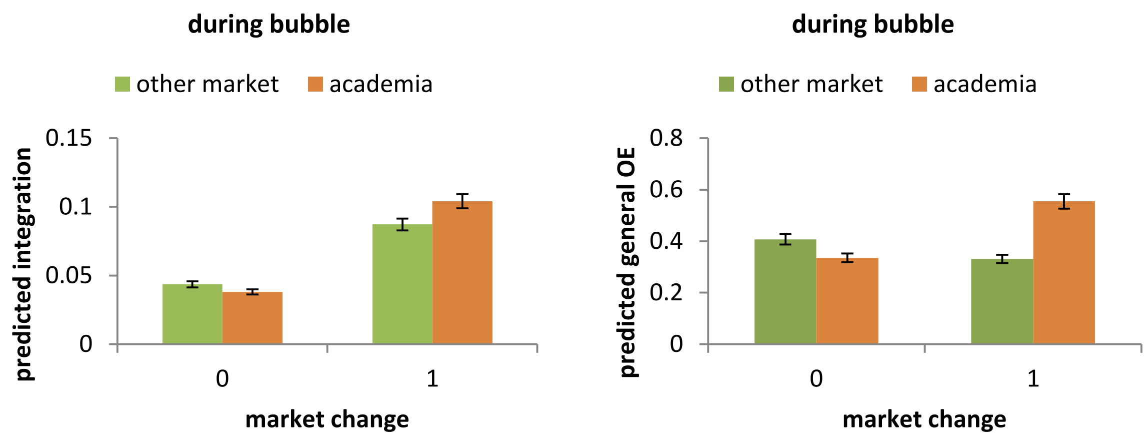


Figure 1.15: Integration and General OE outcomes after a market change for inventors switching out of specific market applications during the bubble

On average, inventors who switched out of markets applications post-burst had no changes in integration patenting. Inventors who left 'other markets' increased general OE patenting while those who left diversified with telecom decreased general OE patenting. While this is true on average, outcomes often differ for inventors with different productivity profiles.

In order to fully tease out this post-burst behavior, we turn our attention to the different inventor productivity profiles and the market applications they are switching out of at different periods. Again, we compare outcomes for inventors leaving telecom, diversified with telecom, diversified without telecom, academia and "other" (everything else) market applications for inventors who are Super Stars, Sustaining Stars, Evanescent Stars and Non-Stars.

During the bubble, sustaining Star inventors who leave diversified-without-telecom and Non Star inventors who leave academia increase general OE patenting. Non-Star inventors who leave a period of unemployment, other markets and academia during the bubble all increase their integration patenting. This is shown in Figure 1.16 below.

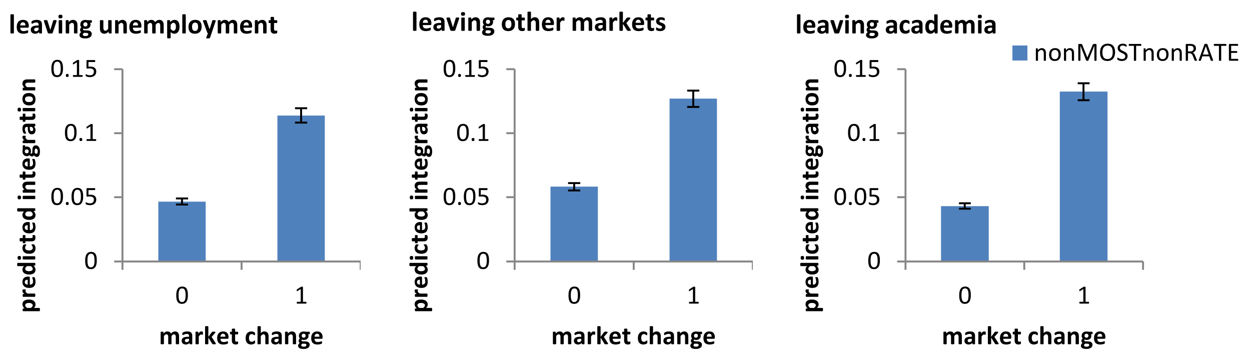


Figure 1.16: Integration outcomes after a market change for non-star inventors switching out of specific market applications

Post-burst, sustaining stars that leave telecom and super stars who leave other markets and diversified-with-telecom increase their general OE patenting. Super stars that leave diversified-with-telecom post-burst increase integration patenting by 55%. This is shown in figure 1.17 below.

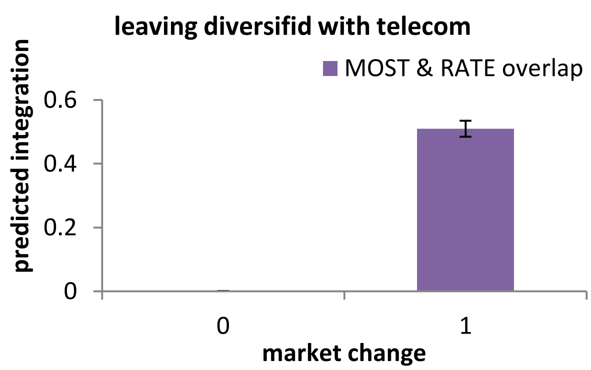


Figure 1.17: Integration outcomes after a market change for super-star inventors switching out of specific market applications

The question now is, into which market applications are these super stars switching?

J. Inventors Changing Market Applications Into Specific Markets and Future Patenting

First we compare simple slopes for <u>all inventors switching into</u> market applications grouped into five groups: telecom, diversified-with-telecom, diversified-without-telecom, academia and all other markets. We identify and classify separately inventors entering a period of unemployment.

As shown in figure 1.18 below, switching into telecom and diversified-with-telecom is associated with increases in integration patenting on average. On the other hand, switching into any market application is associated with a reduction in future general OE patenting - this is the same negative average effect of changing market applications on future general OE patenting that we had seen earlier.

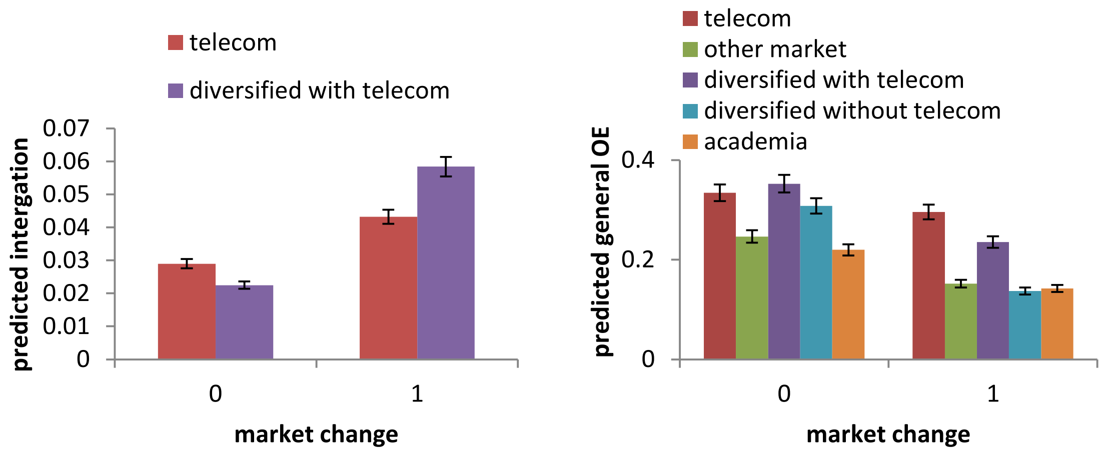


Figure 1.18: Integration and General OE outcomes after a market change for inventors switching into specific market applications

Combining this with the earlier results of switching out of market applications, we realize that on average, a change in market applications is associated with a cost in one's future general OE patents, no matter what market application one is switching out of or into. There was an increase in inventors' switches in market applications post-burst as seen on the mobility map, thereby explaining why general OE patenting reduced.

On the other hand, leaving 'other markets', diversified-with-telecom and diversified-without-telecom, and going into telecom and diversified with telecom is associated with increases in integration patenting. That diversified with telecom would be on both sides of this at first glance appears curious – and lends further evidence to the need to nuance these results by looking at different inventor productivity profiles as well as different time periods.

Therefore we now examine first the effects of switching into these markets at different periods. Switching into telecom and diversified with telecom during the bubble is associated with an increase only in integration patenting. This is shown in figure 1.19 below.

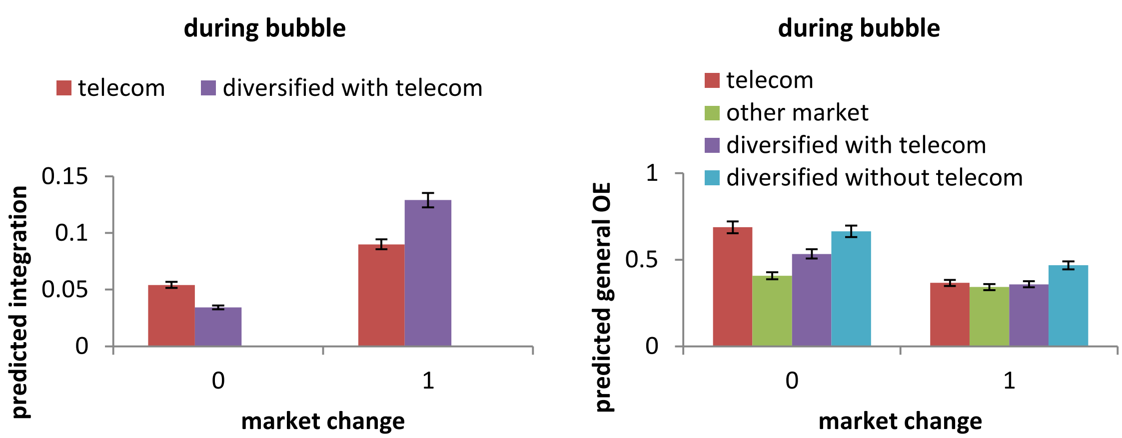


Figure 1.19: Integration and General OE outcomes after a market change for inventors switching into specific market applications during the bubble

Switching into telecom after the burst of the bubble is associated with an increase in general OE patenting on average, but no statistically significant increases or reductions for integration patenting.

While this is true on average, again we have previously seen that outcomes differ for inventors with different productivity profiles. In order to fully tease out this post-burst behavior, we turn our attention to the different inventor productivity profiles and the market applications they are switching out of at different periods. Again, we compare outcomes for inventors leaving telecom, diversified with telecom, diversified without telecom, academia and “other” (everything else) market applications for inventors who are Super Stars, Sustaining Stars, Evanescent Stars and Non-Stars at different periods.

During the bubble, Super Star inventors who enter telecom and Sustaining Star inventors entering other markets increase their general OE patenting. Non Star inventors entering telecom and diversified-with-telecom both increase integration patenting, and this is shown in Figure 1.20 below.

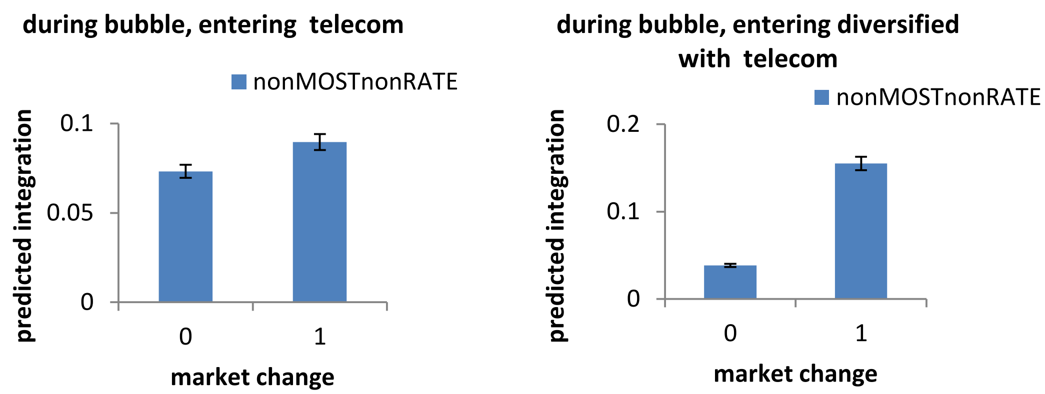


Figure 1.20: Integration outcomes after a market change for non-star inventors switching into specific market applications during the bubble

Post-burst, Non-Star and Super Star inventors switching into telecom increase their general OE patenting, as do Sustaining Star inventors who switch into diversified-with-telecom. Super Star inventors switching into telecom are the only ones who increase their integration patenting and they do this - by 43%. This is shown in figure 1.21 below:

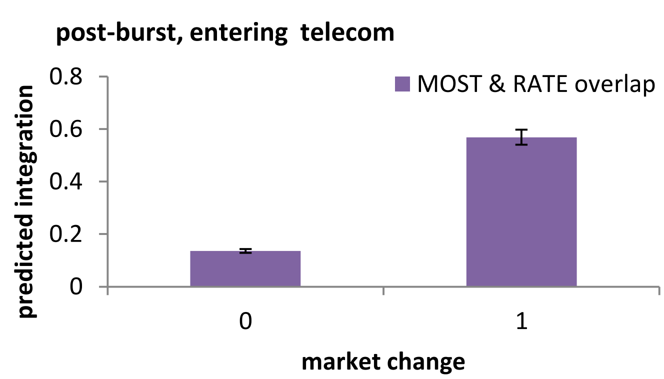


Figure 1.21 Integration outcomes after a market change for super-star inventors switching into specific market applications post-burst

Synthesizing the above results, we summarize that,

(1) Non Stars who left a period of unemployment, other markets and academia during the bubble and went into telecom and diversified-with-telecom increased their integration patenting.

(2) Super Stars who left diversified-with-telecom and went into telecommunications post-burst increased integration patenting.

1.7.4 Oral Histories: Why Do Super Stars go into Telecom Post-Burst?

In order to understand why super stars are behaving this way, we have embarked upon collecting oral histories in order to understand the reasoning for their decisions. So far, we have collected histories of three super stars. The emerging theme seems to be faith in the quality of the technology that they had created and were introducing, and their ability to create a team that could accomplish the desired goals. In their own words:

Quote	**Outcome**
"By late 2000 we knew the bubble had burst. I was at Intel Capital and I knew it had burst because we had ratcheted down all the terms on our term sheets. And I went and started a firm the next year. It was like going into the eye of the storm. I was either being an entrepreneur or being very stupid. But I had a novel **technology** I believed in, I had access to some capital, and I could assemble a world class team"	Acquired in 2003
"It was a natural evolution to start a company… I didn't think about bubble or burst. I had a niche **technology** for short-distance data-com and that market continued to grow in volume year by year "	Acquired in 2004

Table 1.11: Quotes from our super star oral histories

These findings of ours corroborate a quote from a publicly available oral history of David Welch, founder of Infinera (Kinnane, 2011), whose start-up went on to an initial public offering in 2007 and remains one of the leading innovators in the emerging enabling GPT.

> You're starting a new company … in the start of the worst crash … unaware of whether you're going to come out of it okay or not. But we decided it was a good

> challenge. It was a very exciting time to try and do that. The competition at that time, all they were doing was trying to protect against a downside of their current business as opposed to [investing] in the future of where the business needed to go because their revenues were dropping. They were cost-cutting. They were trying to save programs. And they weren't able to invest in new **technology.**

On the other hand, it is important to note that the third super star persisted in Bell Labs until 2008 when he eventually left. It would be therefore important to expand the pool of oral histories collected to encompass not only super-star inventors who went into telecom post-burst but also others who never left. It might also be interesting to find out what the non-stars have to stay about their role in the development of the technology during different business cycles.

1.7.5 .Robustness Checks

1.7.5.1 Sensitivity to Cut Off For Star

We test the sensitivity of our models to the definition of a star, using 0.5% and 3%. We report the sensitivities to our main results. Non Stars at the 0.5% level who leave unemployment, other markets, and academia during the bubble and go into telecom and diversified-with-telecom still increase integration patenting. In addition, these Non Stars at the 0.5% level who go into telecom post-burst also increase integration patenting. As this robustness check has re-assigned individuals between the top 0.5% to the top 1.5% to the "non-star" category, this result is not particularly surprising.

Non Stars at the 3% level who leave unemployment, other markets, and academia during the bubble and go into telecom and diversified with telecom still increase integration patenting. In addition, Super Stars at the 3% level who go into telecom during the bubble also increase integration patenting, but it is not clear which applications these Stars are leaving from.

Super Stars at the 3% level who leave diversified with telecom post-burst and go into telecom also still increase integration patenting

1.7.5.2 Sensitivity to Date Of Bubble Burst

The base case we have been examining has been based on the burst of the bubble being in the year 2000. We test the sensitivity of our results to shifting the cut off for the burst of the bubble to 2001, thereby increasing the window of the bubble by one year. We find our results to be robust to this change. Specifically, we still find that on average, inventors who change markets reduce their future general OE patenting at all times. On the other hand, inventors who change markets during the bubble increase their future integration patenting.

Non-stars who change market applications during the bubble still increase their integration patenting. They are still leaving unemployment, “other markets” and academia and going into telecom and diversified with telecom.

Super stars that change markets post-burst still increase their integration patenting. They are still leaving diversified with telecom and going into telecom.

1.7.5.3 Sensitivity to Cut Off Of Sample

Our analysis has been based on a categorization of inventors by their patenting patterns pre-bubble. We also ran an analyses categorizing our inventors by their patenting patterns pre-burst – that is, whether they were a Super Star, Sustaining Star, Evanescent Star or Non Star by Dec 31, 1999. We ran our analyses for market changes post-burst and found that Super Stars who left diversified with telecom and went into telecom were still the ones increasing integration patenting. This suggests that this set of Super Starts were the same ones who have been in the industry pre-bubble, not a newly minted set created by the bubble.

1.8 Implications and Conclusion

Business cycles are known to be associated with national GDP, employment and real income, but less is known about their relationship to the rate and direction of innovation. This paper explores the relationship between the burst of the telecommunications bubble and the rate and direction of innovation of inventors in optoelectronics, a technology pivotal to the telecommunications industry.

Leveraging a unique dataset of 790 inventor resumes including the inventors' institutional and patenting histories, we use a two-stage regression model and difference-in-difference methods to analyze optoelectronics inventor market shifts and associated innovation outcomes between before, during and post the telecommunications bubble covering from 1962 to 2007. In contrast to papers that use patent data to estimate both productivity and mobility, we collect and use inventor CVs. CVs have the advantage of (1) eliminating the forced correlation between career length, mobility and patenting, as we can now see inventors who work for a company for several years before they first patent, as well as inventors who move but do not patent after they do. Being able to see inventors even after they move even if they don't patent has particular value, especially in contexts such as economic downturns, where we may expect people to lose their jobs. (2) Furthermore, hand-matched CV to patent data eliminates several errors that disambiguation algorithms overlook in matching inventors to their patents. Finally, (3), patent data tells us nothing about the background characteristics of the inventors.

We find that the burst of the bubble disproportionately reduced inventor innovation in the rest of the field compared to the emerging general purpose technology (GPT) enabler. An increase in the emerging GPT-enabler post-burst is driven by Super Star inventors (top 1.5% both by cumulative patents and annual patenting pre-bubble) who switch markets applications post-burst out of diversified firms with telecommunications divisions and into firms focused exclusively on telecommunications. These Super Stars continue an increase in integration patenting that was driven during the bubble by Non Stars who left a period of unemployment, other markets and academia and went into firms focused on telecommunications and diversified firms with telecommunications. These results are robust to changing the cut off for star from top 1.5% to top 0.5% and top 3%, changing date of the bubble burst by one year, and categorizing inventors based on patenting pattern pre-burst rather than pre-bubble. The significance of the super stars is not altogether surprising. As Azoulay et al argue (2012), the distribution of publications, funding, and citations at the individual level is extremely skewed (Lotka 1926; de Solla Price 1963) and only a tiny minority of scientists contribute through their published research to the advancement of science (Cole and Cole 1972).

We make contributions in the area of innovation and mobility as well as to the relationship between business cycles and technology directions. Previous research in the field of mobility and innovation that has used patent data to estimate mobility is limited by the fact that inventors only show up in patent data if they patent after they move, thus biasing the observed sample. CV data allows us to disentangle the relationship between mobility and patenting. With respect to business cycles, our results suggest that both non-stars and super-stars may have important roles in pushing innovation frontiers during different parts of the business cycle. While super-stars advance the emerging technology during resource-constrained parts of the business cycle, their efforts build on the innovation efforts on non-stars during less constrained times.

1.9 Policy Implications

In this study, we find that innovation in the emerging GPT enabler still grew following the burst of the bubble. This growth was driven by super-stars, who continued an increase that was driven during the bubble by non-stars. At first blush, these results may suggest that the most efficient outcomes prevailed. This could have important implications as it is equally important for the government to know when action is not needed in addition to when it might be. However, we know that R&D and general purpose technologies can be under-invested in privately when compared to what would be socially optimal (Trajtenberg, 2009). There will be no easy policy answers, as there is no counterfactual and we can't know what would have happened to innovation had there not been a bubble and its burst.

We have not explored in this research what happens to the non-stars who pushed forward innovation in the emerging GPT enabler during the bubble, nor have we studied in greater depth the inventors in our sample that lost their jobs. Understanding what happens to both of these individuals and to their human capital will be important future policy research.

Furthermore, the superstars do not act in an institutional vacuum: while they were able to get funded by venture capital during the downturn, these super-stars have a long history in the field and at other institutions prior to the bubble and its burst. To understand the full policy implications of this work, it is important to investigate the institutional history of the industry, the technology and these super stars, to better understand the conditions under which they grew. We start to explore this in the next section.

II

Following The Light: Technology And Innovation In The Optoelectronics Industry, 1955 - 2010

2.1 Abstract

There are several factors that influence the growth of innovation in a particular technology. These include the location of the research - housing basic research in industry and not just in academia has been shown to have disparate effects on the growth of innovation (Servos, 1994, Tiffany, 1986, Swann 1988); within industry, there is often a disparity between the kinds of innovation carried out by large incumbent firms versus by smaller firms (Henderson, 1993), and government funding and government regulation often influence innovation.

This paper seeks to understand in what ways these factors have combined to influence innovation in optoelectronic technology. We analyze patenting patterns in optoelectronics between 1955 and 2010 and identify the most influential firms, government agencies, and individuals responsible for leading innovation in this field. We leverage archival data on firms' decisions and market applications from ProQuest historical newspapers, as well as the International Directory of Corporate Histories. We also collect oral histories of a carefully selected sub-sample of the key individuals. We find that early on, there exists evidence for co-operation as well as competition between academia and industry. We also find that while large

firms lead in total innovation in optoelectronics, patents filed by smaller firms often go on to be more influential. Government funding is pervasive throughout the technology, funding undergraduate and graduate education, academic research, and industrial research. Finally, U. S. government regulation influenced innovation in at least two unexpected ways: first, by limiting U. S. permanent residents from working on government-funded research in photonics until the 1990s, and second, by inspiring new ventures when mergers were delayed.

2.2 Theoretical Background

Scholars of the history of industrial research often debate the relative merits and drawbacks of housing basic research in universities and government laboratories versus in industrial research labs, and of that research being funded by corporations versus by the government. Some believe that the purity of basic research would be tainted either by industry funding or by collaboration with industry researchers who have shorter term goals. For example. John W. Servos, in his study of the history of the Chemical Engineering Department at MIT, warns of potential drawbacks of yoking university to industry without adequate care being taken to limit the influence of industry. As a result of the vision of a leader who wanted to develop novel and more effective methods for training applied scientists through close ties to industry, the Research Lab for Applied Chemistry forced out a competing basic-science oriented laboratory head and ended up doing the majority of its work on narrowly defined questions that industrial patrons wanted answered. However, when the economy soured, the lab lost its patrons, and it took a complete reform for MIT to get back on the right track (Servos, 1994).

The term basic research in industry need not be an oxymoron, however. Mowery tells that the industrial laboratories first appeared in the German chemical industry (Mowery, various). In the

US, General Electric (GE) established the first industrial laboratory in 1900, and later-comers like Bell Laboratories, Alcoa and Dupont followed GE’s model. Companies then often used their central R&D lab not only for in house basic research but also as a means of acquiring new technology from far and wide. Kodak, for example, turned to industrial R&D in order to support diversification and growth because of the Justice Department opposition to horizontal mergers which had previously performed this function (Sturchio, 1985). Dupont too used industrial laboratories as a means of diversification (Hounshell and Smith, 1989).

Despite the troubles of the larger economy, industrial research continued to thrive during the Great Depression. Not only did the employment of research scientists grow (Mowery, 1989), but Field argues that the Great Depression was the most technologically progressive decade of the century (Field, 2003, 2011) as there were several advances that came out of the basic research being performed at these various industrial research laboratories. Dupont and Bell Labs are only two examples of several corporations that had performed basic research well, at least for a time. On the other end of the spectrum, US Steel half-heartedly invested in basic research, procrastinating on a decision to pursue research, carrying out the plans as slowly as humanly possible, and installing the new research department in cramped quarters instead of a new building as had been promised. Working in this atmosphere, it is little wonder that US Steel missed key technological breakthroughs that would determine worldwide leadership in industry (Tiffany, 1986)

However, from the work of John P. Swann, we see that symbiosis can occur when division of labor with cooperation exists between universities and industry, and between basic and applied research (Swann, 1988). There were tensions in the field of biomedical research in particular between academia and industry: most researchers in academia were reluctant to patent and believed that advances should be published to benefit all humankind, while firms wanted to reap monetary rewards for discoveries. Industry, for its part, was not completely undeserving of censure. Some drug companies peddled questionable remedies, sometimes using the names of professors without their knowledge. Between the two World Wars, pharmaceutical firms began to recognize the value of basic research as a necessity for the discovery of new products, and started to increase research staff and budgets. The dearth of imports from German firms during the First World War had in particular emphasized the vacuum that had existed in research-based new product development. At the same time, academic researchers became more willing to address their work to the needs of society, and academia's view of industry started to improve. Thus, as firms established special laboratories devoted to research, they were able to employ prominent academic scientists as research directors. Furthermore, the contraction in the economy had caused universities' support from philanthropic organizations to wane. Industries stepped in to support fundamental work in universities through direct grants and awards administered by scientific societies.

The partnership was not without suspicion. As firms used patents to protect their investments in research, universities used patents too, to prevent firms from monopolizing the discoveries and to maintain quality standards among firms that licensed their products. Royalties also padded universities' research coffers, but some universities forbade patenting for benefit of the discoverer or the university. It would appear that some semblance of symbiosis was achieved. University programs benefitted from industry support in the post-philanthropic, pre-large-scale government research-investment era; industry willingly gave this support as their labs could not carry out all the research needed. Therefore, firms depended on universities not only for research personnel but also for know-how to remain competitive and benefited from sales and profits that resulted. Indeed, Furman and MacGarvie (2008) find that firms that collaborated with universities produced greater number of patented outputs and grew more quickly than those that did not. Public health also benefited as a result of drugs discovered from said co-operation.

The first question, therefore, is, in the case of optoelectronics, where does innovation thrive, in academia or in industry? Is innovation in optoelectronics dependent on academic research? Or is it dependent on industrial funding? If so, is its success tied to the highs and lows of the business cycle? Does co-operation between universities and industry lead to a symbiosis that pushes forward optoelectronic innovation?

There also exists the question of appropriate levels of government investment in basic and industrial research. In 1945, after World War II, Vannevar Bush published his famous manifesto, *Science the Endless Frontier*, which assumed that any country that wanted to become a continuing economic power in the world had to have an ongoing, R&D-based, basic scientific tradition. As government infused more money into university research, industrial ties with universities weakened in the 1940s. Indeed, Mowery in his study of industrial R&D in the US, reports that in the 1945 – 1985 period, federal support for R&D increased (Mowery, 2009). However, this federal support was almost always defense-related, and occurred in not just federal laboratories, but also in universities and in firms. Industry support for R&D conducted in universities at the same time waned. Mowery quotes others who suggest that "increased federal funding for academic research may have reduced the incentives of faculty and academic administrators to seek funding from industry. At the same time, stricter enforcement of antitrust law reduced the ability of firms to technology innovations in related industries through purchase and led them to bolster their internal R&D capabilities. It also led to even further diversification as firms acquired other firms in unrelated lines of business. Finally, as new technologies in fields such as computers, semiconductors and biotechnology were discovered and introduced post 1945, smaller firms began to play a much larger role in the commercialization of technologies. Mowery attributes this larger role to "large basic research establishments universities, government and some private firms that served as 'incubators' for the development of innovations that 'walked out the door' with individuals who established firm to commercialize them." The second question therefore, is, what role does government funding play in pushing forward innovation in optoelectronics? Are large firms serving as incubators for new innovations that walk out the door with individuals who go on to establish firms?

Finally, we turn our attention to the question of appropriate levels of government regulation of the behavior of companies. While patent law protects the inventor and assignee, it also sets a limit on how long a patent can enforced, known as the patent term. Countries create antitrust law to regulate the conduct and organization of corporations in order to promote fair competition for the benefit of consumers. Court decisions based on these laws have directly influenced the actions of companies, in terms of what companies they can merge with, what market applications they can focus on and what technologies they invest research dollars in. Anti-trust policy limits the ability of companies to merge, and therefore restricts those who use mergers as a means of acquiring technology. As a result of an antitrust suit filed in 1949, a 1956 anti-trust consent decree instituted limitations on AT&T Bell Labs' operations to 85% of the United States' national telephone network and certain government contracts, and precluded the Bell System from extending its reach into the fledgling computer and microelectronics industry (AT&T Corp History). Several small start-up firms entered the microelectronics industry instead. However, a 1982 consent decree lifted the constraints of the 1956 decree, broke up the Bell System into local and long-distance telephone companies, and had AT&T agree to divest itself of all Bell operating companies. Similarly, a 1958 consent decree on RCA ended its packaged license practices, forcing it to make 100 color TV patents and 12000 other radio-TV patents available royalty-free, effectively killing the source of income for its basic research and encouraging the corporation to turn to computer research(Gross, 2011). Finally, a 1975 consent decree forced Xerox to license 1700 patents for a small royalty and abandon what the government considered questionable marketing practices (Buderi, 2000, Tom, 2001). Subsequently, Xerox's share of the copier market went from 85% in 1972 to 46% in 1980 as Japanese firms entered the market with cheaper prices. The final question is, in what ways, if any, has government regulation influenced the growth of innovation in the optoelectronics industry?

To answer these questions, we will use an in-depth study of the optoelectronics industry. We will start our journey by tracing the ancestors of optoelectronics technologies to the beginning of the 20th century and specifying what technologies comprise modern optoelectronics technologies. We will skip very quickly to the 1950s and examine the invention of the fiberscope as well as the race to develop various types of laser technology. Next, we will join in with researchers in academia and in industry as they create optical fibers with increasingly lower losses, and then follow the development of the technology as it is adopted for military and commercial uses in the 1970s and the 1980s, and its later applications in markets outside of the above. We will follow the growth of the field through the economic downturn of the early 1990s, the boom of the mid-to-late 1990s, the burst of the telecommunications bubble in the early 2000s, and the subsequent decade.

Over this time period, we will use patents to identify the key firms, individuals, government agencies and other organizations that have been at the forefront of growth in this industry. We will also collect key use oral histories and use publicly available biographies of the individuals, as well as archival data on the company histories of the firms and agencies.

2.3 Optics at the Turn of the Century

There were several inventions that attempted to manipulate light in the late 19th century. They never saw commercialization but are direct ancestors of various forms of optoelectronic technology today. Students of physics learn about Snell's law and total internal reflection: a propagating wave along a medium encounters a boundary that it cannot pass through, because the refractive index is lower on the other side of the boundary and its incidence angle is greater than the critical angle. The wave is therefore entirely reflected. As early as 1870, this principle had been demonstrated using light waves in water, in an experiment performed by John Tyndall and later recorded in his Six Principles was the first recorded research into the guided transmission of light (Tyndall, 1885). Another scientist, William Wheeling, patented an application of this principle to illuminate rooms from a single source by "piping light" by way of mirrored pipes (Wheeling, 1880). However, the idea proved to be ineffective in practice in the form that he had envisaged, and it took almost a century for the propagation of light to find a suitable medium. In the same year that Wheeling proposed piping light, Alexander Graham Bell invented the photophone, a device that allowed one to transmit sound on a beam of light using mirrors and a diaphragm; the transmitted sound was decoded using a parabolic reflector and a light sensitive selenium resistor. However, as was the case with Wheeling's invention, in its initial form this invention was not practical: clouds and other interferences hampered this transmission. But the idea behind manipulating and propagating light had been conceived.

The earliest ancestor of the modern camera were pinhole cameras used by ancient Chinese and ancient Greek (Campbell, 2005). In 1816, a French man named Joseph Nicéphore Niépce created the first photograph of a camera image using a sheet of paper coated with silver chloride, which darkens when exposed to light (Newhall, 1982). Continued work by Neipce and others resulted in the invention of the Daguerreotype in 1836, and the calotype in 1840. Both of these used either a sensitized dry plate or a sheet of paper to record the image. In 1885, George Eastman started manufacturing photographic film, and in 1888 he offered the first film camera, called the Kodak, for sale. These were the ancestors of today's digital cameras.

Right when the capture of still images on film was taking off, others were investigating the capture and transmission of moving images. Before there was the modern electronic television, there was the electromechanical television, the fundamental component of which was the scanning disk, patented by Paul Gottlieb Nipkow in 1884 (Shiers et al, 1997). This design was improved upon in the next few decades, and in 1909 an instant transfer of moving images was accomplished by Georges Rignoux and A. Fournier (Varigny, 1909). In 1927, Bell Telephone Laboratories put up the "best demonstration of a mechanical television system ever made to the time" (Abramson, 1987), transmitting monochromatic moving images and synchronized sound over copper from Washington to New York, and over a radio link from New Jersey to New York. In 1933, RCA demonstrated an all-electronic television at the 1939 New York world's fair (Early Television Museum, 2014). These early ancestors of optoelectronics paved the way for the technologies of today.

2.4 Modern Optoelectronics Technology

The first part of the word optoelectronics refers to optics, or light signals; the second to electronics and electric signals. According to the Optoelectronic Industry Development Association (OIDA), optoelectronics involves light generation, detection, and manipulation (OIDA, 2013).[2] The field of optoelectronics is considered a subfield of photonics, and is concerned with the study, design, application and manufacture of components that source, detect, and control light. Light here includes invisible forms like gamma rays, X-rays, ultraviolet, and infrared, in addition to visible light. Optoelectronics is based on the quantum mechanical effects of light on electronic materials, especially semiconductors, sometimes in the presence of electric fields (Vishay, 2003) These effects include the photovoltaic effect, photoconductivity, stimulated emission, radiative recombination, and photoemissivity.

The photovoltaic effect is the creation of electric current when a material is exposed to light. An example of an application that uses this is photo-voltaic or solar cells. Photoconductivity occurs when a material becomes more electrically conductive due to the absorption of light. An example of an application of this is xerography, or photocopying. Stimulated radiation occurs when a photon of the right energy impacts an atom in an excited state such that a photon is released which has the same energy and travels in the same direction as the stimulating photon, with the same frequency. An example of an application of this is in lasers. Radiative recombination is the process by which an atom in an excited state undergoes a transition to a state with a lower energy, e.g., the ground state, and emits a photon. An example of an application is light emitting diodes. Finally, photoemissivity is the phenomenon whereby electrons are emitted from solids, liquids or gases when they absorb energy from light. An

[2] The OIDA is a not for profit industry-led consortium representing the optoelectronics industries, as well as universities and research laboratories engaged in optoelectronics research

example of an application that uses this is video camera tubes in early televisions and night vision devices (Burns, 1998).

Because they harness the power of photons, optoelectronic devices have higher information-carrying capacity and lower power consumption than pure electronic devices performing the same function. Examples of optoelectronic technologies apart from the examples above include sensors, fiber optic cables, and other telecommunication network components like transceivers, amplifiers, and switches.

Optoelectronic integration is a sub-technology of the field that is concerned with the ways in which multiple optoelectronic functions, such as lasers and modulators, can be combined onto a single chip, thereby enabling reduced size of the final product. One of the advantages of integration is that it enables the application of optoelectronic technology to multiple markets. Optoelectronic technologies can be found in several market applications: telecommunications, data storage, imaging, defense, aerospace, biomedical applications, and energy amongst others.

Inventive activity in optoelectronics is geographically concentrated (Feldman et al., 2009). While patenting takes place in 240 urban areas, 84% of the patents were invented in 30 metropolitan areas and almost 50% attributed to 11 metropolitan areas. Miyazaki et al. find that a marked variation in the way firms' technological trajectories have evolved giving rise to strength in some and weakness in other subfields for the different companies, which are related to their accumulated core competencies, previous core business activities and organizational, marketing and competitive factors. He also suggest that optoelectronics is an area in which Japanese firms may have reached parity with or even overtaken their Western competitors.

2.5 Patenting in Optoelectronics

We seek to understand roles of co-operation and competition between academia and industry in pushing forward optoelectronic innovation. Within industry, we seek to examine the roles of large firms versus startups in leading innovation. We also want to know the roles of government funding and government regulation in influencing innovation. To this end, we examine patents filed in classes designated to be optoelectronics in the USPTO database. We understand that patents are limited in their ability to capture returns to investment, and disputes have arisen over whose patent was filed first (e.g., Elisha Gray versus Alexander Graham Bell over the telephone, and more recently, Gould vs Schawlow and Townes over the laser). In other cases, patent examiners have rejected patent applications that upon further review were granted (e.g., the case of Theodore Maiman and Hughes which will be discussed in further detail later). Yet, patents are still widely accepted in the academic literature as a means of measuring productivity (Kapoor et al., 2007), inventor mobility (Song et al., 2003, Marx et al., 2009, Rosenkopf et al., 2010), and transfer of knowledge (Almeida et al., 1999).

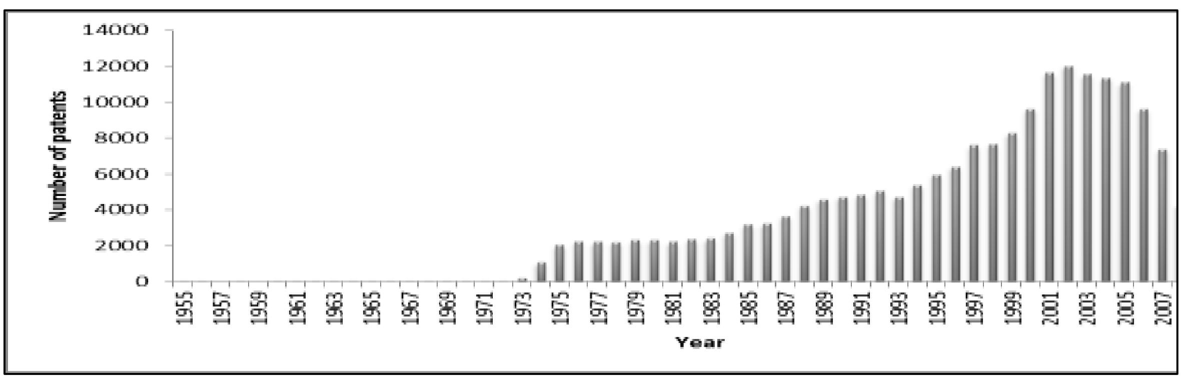


Figure 2.1: Patents *filed* in optoelectronics in the USPTO from 1955 to 2007

We first use the Fuchs Lab Optoelectronics Patent Database first created by Peter Pong and then improved upon by Samuel Valenti. This database uses the USPTO's classification system to identify optoelectronics patents. These classes and subclasses are shown in Appendix 2.1. There are 194,452 patents, 173,189 inventors and 24,910 assignees from all over the world in this database. From this database, we pull for this paper all patents filed in the field of optoelectronics between 1955 and 2007. This is shown in figure 2.1 above. The number of patents filed in each year steadily increased until 2002, when it reached a peak and then started to decline. It is unclear whether this decline is a short-term result of the burst of the telecommunications bubble in the early 2000s or a longer term trend that indicates that the field is matured and technological opportunity is reducing.

We also examine patenting in the US versus the rest of the world, as shown in Figure 2.2 below. Interestingly, while the US led in optoelectronic technology patenting until 1981, the rest of the world drew even in 1982 and has had more patents since 1985.

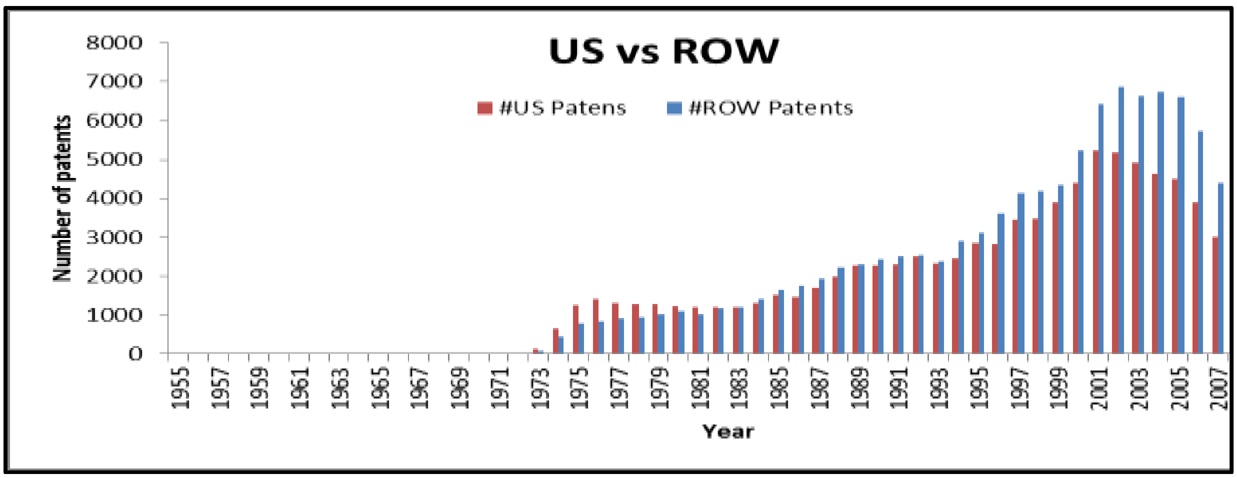


Figure 2.2: Patents *filed* in optoelectronics in the US vs the rest of the world from 1955 to 2007

Of the 193,590 patents in this industry until 2007, 88,699 (49%) were filed by US inventors, 58,664 (30%) by Japanese inventors and 11,063 (6%) by German inventors. This is illustrated in Figure 2.3 below.

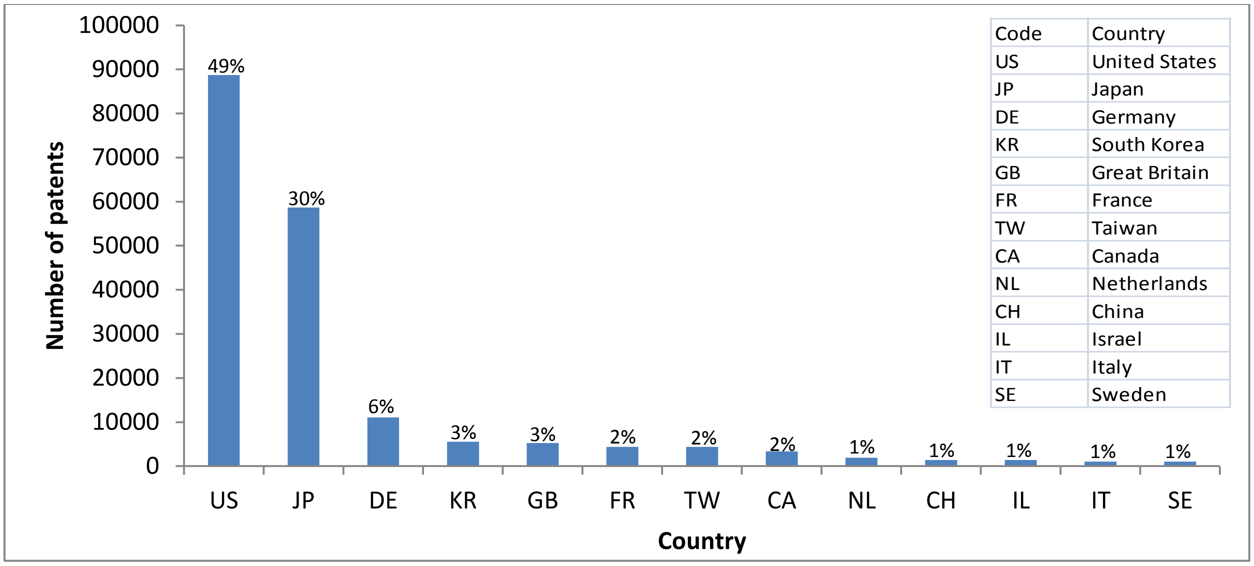


Figure 2.3: Patents *filed* in optoelectronics by country

In terms of industry entrance, Figure 2.4 below shows the number of first-time inventors beginning to file patents in this industry over time. We find that entrance into the industry mirrors the growth of the industry in terms of number of patents, and declines sharply as well following the burst of the bubble.

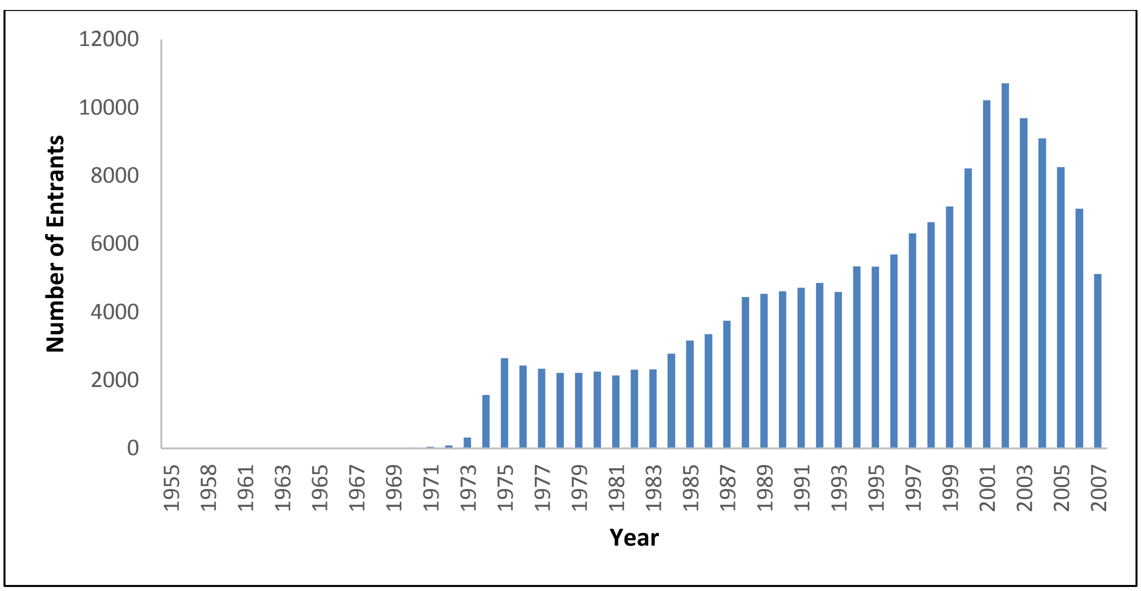


Figure 2.4: Number of entrances into optoelectronics in each year based on filing data

We then identify the top 10 firms and individuals patenting in optoelectronic integration as well as rest of field optoelectronics over time. We select these individuals by the number of patents filed in each decade, the cumulative number of patents filed by the end of each decade, and the cumulative number of citations/patent received by the end of each decade. These tables are shown in Appendices II – VII. We then select key individuals who entered the industry in different decades but emerged to be leaders in innovation in the industry and collect their oral histories. These individuals are Dr. Michael Lebby, Dr. Wenbin Jiang and Dr. X1. Dr X1 did not wish to be publicly identified. We supplement our oral histories with other oral histories publicly available: David Welch (Kinnane, 2011), Eugene Gordon (Bromberg, 1984), and William Bridges (Cohen, 2001).

2.6 Findings

2.6.1 Early years: researchers in academia and industry competed and co-operated

In terms of history, the story of the development of the laser illustrates co-operation and competition between academia and industry. Indeed, we find that all over optoelectronics, key technologies like the laser and later optical fiber came out of basic research in industry and that industry went on to push the frontiers of knowledge. However, they were based on theories proposed in academia. In the creation of these technologies, there was co-operation between individuals at different firms in industry and different universities.

The 1940 PhD dissertation of Valentine A. Fabrikant had proposed that stimulated radiation was theoretically possible. In the mid to late 1950s, various research organizations within the US were embroiled in a competition to create the first laser. The maser, microwave amplification by stimulated emission of radiation, had been invented in 1954 (Gertner, 2012). Considered by many to be the precursor of the laser, the first invented was an ammonia molecule maser by Nikolai Basoc and Alexander Prokhorov and shortly afterward by Charles Townes and his team at Columbia University. All three shared the 1964 Nobel prize in Physics. Soon afterwards a solid state maser was invented at Bell Telephone Labs by Bloembergen & Feher and a ruby crystal solid state maser by Kikuchi & coworkers at the University of Michigan.

On May 16 1960, Maiman invented the first laser at Hughes Research Laboratories, an industrial lab with defense and space applications. For the first time, light could be manipulated, directed, and focused in more complicated ways that were previously impossible. Maiman did not subscribe to the popular notion that the maser was the precursor of the laser. He argued that visible light signals are very different from microwave signals and occupy an entirely different part of the electromagnetic spectrum. If anything, according to him, research on masers was a distraction and may have delayed his invention of the laser.

The term laser was created from the phrase "Light Amplification by Stimulated Emission of Radiation." Lasers are based on the principles that guide the behavior of atoms. Basically, an atom can exist in either a ground state or an excited state.[3]As explained by Maiman, *spontaneous* radiation occurs when an atom in an excited state releases stored energy in the form of an emitted photon, which goes off in a random direction. The electromagnetic waves associated with each randomly emitted photon have arbitrary phase relationships with respect to waves emitted by other spontaneously emitted photons. Because of these arbitrary phase relationships, spontaneous emission of radiation is said to be incoherent. Stimulated radiation occurs when a photon of the right energy impacts an atom in an excited state, a photon is released. The outgoing stimulated photon will have the same energy and travel in the same direction as the stimulating

[3] It can also exist in a satellite state (a state above excited state), metastable state (between ground and excited state) or bench state (between ground and metastable), but for the purpose of this illustration we will stick to the two basic states.

photon; the frequency of the electromagnetic radiation associated with the outgoing proton is at the same frequency as that of the stimulating photon; and the radiation waves are in step with each other. Stimulated emission of radiation is, therefore, said to be coherent. Stimulated absorption occurs when an atom of the right energy impacts an atom in ground state and the atom goes to excited state. When a photon hits an atom, the probability of absorption is equal to the probability of emission. However, the status quo is that there are more atoms in ground state than there are in excited state. Therefore, the absorption process normally dominates. An inverted population is, therefore, desired for stimulated radiation; an inverted population occurs when there are more atoms in an excited state than there are in some lower state.

Townes and his team at Columbia were touting the possibility of an alkali vapor laser. According to Maiman, Townes believed in working out all the equations and theories first and then performing an experiment that must work. Schawlow at Bell Labs was trying to also develop an alkali vapor laser. Townes and Schawlow, whose wives were also sisters, wrote a paper in 1958 and were issued a patent in 1960; however, Maiman points out that the laser they "invented" was never actually built and could not actually have worked. Sanders and Javan at Bell Labs were also working on a gas laser, as was Gould at TRW. In addition, there were several other companies and universities involved in this race: MIT, GE, IBM, RCA, and Westinghouse. And of course, there was Maiman at Hughes.

Maiman was a self-described "maverick scientist" who chose to continue exploring using ruby crystals to create a coherent beam of light when the "establishment" of the day, as represented by Schawlow of Bell Labs and Townes and his team at Columbia, had ruled out the possibility (Maiman, 2000). Maiman had decided to go the road less travelled on his own laser odyssey by investigating a solid state crystal laser for the following reasons. First, unlike gas, a solid state crystal had very few possibilities for energy states system and could therefore be quantitatively analyzed. Furthermore, it has a relatively high gain coefficient: that is, amplification in a given length of material is of reasonable proportion. To illustrate this, Maiman points out that the first crystal laser was only 2cm long, unlike the first gas laser, which was 100 cm long. Finally, because of the solid medium, there would be no need for vacuum pumps, there impurity problems, gas handling apparatus or complex mirror mechanism.

Maiman reports that he was said to be obsessed with making a practical laser. While this reads first as a compliment, it turns out that it was apparently conceived of and evidently received as an insult. Maiman argues that rather than practicality, he was obsessed with simplicity. The idea that practicality is something to be eschewed highlights the tension between academic-type research that was going on in Columbia and even at Bell Labs and industrial research; the fact that Maiman saw the need to defend himself shows that even in industry the idea of research for practicality was still somewhat anathema. However, if he had not been so obsessed with simplicity, it might have taken more years before the laser was invented.

Maiman is a complicated character. He aptly captures the phenomenon that so many scientists, researchers, and graduate students experience: the idea of uncharted waters being a psychological barrier to invention. He argues that despite the fact that there were multiple competing streams of research going on at Hughes, Bell Labs and MIT, it was not until he successfully proved that he could create a laser that the psychological barrier was removed both for himself and for other scientists. He also argues that his demonstration renewed interest in the field and created renewed funding for scientists all over the nation, including himself, who had previously been getting perilously close to being defunded. According to Maiman, Javan's team at Bell Labs had been very close to being defunded before Maiman created his working laser;

Furthermore, Bell Labs' laser was similar in shape to the picture of Maiman's non-laser that had been published. There may therefore be evidence that Bell Labs may have benefitted from the added momentum that Maiman's invention gave the field.

After the development of the laser, Ali Javan and two other physicists at Bell Labs created the first gas (helium and neon) laser, which was capable of continuous operation3 and at an "at an unprecedented color purity and accuracy." On December 13, 1960, Javan successfully tested his invention via telephone conversation using laser beam transmission. Meanwhile, research had continued at Hughes Research Labs into lasers and its possible applications, and in 1964 William Bridges invented the argon laser which was, capable of producing blue light almost by accident. After conversations with Eugene Gordon and other colleagues at Bell Labs, they later got the argon to work continuously, and this resulted in a joint paper between Bell Labs and Hughes Research Labs, something unprecedented at the time. This led to the development of an application by Hughes called the laser line-scannning night reconnaissance systems. In Bridges' oral history, he noted, "Hughes being Hughes, we found a military application" (Cohen, 2001).

It is interesting to note that Hughes passed on filing a patent on the laser at first. We also do not see a patent by William Bridges or Kapany or Javan earmarked as optoelectronics. It is unclear whether this is as a result of their companies' not filing the patents; or whether the companies filed the patents and did not name them as inventors; or whether the patents were not granted as they were too similar to the non-working patent already filed by Schawlow and Townes. For its part, laser technology continued to advance steadily for over 30 years in various forms, which served non-competing markets, until the introduction of highly competitive diode-pumped solid state (DPSS) lasers in the late 1980s that forced several older laser producers out of the industry (Bhaskarabhatla and Klepper, 2013).

Oral histories we collected of top individuals in this technology especially shed light on the similarities between academia and industry, especially at Bell Labs. Lebby's bachelors' degree was a sandwich half-classroom half-industry program sponsored by the ministry of defense, and he subsequently did his PhD at Bell Labs from 1985 to 1987, and served there as a post-doc fellow from 1987 to 1989. Lebby did not think Bell Labs was a conducive area for team work, he calls it "chicken-hatch research, a bunch on inventors in rows with millions of dollars of equipment and told to produce papers." According to him, similar to academia, the rule was publish or perish, and 50-75% of his cohort while he was in Bell Labs are university professors today. Lebby took a job at Motorola, where the focus was on commercialization and patents rather than publications. The downside of this, however, was that Motorola closed down its photonics research division in 1998 as a result of a strain on the company that occurred after having bet on analog cell phones. This is one case where industrial research was very much tied to corporate performance.

One of the super stars whose oral history we collected, Dr. X1, also did his PhD research at Bell Labs and subsequently joined Bell as well. He seemed to have enjoyed his own experience at Bell more, staying on after his PhD ended in 1999 until 2008. However, according to him, Bell Labs / Lucent, despite its close ties to government funding, was not shielded from economic downturns. While Bell/Lucent first turned to more externally funded projects from other companies and from DARPA, Dr. X1 eventually left the research division in 2008 as it became evident that the end was near.

2.6.2 The Most Prolific Organizations are not the Most Influential

We found that innovation differed across different types of organization in different decades. In the emerging GPT enabler, telecoms firms start out being most prolific and most influential. But then that shifts to non-telecom. In the rest-of-field OE technology, defense organizations more prolific but smaller firms more influential.

We identified the top assignees by total number of patents filed in each decade, a measure of current innovation; top assignees by the number of patents filed from 1955 until the end of each decade, a measure of total innovation; and top assignees by the number of citations per patent, a measure of influence. These are shown in appendices II through IV.

Overall, we find that early on the top emerging GPT enabler (integration) patent assignees in each decade, as well as by the end of each decade, are large telecom firms. These were AT&T in the 1970s, 1980s and 1990s. By the 2000s, the top firm was Intel. The most influential integration patent assignees in each decade, are the International Standard Electric Corporation by 1980, Rockwell by 1990, The University of Delaware by 2000 and a Canadian government agency by 2010. The International Standard Electric Corporation was a US telecom firm that used to be a division of Western Electric and later became Standard Telephones and Cables. It was eventually acquired by Nortel in 1991. Also, it is interesting to note that David Welch, the CEO of Infinera, one of today's leading optoelectronic integration firms is an alum of the University of Delaware (Kinnane, 2011). According to him, the university not only had exceptional physics and electrical engineering programs but also a good tie with the industrial communities, a result of the prolonged association between the university and Dupont from 1902 onwards. In summary, we see here the locus of the most influential integration innovation moving from US telecom, through US academia and out to a non-US agency by 2010.

In terms of patent counts, the top rest-of-field optoelectronics patent assignees in the 1950s, 1960s and 1970s are US defense organizations, and in the 1980s, 1990s and 2002 it's Canon, the Japanese imaging firm. The same pattern persists for the top assignees by cumulative patents the end of each decade. However, the most influential rest of field optoelectronics patents belong to small firms most people today have not heard of: Rema Electronic and Solergy by 1980, Space Lyte International by 1990, Insight Telecase Inc by 2000, and Cambridge Research and Innovation Limited by 2010. Rema Electronic appears to have been a diversified Swedish firm that did not have telecommunications applications, and Solergy was a US firm in energy. There is no current information available, however, for Space Lyte International, a firm incorporated in the US. Insight Telecast was a US telecom firm, and Cambridge Research and Innovation Limited by 2010 is a British venture capital firm specializing in seed investments. Once more, the most influential optoelectronic non-integration innovation has moved from a US and a Swedish firm, through a US telecom firm, to a non US venture capital firm. These two shifts illustrates changes that have occurred in innovation in the industry both geographically and by type of firm.

From our oral history of Michael Lebby, we find that inventors from large firms can sometimes consider themselves "interpreneurs", people who generate new technologies and products within a large firm (Pinchot, 1983). Furthermore, he argues that small startup firms' "new" innovations are often based on technology that they had been working on for ten years prior at their larger corporate R&D labs.

2.6.3 Government Funded Innovation in Optoelectronics Directly and Indirectly

Government funding is pervasive through the development of this technology. This was done both indirectly, by establishing contracts with privately owned firms, and directly, by setting up own research organization. In addition, the government also led in the adoption of key optoelectronic technologies.

We have seen that Maiman worked for Hughes, which according to his account had defense applications and worked with defense contracts. In 1971, according to William Bridges, Hughes built a demonstration system in the adaptive optics area and sold the idea to DARPA to make a more advanced system. Hughes also made hydrogen maser clocks for satellites that would form the basis of GPS. Similarly, according to Eugene Gordon's Oral History, Bell Labs often used license contract funding: In 1959, Bell Labs got money from Fort Monmouth to make a DC-excited version of the Javan infra-red helium-neon laser.

Indeed, from our oral histories, Dr. X1 reports that "we turned to DARPA" when Bell Labs faced financial difficulty as their external sources of projects dried up following the burst of the bubble. In addition, Michael Lebby referred to Bell Labs as "government-funded academia, shrouded by AT&T or Ma Bell."

When we look at the patents themselves, we find more evidence for government funding in this technology and its innovation. One of the very first patents was filed in this technology was for the United States Army, a defense organization. In the 1960s, the top patent assignee in rest-of-field optoelectronics was the Navy, another defense organization. In fact, four of the top ten assignees had market applications in defense. The Navy retains its top spot in the 1970s, but does not show up again subsequently. The NRL in particular led in communications research in the 1950s: communication through a passive Moon circuit in 1951, transmission of human voice through space in 1954, transcontinental satellite communication in 1955, and the world's first operational satellite communication system in 1959 (NRL, 1998). The Navy also developed fiber-optic biosensors and optical fiber gyroscopes. In terms of optoelectronic integration, the US Army was in the top ten of assignees in the 1970s, but did not show up in subsequent decades.

In addition to all of this, the story of optical communications illustrates the role that government funding also played in developing optoelectronic technology. Optical fibers had attenuation of over 1000dB/km – that is, the signals being transmitted lost 1000dB of amplitude for every 1km travelled. A 1966 British academic paper published by Charles Kao and Charles Hockham suggested that improvements in the attenuation of optical fiber, up to 20dB/km, could result in that medium's being suitable for the transmission of laser signals.

It is upon the principle of total internal reflection that optical fibers are based. In the words of an academic expert,

> An optical fiber is a flexible strand of glass. A fiber optic cable is usually made up of many of these strands, each carrying a signal made up of pulses of laser light. The light travels along the optical fiber, reflecting off the walls of the fiber. With a straight or smoothly bending fiber, the light will hit the wall at an angle higher than the critical angle and will all be reflected back into the fiber. Even though the light undergoes a large number of reflections when traveling along a fiber, no light is lost (Buphy, 2000).

In 1970, a team of Corning researchers developed the first optical fiber capable of maintaining the strength of laser light signals over large distances. Corning was especially motivated to invent. Its major television glass business had suffered a great blow when in the late 1960s its largest customer, RCA, built its own plant capable of manufacturing the most profitable tube blanks that had previously been supplied by Corning (Graham and Shuldiner, 2001). Despite the 1970 invention, however, commercial feasibility was still not guaranteed. Furthermore, the perception of management was that it would be hard for Corning to break into the telecommunications market, as AT&T controlled 80 – 90% of the potential market (Graham). When in 1972 Corning successfully invented a fiber that had attenuation of only 4dB/km, it was able to compete with AT&T for this higher performance technology market. However, it had to go abroad to find its first customers.

In the US, the military was the first to install optical communications systems: the US Navy in the 1970s and the Air Force in 1976. Military R&D programs were also funded to develop "stronger fibers, tactical cables, ruggedized high-performance components and demonstration systems in aircraft and in undersea systems" (Sterling, 2008).

2.6.4 Government Regulation Influenced Optoelectronic Innovation

Although one often thinks about antitrust and patents, there are other ways in which government influences innovation. In this section, we will highlight two novel ways government influence innovation in this technology as discovered through oral histories.

First, sometimes the government can influence what research one can be involved in, depending on one's immigration status. Lebby, at the end of his post-doc in 1989, had been at Bell Labs on a green card. But for all the jobs in photonics, you had to be a US citizen because of the security clearances required in the government contracts related to photonics. His only two options were Motorola and HP, because they had consumer equipment. This led to his going to work for Motorola.

Second, in 2000, a Department of Justice (DOJ) investigation delayed a merger between SDL and JDSU for five months, between July 2000 and February 2001 (Kinnane, 2011) because of concerns over monopoly. The deal eventually closed in February of 2001, but the delay gave David Welch the time to conceive of starting his own firm. In his own words, "we eventually then closed the transaction through the shareholders, et cetera, in February of 2001. **In the intervening months leading up to that,** I decided that after seventeen years that it was time for me to stretch my wings a little bit and see if there were other options out there for me to pursue." David Welch went on to found Infinera.

With respect to the 1975 consent decree on Xerox forcing to license its entire patent portfolio of 1600 patents out, we find that Xerox had about 265 patents in optoelectronics by that time that would have been a part of that decree. In addition, by 1990, Xerox was one of the top ten most influential patent assignees in optoelectronic integration, with 9.5 cites/patent accruing to the firm. This suggests that its optoelectronic integration patents that it had to license out were indeed very valuable.

2.7 Discussion and Conclusions

There are several factors that influence the growth of innovation in a particular technology. These include the location of the research; housing basic research in industry not just in academia, has been shown to have disparate effects on the growth of innovation (Servos, 1994, Tiffany, 1986, Swann 1988); within industry, there is often a disparity between the kinds of innovation carried out by large incumbent firms versus by smaller firms (Henderson, 1993), and government funding and government regulation often influence innovation.

This paper sought to understand in what ways these factors combined to influence innovation in optoelectronic technology. We analyzed patenting patterns in optoelectronics between 1955 and 2010 and identified the most influential firms, government agencies, and individuals responsible for leading innovation in this field. We leveraged archival data on firm decisions and market applications from ProQuest Historical Newspapers, as well as the International Directory of Corporate Histories. We also collected oral histories on a carefully selected sub-sample of the key individuals. We found evidence for co-operation as well as competition between academia and industry as this technology grew. We also found that while large telecom firms led in total innovation in optoelectronics, patents filed by smaller firms often were more influential. Government funding was pervasive throughout the history of this technology, funding undergraduate and graduate education, academic research, military reseaech and industrial research. Finally, U. S. government regulation influenced innovation in at least two unexpected ways: first, by limiting U. S. permanent residents from working on government-funded research in photonics until the 1990s, and second, by inspiring new ventures when mergers were delayed.

2.8 Policy Implications

This work offers important insights for policy makers. First, all the super stars to whom we spoke had their training in institutional models that no longer exist today. Large corporate R&D labs (often with government funding) were key training grounds for many of the super stars. In addition, the government played a key role in funding, developing and procuring early technology developments. Without large corporate R&D laboratories and with a reduced role of government, ongoing government action may be important to ensure that the US continues to train tomorrow's super stars and lead in the emerging GPT enablers.

Access to capital may be particularly important to ensure that super-stars are able to bring together teams to push forward the frontiers of technology even during downturns. With the current reduction in levels of venture capital activity (NAS, 2010) and without large vertically integrated R&D laboratories, there may be a role for government provision of capital during downturns (when less access to capital exists) either though directly seeding start-ups or through more government venture capital organizations like the SBIR (Lerner, 1996). Funding of super-stars with proven track records interested in high-risk research has already proven to be beneficial in the academic life sciences (e.g. Azoulay et al, 2011). This could be particularly important in basic research and general purpose technologies where private investment has been shown to be less than socially optimal (Rosenberg and Trajtenberg, 2004).

The decline of corporate R&D and the decline of vertical disintegration of R&D has been shown to create challenges for long term technology development because of the need to co-ordinate across firm boundaries. Optoelectronics technology embodies this trend. This research shows the significant roles played by both government and corporate R&D in the early years of the technology. While the earlier section of this dissertation on economic downturns initially suggests that the innovation in the emerging GPT enabler continues to grow following the burst of the bubble, more research is necessary to understand the full implications of the bubble and its burst on the advancement of the technology. With insights from this second section, we suggest that further research may be necessary to understand if additional support, such as government funding through public-private partnerships, is needed to enable collaboration between academia, industry and government.

We also found, in the case of a super-star whose oral history we collected, that government regulation restricted his applications based on non US citizenship. This suggests an opportunity for government to expand the opportunities available for advanced foreign workers. This may help increase the breadth of their contribution to R&D within industry and beyond. An example of this would be STAPLE Act, which would accord international PhD graduates from U. S. institutions permanent residency, thereby allowing them the freedom to work in R&D labs and emerging GPT enabler applications from which they are currently restricted.

III: Addendum

Empirical Data Platform

3.1 Abstract

We hand-built a proprietary 930 CV database for use in this dissertation from a variety of sources over three years, from May 2010 to May 2013. It assigns a market application in each year for each of the 2100 firms represented by the inventors in the database, as well as a technology focus and governance structure. The CV database provides an alternative to on patent data alone for researchers who want to study productivity, innovation, mobility and the transfer of knowledge. The CV samples resemble the populations from which they were drawn. This database provides a way to improve the accuracy of mobility, career length and innovation variables that are estimated based on patents, and provides background information that one does not get with patents. This addendum describes the process of collecting these data and the resulting robust CV database.

3.2 Introduction

In order to create proprietary robust 930-CV database of US inventors in optoelectronics we first identified the populations of interest. Next, I characterized those populations in order to gauge their appropriateness for the research questions that were to be explored. We worked with the three largest societies in photonics: SPIE, the Optical Society of America and IEEE"S Photonics Society to gain access to inventor contact information. We also performed web searches for biographies, posted CVs and Linked In profiles that would shed light into inventors' background characteristics. I assigned the 2100 firms represented in the raw CV database to one of ~20 market applications in each year of their existence, and also to a technology specialization and a governance structure, and worked with a statistics team to create hand-matched patent data for the CV database.

In section 3.3, I describe the motivation for creating the database and the sub-populations that were targeted. In section 3.4, I describe the CV data collection process and in section 3.5, the resulting raw CV data. In section 3.6, I describe the process of assigning the firms represented in the CVs to market applications, technology foci and governance structures. In 3.7, I briefly explain how we worked with a statistics team to create "true patent data" for each inventor. In section 3.8, I show the resulting robust database triangulated from all these sources. Finally, in section 3.9, I show some descriptive statistics on the resulting robust CV database by sample, comparing each sample to the population which it represents.

3.3 Motivation and Sub Population Descriptions

3.3.1 Motivation

Past academic research has used publicly available patent data to measure productivity (Kapoor and Lim, 2007, Fleming 2007), inventor mobility (Song et al, 2003 Correidora and Rosenkopf, 2010, Marx et al 2009, Agarwal, 2009), and transfer of knowledge (Almeida & Kogut, 1999, Song et al, 2003, Correidora and Rosenkopf, 2010). However, these analyses suffer from many challenges. The lack of individual inventor IDs in the USPTO database mean that the accuracy of one's data is based on one's disambiguation algorithm. One of the first efforts was made by Trajtenberg et al, in 2006. Even more importantly, patent data will not identify inventors as having moved if they do not patent after they move, nor the career length of inventors who stay with a firm but do not patent. Furthermore, patent data tells us nothing about the background characteristics of the inventors. In order to address these challenges, we decided to create a CV database.

3.3.2 Sub-Population Descriptions

The CV database was created from carefully selected inventor sub-populations. The sub-populations were classified based on inventors' patenting patterns in optoelectronics pre-burst, that is, by December 31, 1999. In order to identify these patterns, I used the Fuchs Lab Optoelectronics database first created by Peter Pong and then improved on by Sam Venutra, who implemented Fleming et al's (2007) F1 disambiguation algorithm with enhancements for middle name matching and more accurate state and country identification. The Fuchslab database identifies optoelectronics and optoelectronics integration patent classes based on classifications detailed in Appendix 2.1.

These sub-populations were:

(i) top 1.5% of inventors by total number of patents (MOST),

(ii) the top 1.5% by average number of patents pre-burst (RATE),

(iii) all inventors with at least one patent in integration (INT), and

(iv) a random sample of rest of field general optoelectronics inventors who had never patented in integration (RAND-NI)

3.3.2.1 Top 1.5% Of Inventors by Total Number of Patents (MOST)

This population is made up of 760 inventors. As a group, this top 1.5% is responsible for 15% of all patents in optoelectronics pre-burst: 16,165 patents, 15,750 in rest-of-field general optoelectronics, and 415 in integration.

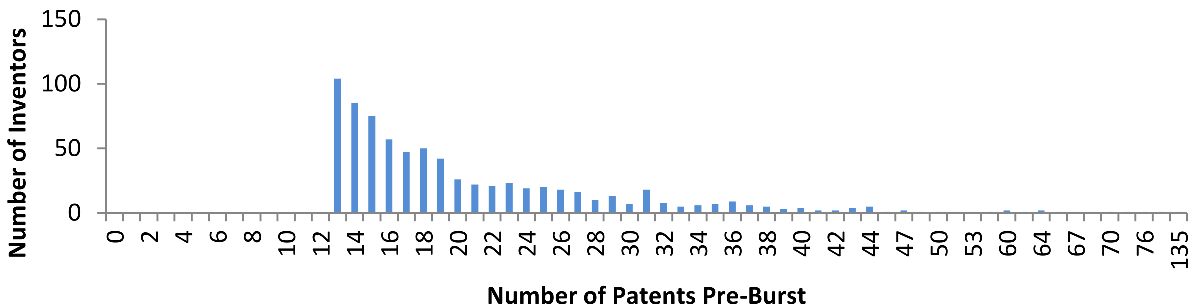


Figure 3.1: **Pre-Burst Patent Distribution in the MOST Sub-Population**

Each inventor in this population had at least 13 patents pre-burst and the most prolific inventor had 135 patents pre-burst. The average inventor had 21 patents pre-burst. The distribution is shown in figure 3.1 above. 78% of this population had patented in integration pre-burst. On average, they had worked for 3 firms pre-burst, and had been in the industry for 15.6 years. 72% of them patent at least once following the burst of the bubble.

3.3.2.2 Top 1.5% By Average Number of Patents Pre-Burst (RATE)

This population is made up for 680 inventors. As a group, this top 1.5% by annual patenting rate (total number of patents pre-burst/career length based on patenting data pre-burst) is responsible for 8% of all patents in optoelectronics pre-burst: 8,210 patents, 7,971 in rest-of-field general optoelectronics, and 239 in integration. Each inventor in this population had at least 2 patents/year pre-burst; the most productive inventor had 12 patents/year pre-burst. In terms of just patents, each inventor in this population had at least 3 patents pre-burst and the most prolific inventor had 135 patents pre-burst. The average inventor had 12 patents pre-burst. The distribution is shown in figure 3.2 below.

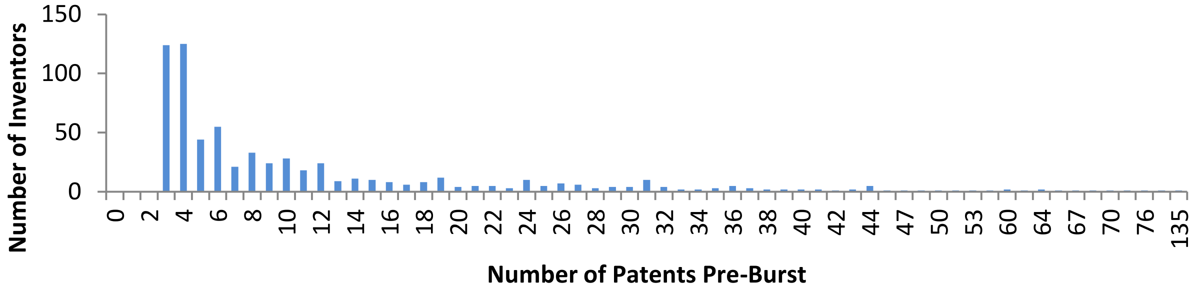


Figure 3.2: **Pre-Burst Patent Distribution in the RATE Sub-Population**

Only 15% of this population had patented in integration pre-burst. On average, they had worked for 2 firms pre-burst, and had been in the industry for 4.4 years. 58% of them patent at least once following the burst of the bubble.

3.3.2.3 Inventors with at Least One Patent in Integration (INT)

This population is made up for 900 inventors. As a group, this group of inventors with at least one patent in integration pre-burst is responsible for 5.6% of all patents in optoelectronics pre-burst: 6,020 patents, 4,922 in rest-of-field general optoelectronics, and 1,098 in integration.

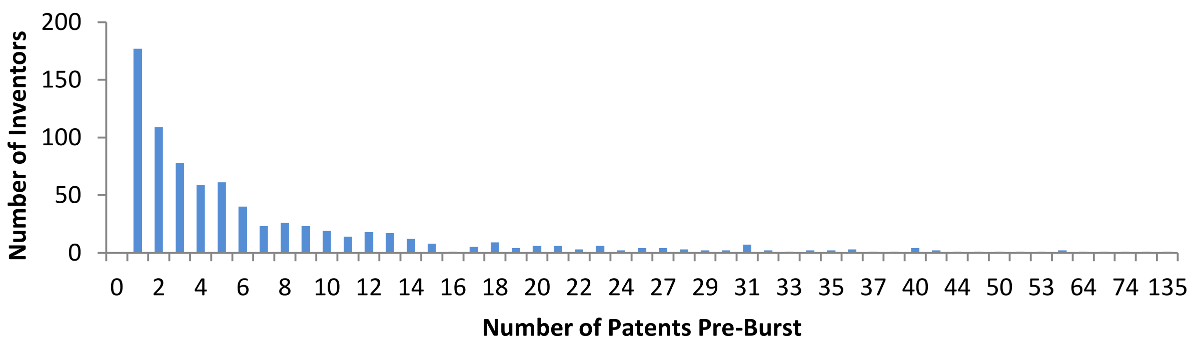


Figure 3.3: **Pre-Burst Patent Distribution in the INT Sub-Population**

Each inventor in this population had at least 1 patent pre-burst and the most prolific inventor had 135 patents pre-burst. The average inventor had 8 patents pre-burst. The distribution is shown in figure 3.3 above. By definition, 100% of this population had patented in integration pre-burst. On average, they had worked for 2 firms pre-burst, and had been in the industry for 8 years. 53% of them patent at least once following the burst of the bubble.

3.3.2.4 Random Sample of Rest-Of-Field General OE Inventors that had Never Patented in Integration (RAND-NI)

This randomly selected population is made up of 1250 inventors. I compared the patent distribution in this random sample with the patent distribution in OE population of >49000 to make sure that it was a truly representative random sample. This is shown in Figure 3.4 below.

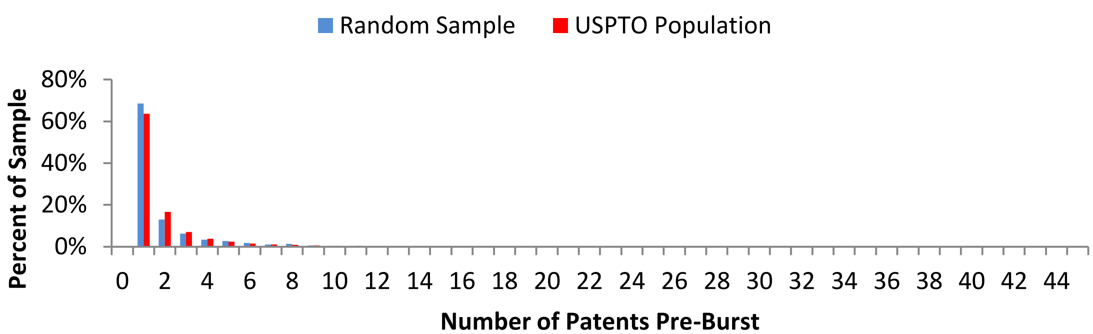


Figure 3.4: **Pre-Burst Patent Distribution in RANDOM Sample vs Entire Population**

This group of inventors with at least one patent in rest-of-field optoelectronics pre-burst is responsible for 2% of all patents in optoelectronics pre-burst: 2,508 patents, by definition all in rest-of-field general optoelectronics. Each inventor in this population had at least 1 patent pre-burst and the most prolific inventor had 45 patents pre-burst. The average inventor had 2 patents pre-burst. The distribution is shown in Figure 3.5 below.

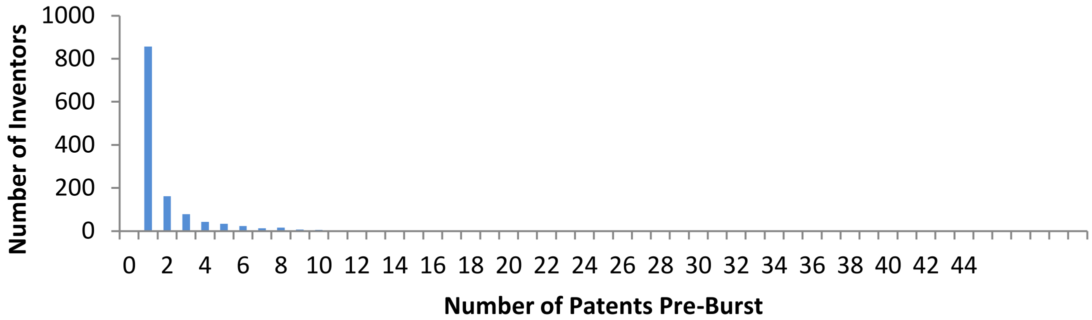


Figure 3.5: **Pre-Burst Patent Distribution in the RAND-NI Sub-Population**

By definition, 0% of this sample had patented in integration pre-burst. On average, they had worked for 1 firms pre-burst, and had been in the industry for 3.7 years. Only 17% of them patent at least once following the burst of the bubble.

A summary of inventor characteristics across the four target populations is shown in Table 3.1 below:

	MOST	RATE	INT	RAND-NI
Population N	760	680	900	1250
Number of rest of field general OE Patents	15,750	7,971	4,922	2,508
Number of Integration Patents	415	239	1,098	0
Number of all OE Patents	16,165	8,210	6,020	2,508
% of USPTO OE Patents responsible for	15%	8%	5.6%	2%
Minimum patents pre-burst	13	3	1	1
Average patents pre-burst	21	12	8	2
Maximum patents pre-burst	135	135	135	45
% that had patented in integration pre-burst	78%	15%	100%	0%
Average number of firms pre-burst	3	2	2	1
Average career length pre-burst	15.6	4.4	8	3.7
% that patents at least once post-burst	72%	58%	53%	17%

Table 3.1: Inventor characteristics across four target populations

3.4 CV Data Collection Process

Before accessing inventor data, all undergraduate research assistants first were certified for Human Subjects Research through Carnegie Mellon University's Institutional Review Board. In addition, I created a general guide for contacting inventors for each inventor category, email and phone protocols for requesting inventor CVs, and a protocol for CV handling. I also created a list of frequently asked questions for the undergrads to reference during their calls.

The process for data collection is shown in figure 3.6 below. After I identified the target populations, we worked with the photonics societies in different ways to get their contact information. For SPIE, we sent our target populations to them and they returned hand-matched contact information. For OSA, we logged in and searched member databases. For IEEE, we searched through a member database they provided to us. We also conducted web searches for biographical sketches, posted CVs, and Linked In profiles.

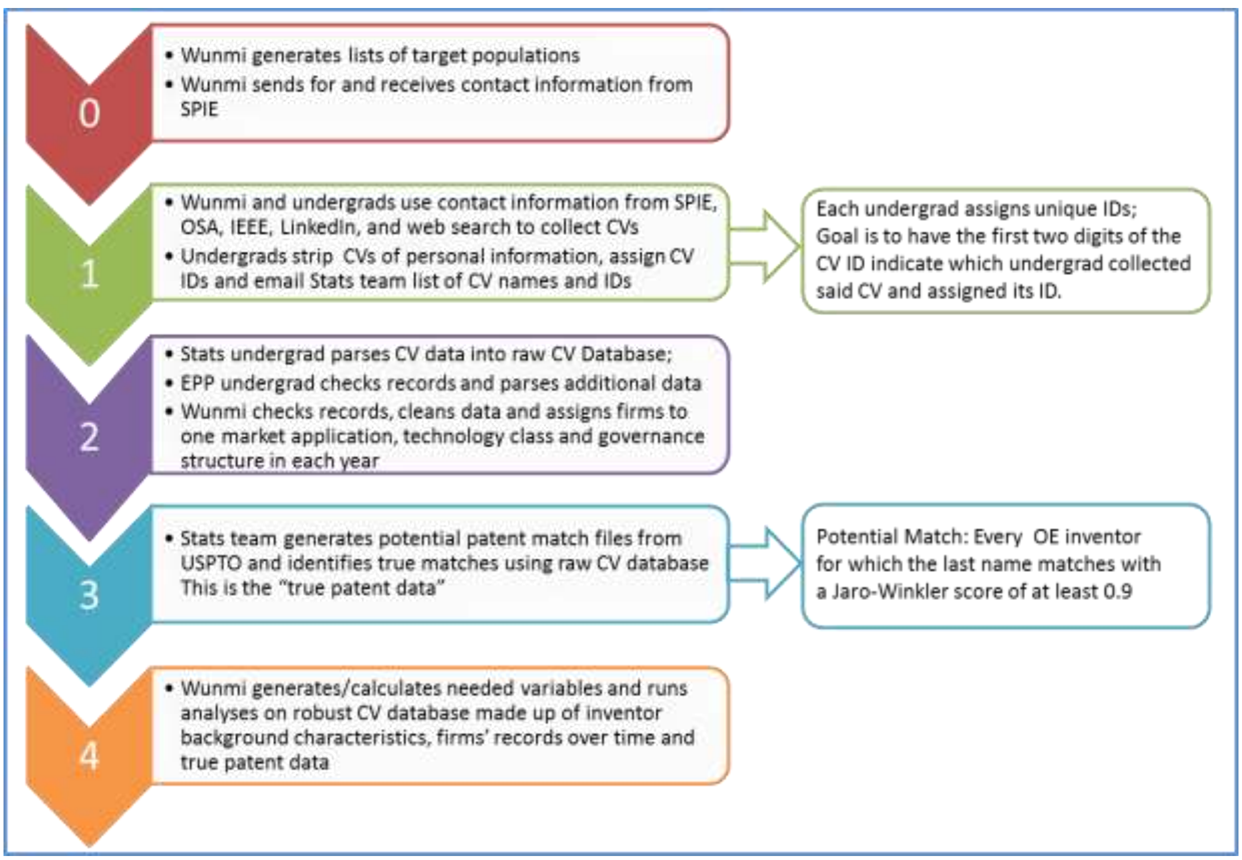


Figure 3.6: CV Data Collection Process Overview

For each inventor, we created an anonymized CV file with all the data we found from all the sources, which the stats team then parsed into a raw CV database. We had two people go over these records that had been parsed. First an EPP undergrad checked the records and also parsed additional information like whether or not they had founded a company that we realized would be useful. Then, I checked the records as well, cleaned the data, and assigned each firm to a market application, technology class and governance structure in each year. Meanwhile, the stats team hand-identified an inventor's true set of patents. I discuss what goes into each step from initial inventor contact to analysis in the following sub sections.

3.4.1 General Guide for Contacting Inventors

All undergraduate research assistants were given both a phone and an email protocol that I created (exhibits 3.1 and 3. 2). They used this to guide their contacts with the inventors.

If we had both email and phone information available: we would email first, and then call 24 - 48 hours later. If we had just email information, we would email first, wait 24 – 48 hours, and then email again. If we had just phone information available, we would call and follow script. If it was not a good time, we would ask when would be a good time. If they did not pick up, we would try again five minutes later. If they still didn't pick up, we would leave a voicemail, and then try again 24 hours later. In the event that an inventor did not have a CV handy, we sent him a background information form that I created for him to complete (Exhibit 3.3)

We made sure that we called between 8.00am and 6.00pm in their time zone (based on their phone numbers). If we had just LinkedIn Information, we would scrape their information from Linked In, and also send them a request to connect with a shortened version of our email script. We also performed web searches on all inventors whether or not they sent us their CVs.

3.4.2 Logs for Contacting Inventors

Each undergrad research assistant kept a log of all contacts made to inventors. Such contact included:

- Phone calls: date called, response summary like left message or voicemail box not working, wanted more information on the study, said would send resume and we could follow up on x date if not, received CV, family said deceased etc.)
- Emails: dates emailed, response summary
- LinkedIn: date profile information scraped and invitation to connect sent, response
- Web Search: Found CV or bio on which site, and date retrieved.
- Whether or not interested in being interviewed

> MOST GROUP:
>
> I am an undergraduate research assistant at Carnegie Mellon University performing research with Professor Erica Fuchs and PhD Student Wunmi Akinsanmi in collaboration with SPIE, OSA and IEEE's Photonics Society. Our research investigates the effect of the economic downturn of the early 2000s on innovation in the optoelectronics industry. We are especially interested in the careers of the creators of innovation like yourself: your job changes, your patenting activities, the technologies and market applications you worked in, and any shifts in the central organizations supporting photonics patenting work. We hope to aggregate individual trends to get a clear picture of what was happening in the US nationally. To this end, we are collecting the professional resumes of inventors who are in the top 1.5% by total number of patents between 1976 and 1999 in the optoelectronics industry. Would you be willing to send me your professional resume or curriculum vitae for use in this research effort? Any information you provide will be used solely for the purpose of our academic research, and no individual identifying information will be released without your express permission. If you prefer I can also send you a form to fill in.
>
> As a follow up, we might be interested in interviewing you to understand more about the industry at the time you made your career decisions. These interviews would take place in the next year. Would you be willing to participate in a 30-minute phone interview?
>
> Thank you very much for your consideration and I look forward to hearing from you.

Exhibit 3.1: Sample Email Protocol

Here's a guide to what I say on the phone. Replace with your name/information:

Hello, my name is [Wunmi Akinsanmi]. I'm a [PhD Student] at Carnegie Mellon.
I'm calling because my research group is conducting a study on innovation trajectories in the optoelectronics industry following the economic downturn of the early 2000s.
You have several patents in this industry and so we would like you to be a part of the study. All we need is your educational background information as well as info on the types of companies you have worked with
You can do this by sending your resume, or filling out a form that I can email you.
Our sample size is really small so I hope you can participate.
I would be delighted to answer any questions you may have.

If I get voicemail, same as above and I add: My callback number is […]. Again, my name is [Wunmi Akinsanmi] calling from Carnegie Mellon, and I hope to hear from you soon. Thank you!

Y

Great, thank you! Do you have a working copy that you can send immediately?
[wait for response]
Thank you so much. When would be a good time to follow up if we have not yet received your resume?

N

Your participation would be critical to this research as we hope to help inform future policy decisions that would better support the industry during economic downturns. It would be really useful to have your CV to understand how you navigated the burst of the telecom bubble. Could you please reconsider sending us your CV?

Y

N

In the near future, we would like to perform some interviews to understand more about the industry and your career decisions. These will be in the next year. Would you be interested in being interviewed?

Y

Great, what is the best way to reach you to schedule a time? (*Confirm phone number or email address)*

Thank you very much for your time and for participating. Have a great day.

N

Thank you very much for your time. If you change your mind you can reach us at eyiwunmi@cmu.edu. Have a great day.

Exhibit 3.2: Phone Protocol

Carnegie Mellon

Department of Engineering and Public Policy
Carnegie Mellon University
Pittsburgh, Pennsylvania 15213-3890
Telephone: 412 268-1877
Fax: 412-268-3757

OPTOELECTRONICS INDUSTRY STUDY: ECONOMIC DOWNTURNS, TECHNOLOGY TRAJECTORIES AND THE CAREERS OF SCIENTISTS

Thank you for participating in our study. Please take a few minutes to fill out this background information form in lieu of sending us your CV. There are five sections: work history, educational background, patents and publications, society memberships, and other information.

You can copy/paste sections to extend them as you need.

Section I: Work History

MOST RECENT WORK EXPERIENCE

Employer Name, City and State	
Start Date	
End Date	
Title	
Description of Role	

PREVIOUS WORK EXPERIENCE (PLEASE COPY AND PASTE AS MANY TIMES AS NEEDED)

Employer Name, City and State	
Start Date	
End Date	
Title	
Description of Role	

Section II: Educational Background

MOST RECENT EDUCATION

University Attended	
Degree Earned	
Major and Field of Study	
Start Date	
End Date	
Honors/Awards	

PREVIOUS EDUCATION 1 (PLEASE COPY AND PASTE AS MANY TIMES AS NEEDED)

University Attended	
Degree Earned	
Major and Field of Study	
Start Date	
End Date	
Honors/Awards	

Section III: Patents and Publications

LIST OF PATENTS

You can copy and paste to replace this table if you have an existing list; you can also add rows as needed.

	Patent Number	Date Issued	Title
1			
2			
3			
4			
5			

LIST OF PUBLICATIONS

You can copy and paste to replace this table if you have an existing document. You can also add rows as needed.

	Article Title	Journal	Date of Publication
1			
2			
3			
4			
5			

Section IV: Professional Organizations

Are you a member of any of the following societies?

1. IEEE Photonics Society: YES / NO
2. Optical Society of America YES / NO
3. SPIE YES / NO
4. Other society/organization (please specify):

Section V: Other Information

Please use this section to tell us any other information about yourself that you might normally have put on a CV. For example, if you have ever been on the board of a company or founded/co-founded a startup. You can also list professional honors and awards here.

Exhibit 3.3: Sample Inventor Background Information Form

3.4.3 CV Handling Protocol

Once each CV was received, it was stripped of all identifying information and assigned a 4-digit code to protect the inventors' identity. Within a week, the following steps were followed:

1. A thank you note was sent to the inventor
2. Our records were updated with contact information from the CV
3. The inventor CV was stripped of the inventor's name i.e., everywhere his name appeared, we replaced with a unique 4-digit code. The file was then saved as the 4-digitcode.docx
4. All CVs were uploaded to the research group server and deleted from the research assistant's personal computer
    a. The original CV into the non-modified CVs folder
    b. The stripped copy into the modified CVs folder

After a few duplicates from multiple undergrads working on the same set of inventors were identified and removed, we created and only used a centralized ID map.

3.5 Raw CV Data

SUB-SAMPLES	NUMBER
MOST	117
INT	181
RATE	135
RAND-NI	163
MOST&INT	36
MOST&RATE	58
MOST&RAND-NI	2
INT&RATE	12
RATE&RAND-NI	4
MOST&INT&RATE	20
MOST&RATE&RAND-NI	0

Table 3.2: CV Sample

We parsed the data from the anonymized CV files. Table 3.2 above shows the CVs in each sample and their overlaps. By definition, the INT and RAND-NI samples are mutually exclusive.

The different tabs and tables that made up the inital CV database were:

1. Inventor information: inventor code, street address, city, state, zip code and country
2. Inventor firm (each one of which was also assigned a code), assignee name, city, state, zip code and country; the employment start date and end date for each job.
3. Education history: Number of degrees, highest degree achieved, and their dates
4. Patents: We scraped patents that inventors listed on their CVs into a database.
5. Other information: We stripped information on society memberships, academic honors, company foundings, boards, birthdates, and any other personal information marital status. 15% of the inventors had founded a company, 17% had sat on the board of a company and 3% listed that they were married and had children.

3.6 CV Firms' Market Applications

There were 2100 firms represented in the CV database. For each one, I assigned a market application, technology focus and governance. I used the firms' own websites, the International Directory of Corporate histories, Mergent Webreports, LexisNexis Corporate Affiliations, Hoover's and news archives. This historical data was especially important because diversified firms often entered and exited different market application over the course of their history.

3.6.1 Marker Application Definitions

I assigned each firm, and by extension, each inventor, to an employment state and market application. By employment state, I mean I distinguished between the period before first known job versus a gap in employment details between known jobs; the former was labelled pre-employment while the latter was labelled unemployment.

Firms that stayed in one market application had that one market application over time. About 10% of the firms were diversified, however, meaning that they were I more than one market application either in the same year or over time. I also identified these, separating between those that were diversified including a telecommunication application and those that were diversified but did not have any telecommunications applications. Example market application maps for those diversified firms are shown in Figure 3.7 above. From their corporate histories, we see Corning had been in telecom since the 1960s but 3M went into telecom in 1997.

Code	Market Application Definition	Code	Market Application Definition
0	Unemployment – gap between known employment	**15**	industrial and manufacturing equipment
1	telecom firms - wired, fiber-optic cables	**16**	analytical and scientific research equipment
2	telecom firms - wireless applications	**17**	Imaging - cameras, printing and displays
3	computer components e.g., memory, disk storage	**18**	specialty glass – electrooptical, electromatic
4	complete computing systems and software	**19**	automotive
5	biotech, medical and other life sciences	**20A**	diversified, with telecom, multiple technologies
6	defense and security	**20B**	diversified, without telecom, multiple technologies
7	aerospace, space and aviation	**21A**	diversified, with telecom, single technology
8	renewable energy as well as energy storage	**21B**	diversified, without telecom, single technology
9	oilfield & gas	**101**	academia
10	lighting	**200**	consulting and professional services
11	environmental	**201**	professional society
12	chemicals	**202**	other nonprofit organizations
13	materials and semiconductor substrates	**999**	pre-employment: time before first known job
14	semiconductor manufacturing	**90**	unknown firm

Table 3.3: Employment states of inventors and market applications of firms in the CV database

Corning:

	1875	1880	1912	1915	1934	1940s	1950s	1960s	1970s	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
telecom-wired	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
telecom-wireless	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
electronic and computing components	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
computing systems, software & services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
health & life sciences	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
defense & security	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
space & aviation	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
renewable energy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
oil & gas (and coal?)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lighting	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
environ-mental	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
chemical	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
specialty materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
semicond manuf	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
ind & manuf eqp	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
anal & sci res eqpt	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
imaging	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty glass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
automotive & transportation	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
telecom-wired	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
telecom-wireless	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
electronic and computing components	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
computing systems, software & services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
health & life sciences	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
defense & security	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
space & aviation	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
renewable energy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
oil & gas (and coal?)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lighting	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
environ-mental	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
chemical	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
semicond manuf	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ind & manuf eqp	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
anal & sci res eqpt	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	1	1
imaging	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty glass	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
automotive & transportation	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

3M

	1902	1910s	1920s	1930s	1940s	1950s	1960s	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
telecom-wired	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
telecom-wireless	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
electronic and computing components	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
computing systems, software & services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
health & life sciences	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
defense & security	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
space & aviation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
renewable energy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
oil & gas (and coal?)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lighting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
environ-mental	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
chemical	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
semicond manuf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ind & manuf eqp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
anal & sci res eqpt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
imaging	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty glass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
automotive & transportation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
telecom-wired	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
telecom-wireless	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
electronic and computing components	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
computing systems, software & services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
health & life sciences	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
defense & security	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
space & aviation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
renewable energy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
oil & gas (and coal?)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lighting	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
environ-mental	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
chemical	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
semicond manuf	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ind & manuf eqp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
anal & sci res eqpt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
imaging	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
specialty glass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
automotive & transportation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Figure 3.7: Examples of some diversifeid firms’ market applications maps over time:

3.6.2 Technology Focus

I assigned each firm a technology focus based on the product offerings on their websites. Sometimes, the technology focus determines if a firm can go into multiple market applications. A firm that makes sensors, for example, could apply it to multiple markets; however, a firm that makes network components is almost always focused on telecommunications.

As we can see from Table 3.4 below, 51% of the firms had more than one technology focus, while 10% were focused on network components. For 8% of them, they either didn't actually make anything themselves (think intellectual property law firms that the inventors sometimes worked at after their initial career) or the firm could not be identified through any archival sources.

Code	Technology Definition	%	Code	Technology Definition	%
A	sensors, detectors, monitors etc.	2%	M	software and services	4%
B	lasers as end products and as input to other processes	3%	N	integrated circuits and other hardware	3%
C	LEDs and lights	1%	O	contract foundries	0%
D	test, measurement and instrumentation	2%	P	integrated healthcare systems	1%
E	other network components like transceivers, amplifiers, switches etc.	10%	Q	signal processing	0%
F	materials and substrates being used in other applications	1%	R	industrial equipment and machines	1%
G	image display, includes pictures and video	2%	S	holograms and barcodes	0%
H	image capture and inspection; includes cameras, x-ray	2%	T	energy storage	3%
I	image printing	1%	U	optical glasses and lenses	1%
J	optical data storage includes holographic	1%	V	chemicals and polymers	1%
K	cataract, retinal and refractive technologies	1%	X	No actual technology/unknown tech	8%
L	medical research and biotechnology	4%	Z	diversified – more than one technology	51%

Table 3.4: The technology focus of firms in the CV database

3.6.3 Governance

I assigned each firm a governance structure based on their websites and publicly available information. 4.8% of the firms represented were owned by the government, either of the US or some other country. 30.3% were universities, while 64.5% were private organizations – meaning they were not owned by a government. This last category includes both firms that have never been traded on the stock market and those that have been. Finally, I could not tell what kind of governance structure 0.4% of the database had.

Code	Governance	% of sample
100	Public	4.8%
101	Universities	30.3%
102	Private Organizations	64.5%
XX	Unknown Organization	0.4%

Table 3.5: The governance structures of firms in the CV database

3.7 Hand-Matched Patent Data

Not all inventors listed their patents on their CVs. For all the inventors, whether they listed their patents or not, we worked with a statistics team led to scrape a list of potential matches based on the inventor names, and hand-matched each CV inventor to all of his patents. The potential matches were inventors whose name on USPTO matched our names with a Jaro-Winkler score of at least 0.9. An undergraduate research assistant then hand-matched inventors to their patents by comparing inventor names, locations and previous assignees. This is the “true patent data”

3.8 Triangulated Data for Regressions

The regressions in this dissertation were performed on triangulated data from the sources above. A description is shown in Table 3.6 below.

Column head	**Types of Values**	**Description**	**Data Source**
CV ID	Integer 0 or 1	Unique code assigned to inventor	USPTO
ismost	Integer 0 or 1	Whether is in the top 1.5% by total number of patents by Dec 31, 1999	USPTO
israte	Integer 0 or 1	Whether is in the top 1.5% by patents/year by Dec 31, 1999	USPTO
isint	Integer 0 or 1	Whether had at least one patent in integration by Dec 31 1999	USPTO
isrand	Integer 0 or 1	Whether had no patents in integration by Dec 31 1999	USPTO
sample	0, 1, 2, or 3	0 if inventor belongs to neither MOST nor RATE. 1 if inventor belongs to RATE but not MOST 2 if inventor belongs to MOST but not RATE 3 if inventor belong to both MOST and RATE	CV Database (CV and Bios)
Highest degree	String: DOC = PhD, DSc or MD; MAS = MA, MSc or MBA; BAC = BSc or BA; and JUR = JD.	Highest education level attained;	CV Database (CV and Bios)
Earliest employment date	Date	The earliest employment date that we have	CV Database (CV and Bios)
Earliest paten date	Date	the earliest patent date that we have	Hand-matched patents
oe_year	Integer	Number of OE patents filed in each year	Hand-matched patents
int_year	Integer	Number of INT patents filed in each year	Hand-matched patents
firm_change_year	Integer 0 or 1	Whether or not they changed firm in that year	CV Database (CV and Bios)
mkt_change_year	Integer 0 or 1	Whether or not they changed market application in that year	CV Database (CV and Bios)
firm_year	Firm code	Firm in that year	CV Database (CV and Bios)
mkt_year	Market code	Market application in that year	CV Database (CV and Bios)

Table 3.6: A Description of some of the data used for regressions in this dissertation

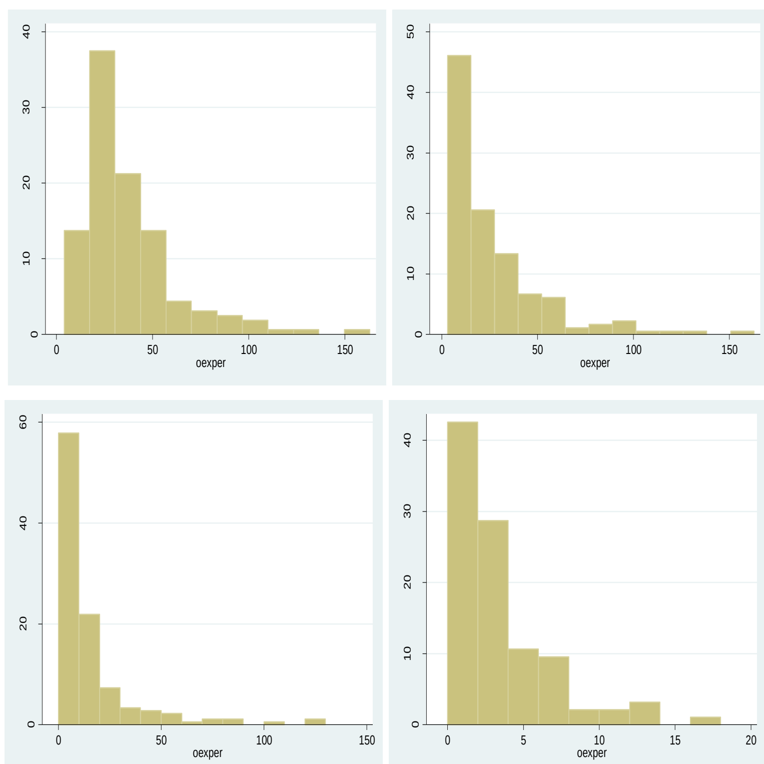
In addition, I created additional variables for investigating specific questions to be explored and for performing robustness checks. These include variables for pre-bubble, during-bubble and post-burst periods and for inventors based on pre-bubble rather than pre-burst behavior.

3.9 CV Sample Data Descriptions

In this section, I present some descriptive distributions on the robust CV database by sample: the total number of rest-of-field general OE patents, the total number of integration patents, career lengths pre-burst, education levels, industry entrance dates and earliest patent dates.

3.9.1 Total Number of OE Patents by Sample

The greatest percentage (38%) of the MOST CV sample (top 1.5% by total number of patents pre-burst) had between 10 and 20 patents total. In contrast, the greatest percentage (48%) of the RATE CV sample had between 1 and 10 patents total. 59% of the INT CV sample has fewer than 10 patents total, while 70% of the RAND-NI CV sample has fewer than 5 patents overall. This is consistent behavior with the overall populations described in section 1.



MOST RATE

INT RAND

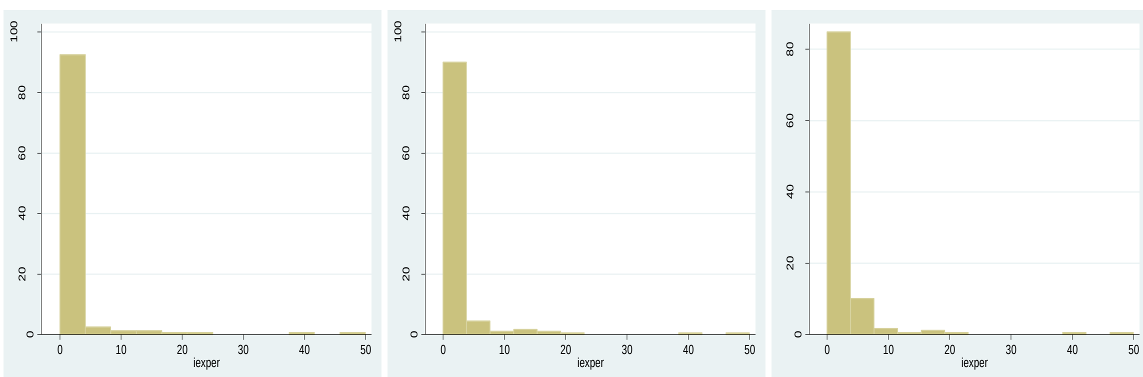
Figure 3.8: Distribution of OE Patents by Sample

3.9.2 Total Number of INT Patents by Sample

From figure 3.9 below, it would appear that 95% of the MOST sample had between 1 and 10 patents in integration total, suggesting that majority of the sample dabbled in integration. However, 62% never patented in integration, while 12.5% only had one patent in integration, and 8% two patents.

Along the same lines, 70% of the RATE sample never patented in integration. 8% had one patent and another 8% had two patents.

Finally, recall that the INT population was defined as having at least one patent in integration. 52% of the sample however only has one integration patent, and another 20% only two.



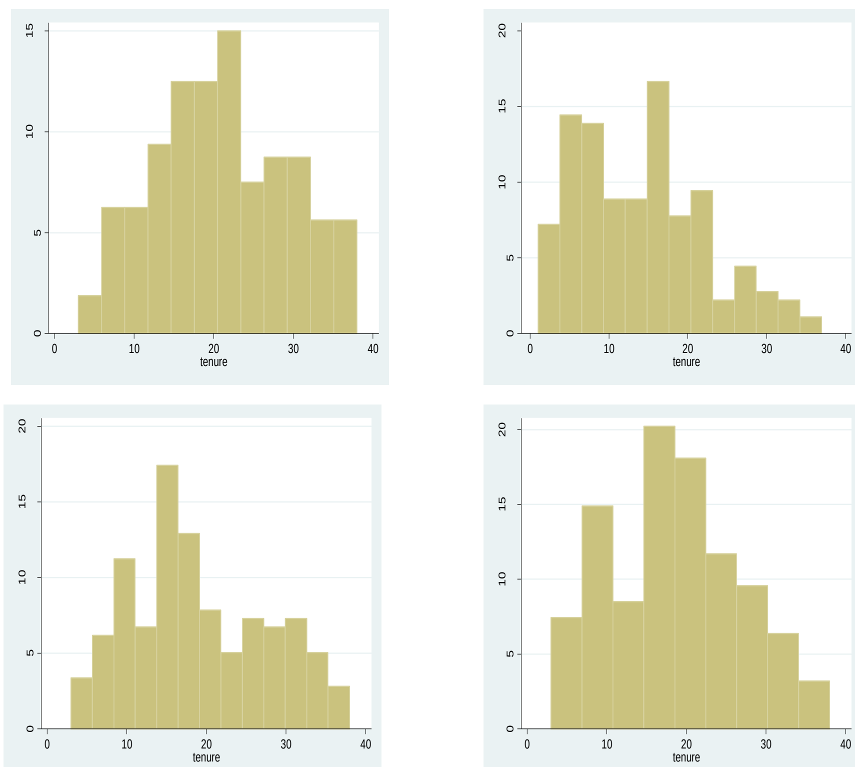
MOST RATE INT

Figure 3.9: Distribution of INT Patents by Sample

3.9.3 Career Length Pre-Burst Burst by Sample (based on CV employment dates)

From observing figure 3.10 below, it is not surprising that the MOST sample is more-bell shaped while the RATE sample is skewed to the right – this reflects the differences in the average ages of the populations from which they were pulled in section 1. The average career length pre-burst for the MOST sample is 21 years; it was 15.6 years for MOST population. Similarly, while the average career length for the RATE sample is 14 years compared to 8.1 years for RATE population. The INT and RAND samples are also slightly right-skewed. While the average career length pre-burst for the INT sample is 19 years, it was 8 for the INT population. Finally, while the average career length pre-burst for the RAND-NI sample is 18.6 years, it was 3.7 for the RAND-NI population.

This corroborates the sample bias finding (Paper I of this dissertation) that we are more likely to have CVs for inventors who have been in the industry for a longer period of time. However this effect is combined with the fact that tenure is now being calculated based on actual employment dates, not based on earliest patenting dates, and inventors are likely to have been in the industry for a few years before filing their first patent.



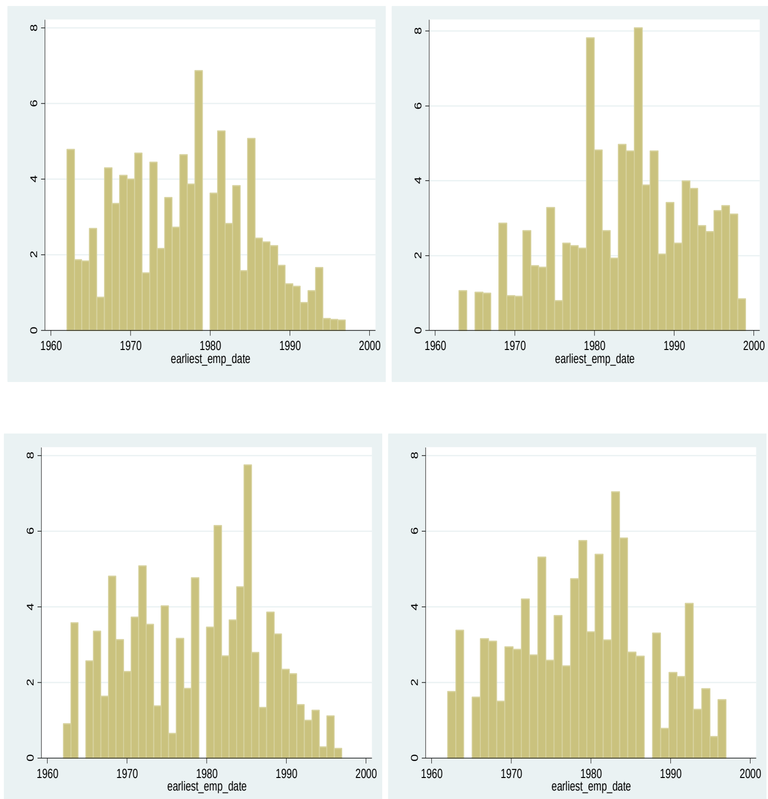
MOST RATE

INT RAND

Figure 3.10: Distribution of Career Length Pre-Burst by Sample

3.9.4 Industry Entrance by Sample (based on CV Employment Dates)

The entrance dates for the MOST sample slightly right skewed, meaning they have earlier entrances and therefore longer careers. The entrance dates for RATE, however, is slightly left skewed, meaning they have later entrances. Yet, the average career lengths we just examined for these two samples is not very different.



MOST RATE

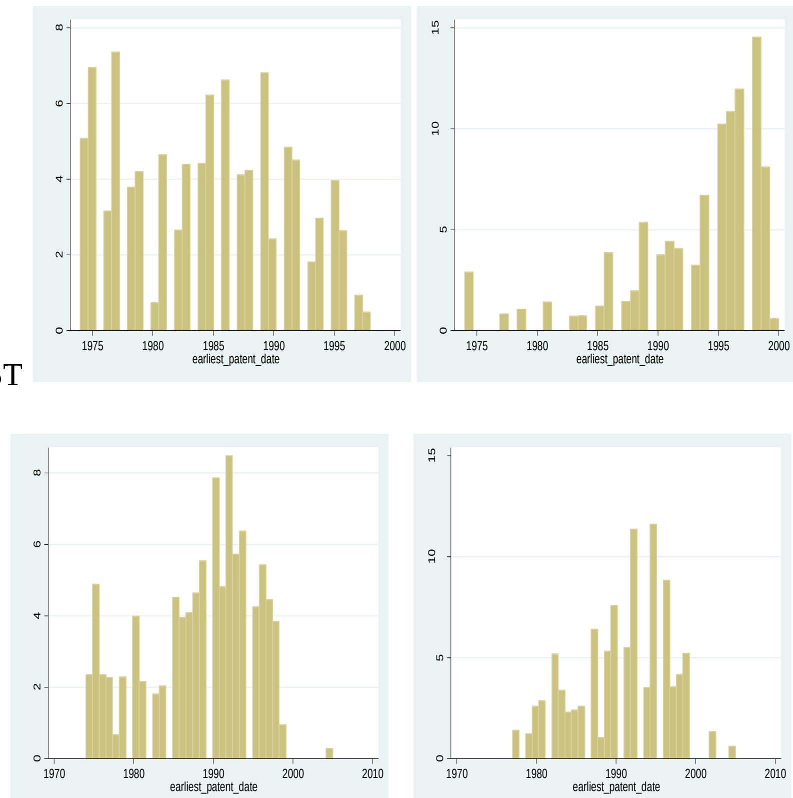
INT RAND

Figure 3.11: Distribution of Industry Entrance by Sample

The INT samples and the RATE samples, which were collected from populations reflecting specialization, not patenting prolificacy, were most bell-shaped. This suggests that patenting prolificacy is very correlated with inventor's industry entrance.

3.9.5 Earliest Patent Dates by Sample

The plots below paint a clearer picture and corroborate the story started by the industry entrance distributions. While the MOST sample was consistently starting to patent in the industry over the entire window of time, the RATE sample disproportionately started to patent between 1995 and 2000. As for INT and RAND, those inventors are actually more likely to have started to patent before 1990.



MOST RATE

INT RAND

Figure 3.12: Distribution of earliest patent date by sample

Interestingly, there are a couple of one-offs in the INT and RAND-NI sample that patented first post-burst. These two samples are drawn from populations that are more likely to have inventors with only one patent, and so an earlier patent that may have been assigned to them based on USPTO disambiguation may not have been theirs.

3.9.6 Education Distribution by Sample

Here, I examine the highest educational degree obtained and compare across the four samples. In the charts below, ASS means Associates Degree, MAS means Master's degree, JUR means a law degree, and PhD means a doctoral degree. If an individual has both a law degree and a PhD, his PhD is considered the highest educational degree obtained.

The INT sample has the highest percentage of PHDs, at 81%. This is not surprising because these individuals all have at least one patent using the specialized knowledge of integration. They are followed by the MOST at 79%, individuals who have a large patent portfolio. The RAND-NI sample is next with 73% and then the RATE sample with 69%. The RATE sample also has the highest proportion of Master's degree holders

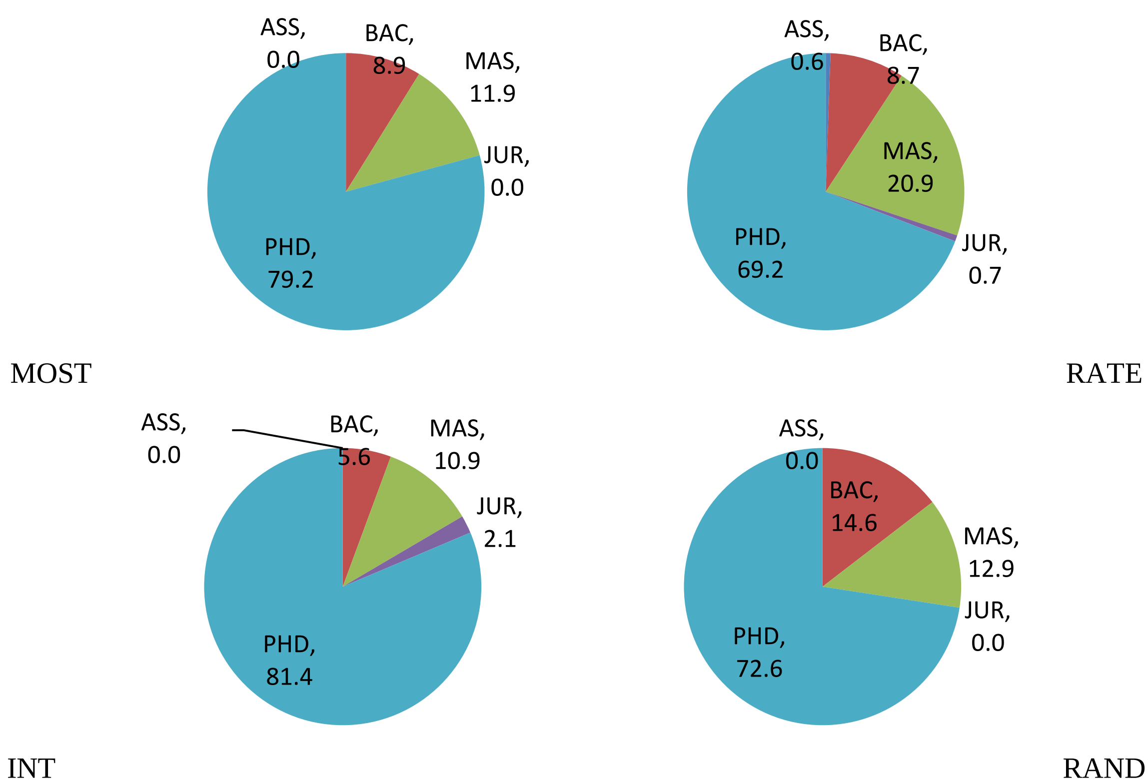


Figure 3.13: Distribution of highest education level achieved by sample

It is also useful to note that the MOST and RAND samples contain inventors with Bachelors, Masters and PhDs alone, while the INT sample has inventors with law degrees and the RATE sample has inventors with associate degrees and law degrees.

3.10 Conclusion

The proprietary 930 CV database used in this dissertation was hand-built from a variety of sources over three years, from May 2010 to May 2013. The CV database provides an alternative to on patent data alone for researchers who want to study productivity, innovation, mobility and the transfer of knowledge. The CV samples resemble the populations from which they were drawn. This database provides a way to improve the accuracy of mobility, career length and innovation variables that are estimated based on patents, and provides background information that one does not get with patents.

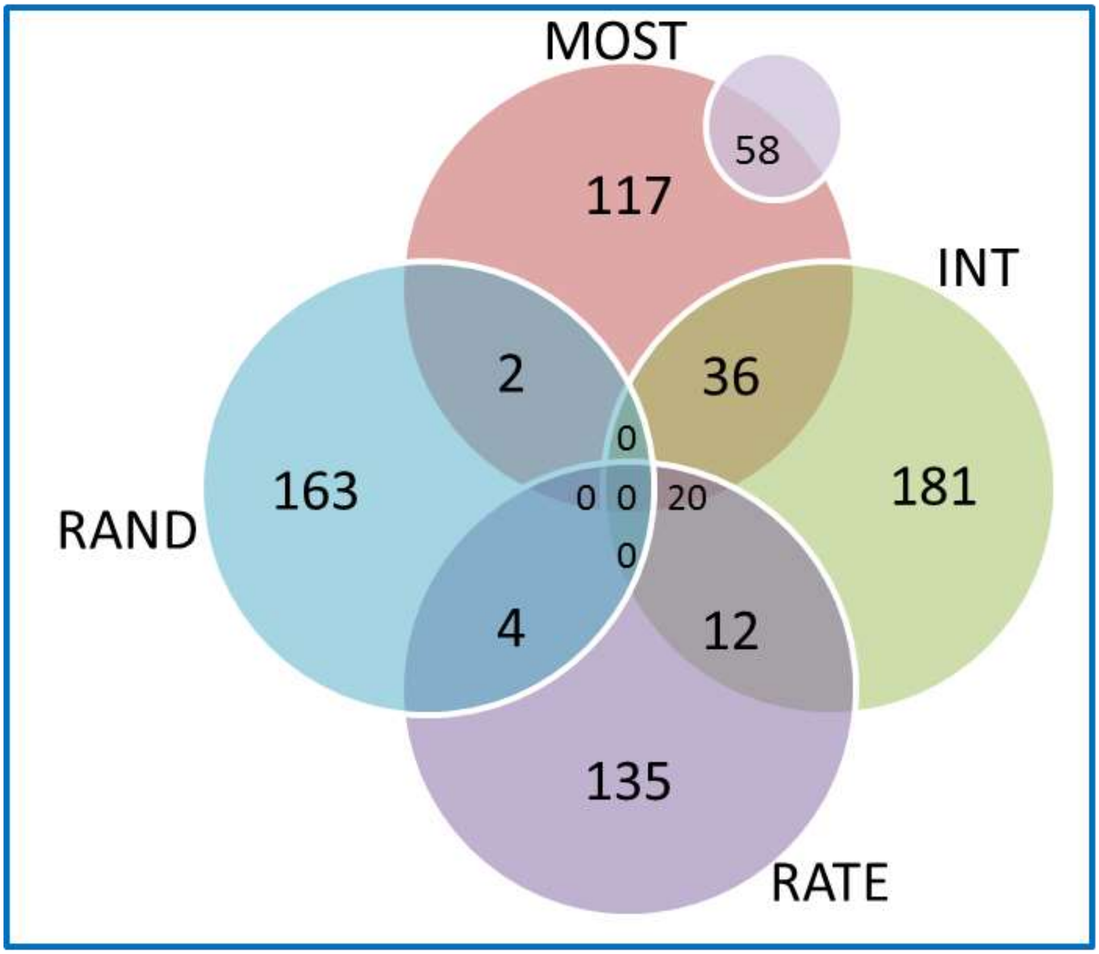
Appendices

Appendix 1.1: CV inventors' market applications

Code	Market Application Definition	Code	Market Application Definition
0	Unemployment – gap between known employment	**15**	industrial and manufacturing equipment
1	telecom firms - wired, fiber-optic cables	**16**	analytical and scientific research equipment
2	telecom firms - wireless applications	**17**	Imaging - cameras, printing and displays
3	computer components e.g., memory, disk storage	**18**	specialty glass – electrooptical, electromatic
4	complete computing systems and software	**19**	automotive
5	biotech, medical and other life sciences	**20A**	diversified, with telecom, multiple technologies
6	defense and security	**20B**	diversified, without telecom, multiple technologies
7	aerospace, space and aviation	**21A**	diversified, with telecom, single technology
8	renewable energy as well as energy storage	**21B**	diversified, without telecom, single technology
9	oilfield & gas	**101**	academia
10	lighting	**200**	consulting and professional services
11	environmental	**201**	professional society
12	chemicals	**202**	other nonprofit organizations
13	materials and semiconductor substrates	**999**	pre-employment: time before first known job
14	semiconductor manufacturing	**90**	unknown firm

Table A1: (Inventor employment states and) Market applications represented by 2100 firms in the CV database

Appendix 1.2: Sample Overlaps



Appendix 1.3: Regression Results

Table A2: Integration Patenting After Firm Change

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lninteg	lninteg	lninteg	lninteg	lninteg
Propensity to change firms	0.037***	0.028***	0.028***	0.024***	0.020***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Changing firms	-0.014***	-0.015***	-0.014***	-0.013**	-0.013**
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Previous Integration	0.043***	0.045***	0.046***	0.006	0.007
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
Previous General OE	0.010***	0.012***	0.012***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
During Bubble		0.014***	0.012***	0.018***	0.024***
		(0.004)	(0.004)	(0.004)	(0.005)
Post Burst		-0.019***	-0.018***	-0.015***	-0.017***
		(0.004)	(0.004)	(0.004)	(0.004)
During Bubble # Switching firms			0.019	0.033**	0.040**
			(0.013)	(0.014)	(0.016)
Post Burst # Switching firms			-0.011	0.023*	0.017
			(0.009)	(0.013)	(0.015)
Switching firms # Previous Integration				0.002	-0.001
				(0.021)	(0.021)
Switching firms # Previous General OE				-0.003	-0.002
				(0.005)	(0.005)
Previous Integration # Previous General OE				0.024***	0.024***
				(0.002)	(0.002)
Switching firms # Previous Integration # Previous General OE				-0.025***	-0.024***
				(0.007)	(0.007)
RATE Alone					0.000
					(0.009)
MOST Alone					-0.009*
					(0.005)
MOST and RATE overlap					0.061***
					(0.009)
RATE Alone # Switching firms					0.008
					(0.021)
MOST Alone # Switching firms					0.008
					(0.013)
MOST and RATE overlap # Switching firms					-0.029
					(0.025)

	(1)	(2)	(3)	(4)	(5)
During Bubble # RATE Alone					0.002
					(0.016)
During Bubble # MOST Alone					-0.033***
					(0.010)
During Bubble # MOST and RATE overlap					-0.095***
					(0.019)
Post Burst # RATE Alone					0.006
					(0.012)
Post Burst # MOST Alone					-0.000
					(0.007)
Post Burst # MOST and RATE overlap					-0.045***
					(0.014)
During Bubble # RATE Alone # Switching firms					0.003
					(0.057)
During Bubble # MOST Alone # Switching firms					-0.031
					(0.035)
During Bubble # MOST and RATE overlap # Switching firms					-0.014
					(0.052)
Post Burst # RATE Alone # Switching firms					0.022
					(0.035)
Post Burst # MOST Alone # Switching firms					0.002
					(0.024)
Post Burst # MOST and RATE overlap # Switching firms					0.019
Constant	0.041	0.043***	0.043***	0.042***	0.036***
	(0.057)	(0.006)	(0.006)	(0.005)	(0.005)
Observations	14,220	14,220	14,220	14,220	14,220
Number of cvid	473	473	473	473	473

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

Year effects for Model 1 are not included

Table A3: General OE Patenting After Fir m Change

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lnoe	lnoe	lnoe	lnoe	lnoe
Propensity to change firms	0.198***	0.221***	0.221***	0.255***	0.241***
	(0.018)	(0.016)	(0.016)	(0.016)	(0.016)
Changing firms	-0.083***	-0.091***	-0.105***	-0.099***	-0.058***
	(0.012)	(0.012)	(0.016)	(0.017)	(0.019)
Previous Integration	-0.045***	-0.054***	-0.054***	0.138***	0.080***
	(0.011)	(0.011)	(0.011)	(0.023)	(0.023)
Previous General OE	0.187***	0.191***	0.191***	0.212***	0.201***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
During Bubble		0.194***	0.193***	0.172***	0.233***
		(0.013)	(0.014)	(0.014)	(0.015)
Post Burst		-0.123***	-0.126***	-0.145***	-0.058***
		(0.014)	(0.014)	(0.014)	(0.015)
During Bubble # Switching firms			0.007	0.030	-0.030
			(0.040)	(0.045)	(0.050)
Post Burst # Switching firms			0.046*	0.077*	0.008
			(0.027)	(0.042)	(0.047)
Switching firms # Previous Integration				0.007	0.025
				(0.066)	(0.067)
Switching firms # Previous General OE				-0.009	0.008
				(0.015)	(0.017)
Previous Integration # Previous General OE				-0.074***	-0.050***
				(0.008)	(0.008)
Switching firms # Previous Integration # Previous General OE				-0.021	-0.021
				(0.021)	(0.023)
RATE Alone					0.205***
					(0.034)
MOST Alone					0.155***
					(0.019)
MOST and RATE overlap					0.575***
					(0.036)
RATE Alone # Switching firms					-0.116*
					(0.066)
MOST Alone # Switching firms					-0.102**
					(0.040)
MOST and RATE overlap # Switching firms					-0.395***
					(0.080)
During Bubble # RATE Alone					-0.035
					(0.052)

	(1)	(2)	(3)	(4)	(5)
During Bubble # MOST Alone					-0.235***
					(0.032)
During Bubble # MOST and RATE overlap					-0.085
					(0.061)
Post Burst # RATE Alone					-0.207***
					(0.039)
Post Burst # MOST Alone					-0.180***
					(0.022)
Post Burst # MOST and RATE overlap					-0.615***
					(0.044)
During Bubble # RATE Alone # Switching firms					-0.010
					(0.180)
During Bubble # MOST Alone # Switching firms					0.102
					(0.110)
During Bubble # MOST and RATE overlap # Switching firms					0.217
					(0.165)
Post Burst # RATE Alone # Switching firms					-0.056
					(0.110)
Post Burst # MOST Alone # Switching firms					0.155**
					(0.077)
Post Burst # MOST and RATE overlap # Switching firms					0.304**
					(0.131)
Constant	0.249	0.358***	0.360***	0.380***	0.303***
	(0.178)	(0.019)	(0.019)	(0.019)	(0.019)
Observations	14,220	14,220	14,220	14,220	14,220
Number of cvid	473	473	473	473	473

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

Year effects for Model 1 are not included

Table A4: Integration after Market Change

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lninteg	lninteg	lninteg	lninteg	lninteg
Propensity to change markets	0.0319***	0.0235***	0.0238***	0.0205***	0.0164***
	(0.00492)	(0.00421)	(0.00421)	(0.00386)	(0.00394)
Changing Markets	-0.00610	-0.00760*	-0.0102*	-0.0133**	-0.00762
	(0.00432)	(0.00430)	(0.00531)	(0.00548)	(0.00633)
During Bubble		0.0134***	0.0120***	0.0184***	0.0260***
		(0.00401)	(0.00409)	(0.00406)	(0.00467)
Post Burst		-0.0191***	-0.0192***	-0.0141***	-0.0159***
		(0.00407)	(0.00409)	(0.00388)	(0.00442)
During Bubble # Changing markets			0.0287*	0.0274	0.0299
			(0.0158)	(0.0175)	(0.0191)
Post Burst # Changing markets			0.00125	0.00121	-0.0106
			(0.00980)	(0.0164)	(0.0176)
RATE Alone					0.00441
					(0.00910)
MOST Alone					-0.00772
					(0.00476)
MOST and RATE overlap					0.0660***
					(0.00938)
RATE Alone # Changing markets					-0.0124
					(0.0216)
MOST Alone # Changing markets					-0.00683
					(0.0139)
MOST and RATE overlap # Changing markets					-0.0601**
					(0.0268)
During Bubble # RATE Alone					0.000928
					(0.0161)
During Bubble # MOST Alone					-0.0344***
					(0.0101)
During Bubble # MOST and RATE overlap					-0.110***
					(0.0186)
Post Burst # RATE Alone					0.00598
					(0.0122)
Post Burst # MOST Alone					-0.00399
					(0.00703)
Post Burst # MOST and RATE overlap					-0.0548***
					(0.0135)
During Bubble # RATE Alone # Changing markets					-0.0873
					(0.0860)

	(1)	(2)	(3)	(4)	(5)
During Bubble # MOST Alone # Changing markets					-0.0457
					(0.0475)
During Bubble # MOST and RATE overlap # Changing markets					0.120*
					(0.0701)
Post Burst # RATE Alone # Changing markets					-0.0161
					(0.0391)
Post Burst # MOST Alone # Changing markets					0.0581**
					(0.0290)
Post Burst # MOST and RATE overlap # Changing markets					0.150***
					(0.0547)
Previous Integration	0.0450***	0.0460***	0.0463***	0.00591	0.00514
	(0.00323)	(0.00322)	(0.00321)	(0.00628)	(0.00634)
Changing markets # Previous Integration				0.0317	0.0477*
				(0.0258)	(0.0264)
Previous General OE	0.00986***	0.0120***	0.0120***	0.00432***	0.00538***
	(0.00144)	(0.00141)	(0.00141)	(0.00144)	(0.00164)
Changing markets # Previous General OE				0.00939	0.00944
				(0.00601)	(0.00657)
Previous Integration # Previous General OE				0.0226***	0.0230***
				(0.00220)	(0.00228)
Changing markets # Previous Integration # Previous General OE				-0.0296***	-0.0382***
				(0.00826)	(0.00900)
Constant	0.0313	0.0392***	0.0398***	0.0398***	0.0326***
	(0.0568)	(0.00542)	(0.00545)	(0.00509)	(0.00532)
Observations	14,220	14,220	14,220	14,220	14,220
Number of cvid	473	473	473	473	473

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

Year effects for Model 1 are not included

Table A5: Integration Outcomes After Switching Out Of (Model 6) And Into (Model 7) Markets

	(6)	(7)
VARIABLES	lninteg	lninteg
Propensity to change markets	0.0165***	0.0159***
	(0.00384)	(0.00384)
Changing market applications	-0.0127	0.00601
	(0.0189)	(0.0213)
During bubble period	0.0168	0.0167
	(0.0232)	(0.0232)
Post-burst period	-0.00989	-0.0101
	(0.0137)	(0.0136)
Evanescent star	0.0596*	0.0596*
	(0.0348)	(0.0348)
Sustaining star	0.00291	0.00294
	(0.0266)	(0.0266)
Super star	0.0408	0.0409
	(0.0532)	(0.0531)
Previous integration	0.0147**	0.0145**
	(0.00615)	(0.00614)
Previous OE	0.00549***	0.00545***
	(0.00165)	(0.00164)
Telecom previous year # During bubble # RATE Alone # Switched markets	-0.0353	
	(0.236)	
Telecom previous year # During bubble # MOST and RATE overlap # Switched markets	0.185	
	(0.241)	
Telecom previous year # Post burst # RATE Alone # Switched markets	-0.0222	
	(0.135)	
Telecom previous year # Post burst # MOST Alone # Switched markets	0.134	
	(0.129)	
Telecom previous year # Post burst # MOST and RATE overlap # Switched markets	-0.0372	
	(0.195)	
Other market previous year # During bubble # RATE Alone # Switched markets	-0.217	
	(0.226)	
Other market previous year # During bubble # MOST Alone # Switched markets	-0.00419	
	(0.163)	
Other market previous year # Post burst # RATE Alone # Switched markets	-0.104	
	(0.116)	
Other market previous year # Post burst # MOST Alone # Switched markets	-0.00817	
	(0.125)	
Other market previous year # Post burst # MOST and RATE overlap # Switched markets	-0.0252	
	(0.182)	
Diversified with telecom previous year # During bubble # MOST Alone # Switched markets	0.0850	

	(6)	(7)
	(0.208)	
Diversified with telecom previous year # During bubble # MOST and RATE overlap # Switched markets	0.0598	
	(0.249)	
Diversified with telecom previous year # Post burst # RATE Alone # Switched markets	-0.304	
	(0.192)	
Diversified with telecom previous year # Post burst # MOST Alone # Switched markets	-0.0693	
	(0.129)	
Diversified with telecom previous year # Post burst # MOST and RATE overlap # Switched markets	0.195	
	(0.204)	
Diversified without telecom previous year # During bubble # MOST Alone # Switched markets	0.110	
	(0.175)	
Diversified without telecom previous year # Post burst # RATE Alone # Switched markets	-0.127	
	(0.165)	
Diversified without telecom previous year # Post burst # MOST Alone # Switched markets	0.374***	
	(0.145)	
Diversified without telecom previous year # Post burst # MOST and RATE overlap # Switched markets	0.0754	
	(0.238)	
Academia previous year # During bubble # MOST Alone # Switched markets	-0.0499	
	(0.203)	
Academia previous year # Post burst # RATE Alone # Switched markets	-0.103	
	(0.181)	
Academia previous year # Post burst # MOST Alone # Switched markets	-0.0112	
	(0.155)	
Telecom current year # During bubble # RATE Alone # Switched markets		-0.0290
		(0.225)
Telecom current year # During bubble # MOST Alone # Switched markets		0.149
		(0.176)
Telecom current year # During bubble # MOST and RATE overlap # Switched markets		0.707***
		(0.232)
1o.market4 # 2o.period # 0b.sample96_1p5pct # co.Changing markets		0
		(0)
Telecom current year # Post burst # RATE Alone # Switched markets		-0.0666
		(0.178)
Telecom current year # Post burst # MOST Alone # Switched markets		-0.00836
		(0.103)
Telecom current year # Post burst # MOST and RATE overlap # Switched markets		0.427*
		(0.221)
Other markets current year # During bubble # MOST Alone # Switched markets		0.124
		(0.152)

	(6)	(7)
Other markets current year # During bubble # MOST and RATE overlap # Switched markets		-0.0321
		(0.234)
Other markets current year # Post burst # RATE Alone # Switched markets		-0.118
		(0.113)
Other markets current year # Post burst # MOST Alone # Switched markets		-0.0447
		(0.0904)
Other markets current year # Post burst # MOST and RATE overlap # Switched markets		0.0203
		(0.217)
Diversified with telecom current year # During bubble # MOST and RATE overlap # Switched markets		-0.0622
		(0.217)
Diversified with telecom current year # Post burst # RATE Alone # Switched markets		-0.275*
		(0.156)
Diversified with telecom current year # Post burst # MOST Alone # Switched markets		0.628***
		(0.116)
Diversified without telecom current year # During bubble # RATE Alone # Switched markets		-0.0108
		(0.246)
Diversified without telecom current year # During bubble # MOST Alone # Switched markets		0.107
		(0.206)
Diversified without telecom current year # Post burst # RATE Alone # Switched markets		-0.147
		(0.163)
Diversified without telecom current year # Post burst # MOST Alone # Switched markets		-0.0231
		(0.115)
Diversified without telecom current year # Post burst # MOST and RATE overlap # Switched markets		0.0190
		(0.291)
Academia current year # During bubble # MOST Alone # Switched markets		0.125
		(0.201)
Academia current year # Post burst # RATE Alone # Switched markets		-0.111
		(0.149)
Academia current year # Post burst # MOST Alone # Switched markets		-0.0354
		(0.107)
Academia current year # Post burst # MOST and RATE overlap # Switched markets		-0.0266
		(0.225)
Constant	0.0356***	0.0349***
	(0.0108)	(0.0108)
Observations	14,219	14,220
Number of cvid	473	473

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

The lower order interactions between switching, period, sample and markets have been removed for brevity

Table A6: General OE after Market Change

	(1)	(2)	(3)	(4)	(5)
VARIABLES	lnoe	lnoe	lnoe	lnoe	lnoe
yhat_m4c	0.178***	0.199***	0.200***	0.231***	0.217***
	(0.016)	(0.014)	(0.014)	(0.015)	(0.015)
Changing markets	-0.084***	-0.102***	-0.120***	-0.113***	-0.071***
	(0.014)	(0.014)	(0.017)	(0.017)	(0.020)
During Bubble		0.193***	0.193***	0.173***	0.231***
		(0.013)	(0.013)	(0.013)	(0.015)
Post Burst		-0.120***	-0.122***	-0.140***	-0.055***
		(0.014)	(0.014)	(0.014)	(0.015)
During Bubble # Changing markets			0.007	0.027	-0.017
			(0.051)	(0.056)	(0.060)
Post Burst # Changing markets			0.065**	0.088*	0.004
			(0.031)	(0.052)	(0.056)
RATE Alone					0.197***
					(0.034)
MOST Alone					0.153***
					(0.019)
MOST and RATE overlap					0.575***
					(0.037)
RATE Alone # Changing markets					-0.074
					(0.068)
MOST Alone # Changing markets					-0.103**
					(0.044)
MOST and RATE overlap # Changing markets					-0.420***
					(0.084)
During Bubble # RATE Alone					-0.028
					(0.051)
During Bubble # MOST Alone					-0.234***
					(0.032)
During Bubble # MOST and RATE overlap					-0.088
					(0.059)
Post Burst # RATE Alone					-0.209***
					(0.039)
Post Burst # MOST Alone					-0.177***
					(0.022)
Post Burst # MOST and RATE overlap					-0.627***

	(1)	(2)	(3)	(4)	(5)
					(0.043)
During Bubble # RATE Alone # Changing markets					-0.273
					(0.271)
During Bubble # MOST Alone # Changing markets					0.185
					(0.149)
During Bubble # MOST and RATE overlap # Changing markets					0.163
					(0.221)
Post Burst # RATE Alone # Changing markets					0.007
					(0.123)
Post Burst # MOST Alone # Changing markets					0.231**
					(0.091)
Post Burst # MOST and RATE overlap # Changing markets					0.641***
					(0.172)
Previous Integration	-0.037***	-0.046***	-0.046***	0.149***	0.091***
	(0.010)	(0.011)	(0.011)	(0.023)	(0.023)
Changing markets # Previous Integration				0.047	0.091
				(0.083)	(0.083)
Previous General OE	0.190***	0.192***	0.191***	0.213***	0.201***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Changing markets # Previous General OE				-0.009	0.002
				(0.019)	(0.021)
Previous Integration # Previous General OE				-0.076***	-0.052***
				(0.008)	(0.008)
Changing markets # Previous Integration # Previous General OE				-0.030	-0.050*
				(0.027)	(0.029)
Constant	0.245	0.354***	0.358***	0.378***	0.299***
	(0.178)	(0.018)	(0.018)	(0.018)	(0.019)
Observations	14,220	14,220	14,220	14,220	14,220
Number of cvid	473	473	473	473	473

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

Year effects for Model 1 are not included

Table A7: General OE Outcomes After Switching Out Of (Model 6) And Into (Model 7) Markets

	(6)	**(7)**
VARIABLES	lnoe	lnoe
Propensity to change markets	0.198***	0.195***
	(0.014)	(0.014)
Changing market applications	-0.045	0.001
	(0.060)	(0.067)
During bubble period	0.189**	0.188**
	(0.074)	(0.074)
Post-burst period	-0.047	-0.048
	(0.045)	(0.045)
Evanescent star	0.244**	0.247**
	(0.114)	(0.114)
Sustaining star	0.128	0.126
	(0.087)	(0.087)
Super star	0.398**	0.401**
	(0.176)	(0.176)
Previous integration	0.072***	0.073***
	(0.022)	(0.022)
Previous OE	0.195***	0.194***
	(0.006)	(0.006)
Telecom previous year # during bubble period # RATE Alone # switched markets	1.189	
	(0.748)	
Telecom previous year # during bubble period # MOST and RATE overlap # switched markets	-0.464	
	(0.757)	
Telecom previous year # post-burst period # RATE Alone # switched markets	0.404	
	(0.424)	
Telecom previous year # post-burst period # MOST Alone # switched markets	0.431	
	(0.404)	
Telecom previous year # post-burst period # MOST and RATE overlap # switched markets	0.219	
	(0.614)	
Other markets previous year # during bubble period # RATE Alone # switched markets	1.387*	
	(0.713)	
Other markets previous year # during bubble period # MOST Alone # switched markets	1.214**	
	(0.516)	
Other markets previous year # post-burst period # RATE Alone # switched markets	0.254	
	(0.367)	
Other markets previous year # post-burst period # MOST Alone # switched markets	-0.041	
	(0.392)	
Other markets previous year # post-burst period # MOST and RATE overlap # switched markets	0.668	
	(0.574)	
Diversified with telecom previous year # during bubble period # MOST Alone # switched markets	0.905	

	(6)	(7)
	(0.653)	
Diversified with telecom previous year # during bubble period # MOST and RATE overlap # switched markets	0.298	
	(0.784)	
Diversified with telecom previous year # post-burst period # RATE Alone # switched markets	-0.082	
	(0.601)	
Diversified with telecom previous year # post-burst period # MOST Alone # switched markets	-0.019	
	(0.407)	
Diversified with telecom previous year # post-burst period # MOST and RATE overlap # switched markets	1.018	
	(0.638)	
Diversified without telecom previous year # during bubble period # MOST Alone # switched markets	2.639***	
	(0.551)	
Diversified without telecom previous year # post-burst period # RATE Alone # switched markets	-0.516	
	(0.518)	
Diversified without telecom previous year # post-burst period # MOST Alone # switched markets	0.503	
	(0.456)	
Diversified without telecom previous year # post-burst period # MOST and RATE overlap # switched markets	0.599	
	(0.745)	
10Telecom previous year # during bubble period # MOST Alone # switched markets	0.798	
	(0.638)	
10Telecom previous year # post-burst period # RATE Alone # switched markets	0.049	
	(0.568)	
10Telecom previous year # post-burst period # MOST Alone # switched markets	-0.661	
	(0.487)	
Telecom current year # during bubble period # RATE Alone # switched markets		-0.238
		(0.708)
Telecom current year # during bubble period # MOST Alone # switched markets		0.198
		(0.551)
Telecom current year # during bubble period # MOST and RATE overlap # switched markets		1.002
		(0.732)
Telecom current year # post-burst period # RATE Alone # switched markets		-1.109**
		(0.561)
Telecom current year # post-burst period # MOST Alone # switched markets		0.121
		(0.322)
Telecom current year # post-burst period # MOST and RATE overlap # switched markets		0.766
		(0.692)
Other markets current year # during bubble period # MOST Alone # switched markets		0.940**
		(0.474)
Other markets current year # during bubble period # MOST and RATE overlap # switched markets		0.152

	(6)	(7)
		(0.738)
Other markets current year # post-burst period # RATE Alone # switched markets		-0.343
		(0.356)
Other markets current year # post-burst period # MOST Alone # switched markets		-0.120
		(0.283)
Other markets current year # post-burst period # MOST and RATE overlap # switched markets		0.331
		(0.679)
Diversified with telecom current year # during bubble period # MOST and RATE overlap # switched markets		0.250
		(0.683)
Diversified with telecom current year # post-burst period # RATE Alone # switched markets		-0.539
		(0.488)
Diversified with telecom current year # post-burst period # MOST Alone # switched markets		0.707*
		(0.364)
Diversified without telecom current year # during bubble period # RATE Alone # switched markets		-0.154
		(0.777)
Diversified without telecom current year # during bubble period # MOST Alone # switched markets		0.585
		(0.645)
Diversified without telecom current year # post-burst period # RATE Alone # switched markets		-0.763
		(0.514)
Diversified without telecom current year # post-burst period # MOST Alone # switched markets		-0.067
		(0.360)
Diversified without telecom current year # post-burst period # MOST and RATE overlap # switched markets		0.943
		(0.909)
Academia current year # during bubble period # MOST Alone # switched markets		0.052
		(0.631)
Academia current year # post-burst period # RATE Alone # switched markets		-0.591
		(0.468)
Academia current year # post-burst period # MOST Alone # switched markets		-0.218
		(0.335)
Academia current year # post-burst period # MOST and RATE overlap # switched markets		0.305
		(0.703)
Constant	0.243***	0.240***
	(0.037)	(0.037)
Observations	14,219	14,220
Number of cvid	473	473

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

The lower order interactions between switching, period, sample and markets have been removed for brevity

Appendix 1.4 Full List of Hypotheses

A1 Inventors Changing Firms and Future Patenting

i. Inventors who switch firms increase their future patenting in integration on average, which is the enabling GPT technology.
Inventors who switch firms decrease their future patenting in general OE on average.

A2 Inventors Changing Firms During Different Economic Periods and Future Patenting

i. Inventors who switch firms during the bubble increase their future patenting in integration, as they are able to take advantage of increased venture capital funding during the bubble to explore new projects in the enabling GPT technology.
Inventors who switch firms during the bubble reduce their future patenting in general OE.

ii. Inventors who switch firms after the burst of the bubble reduce their future patenting in integration as the economic downturn's reduced financial incentives leads to a lack of funding for new technology exploration.
Inventors who switch firms after the burst of the bubble increase their future patenting in general OE as the economic downturn's reduced financial incentives leads them to exploit existing work in the established technology (March 1991).

A3 Inventor with Different Patent Portfolios Changing Firms and Future Patenting

Here, we will estimate:

$$\textit{Future (General OE or Integration) Patenting}_i = \beta_0 + \beta_1(\alpha_0 + \alpha_1 tech\_focus_i + \alpha_2 num\_coauthors_i + \alpha_3 tenure_i) + \beta_2 firm\_change_i \#\# OE\_portfolio_i \#\# INT\_portfolio_i + \mu$$

Given our identification of integration as the GPT enabling technology, we hypothesize that:

i. Inventors who already had many general OE patents as well as many integration patents and switch firms increase their future patenting in both general OE and integration.

ii. Inventors who already had many general OE patents but few integration patents and switch firms increase their future patenting in general OE but not integration.

iii. Inventors who already had few general OE patents but many integration patents and switch firms increase their future patenting in both general OE and integration.

iv. Inventors who already had few general OE patents as well as few integration patents and switch firms reduce their future patenting in both general OE and integration.

A4 Inventors with Different Productivity Profiles Changing Firms in Different Time Periods and Future Patenting

Here, we will estimate:

$$Future\ Patenting_i = \beta_0 + \beta_1(\alpha_0 + \alpha_1 tech\_focus_i + \alpha_2 num\_coauthors_i + \alpha_3 tenure_i)$$
$$\beta_2 firm\_change_i \ \#\#\ i.economic\_period\ \#\#\ i.inventor\_profile + \beta_3 firm\_change\ \#\#$$
$$OE\_portfolio_i\ \#\#\ INT\_portfolio_I + \mu$$

We hypothesize that:

i. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who change firms during the bubble increase their future patenting in integration as well as in general OE.
Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who change firms post-burst increase their future patenting in integration as well as in general OE.

ii. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) inventors who change firms during the bubble increase their future patenting in integration but not general OE
Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) inventors who change firms post-burst increase their future patenting in general OE but not in integration

iii. Evanescent Star (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) inventors who change firms during the bubble increase their future patenting in integration but not in general OE
Evanescent Star (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) inventors who change firms post-burst decrease their future patenting in both integration and general OE

iv. Non-Star inventors (everyone not in any of the previous Star categories) who change firms during the bubble increase their future patenting in general OE but not in integration
Non-Star inventors (everyone not in any of the previous Star categories) who change firms post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

B1 Inventors Changing Market Applications and Future Patenting

i. Inventors who switch market applications reduce their future patenting in general OE but not in integration, the GPT enabling technology

B2 Inventors Changing Market Applications During Different Economic Periods and Future Patenting

ii. Inventors who switch market applications during the bubble reduce their future patenting in general OE but increase their future patenting in integration.

iii. Inventors who switch market applications firms after the burst of the bubble increase their future patenting in general OE but reduce their future patenting in integration.

B3 Inventors Changing Market Applications with Different Patent Portfolios and Future Patenting

i. Inventors who already had many general OE patents as well as many integration patents and switch market applications increase their future patenting in both general OE and integration
ii. Inventors who already had many general OE patents but few integration patents and switch market applications increase their future patenting in general OE but not integration
iii. Inventors who already had few general OE patents but many integration patents and switch market applications increase their future patenting in both general OE and integration
iv. Inventors who already had few general OE patents as well as few integration patents and switch market applications reduce their future patenting in both general OE and integration

B4 Inventors Changing Market Applications with Different Productivity Profiles and Future Patenting

i. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who change market applications during the bubble increase their future patenting in integration as well as in general OE.
Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who change market applications post-burst increase their future patenting in general OE but not in integration

ii. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who change market applications during the bubble increase their future patenting in integration but not general OE
Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who change market applications post-burst increase their future patenting in general OE but not in integration

iii. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who change market applications during the bubble increase their future patenting in integration but not in general OE
Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who change market applications post-burst decrease their future patenting in both integration and general OE

iv. Non-Star inventors (everyone not in any of the previous Star categories) who change market applications during the bubble increase their future patenting in general OE but not in integration
Non-Star inventors (everyone not in any of the previous Star categories) who change market applications post-burst reduce their future patenting in general OE as well as in integration

B5 Inventors Changing Market Applications out of Specific Markets and Future Patenting
Here we will estimate:

$$Future\ Patenting_i = \beta_0 + \beta_1(\alpha_0 + \alpha_1 tech\_focus_i + \alpha_2 num\_co\_authors_i + \alpha_3 tenure_i) + \beta_2 i.market\_lag_i \#\# c.market\_change_i \#\# i.economic\_period \#\# i.inventor\_profile + \beta_3 c.market\_change_i \#\# i.OE\_portfolio_i \#\# INT\_portfolio_i + \mu$$

i. Inventors who switch out of telecom during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of telecom during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of telecom during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of telecom during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of telecom during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch out of telecom post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of telecom post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of telecom post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of telecom post-burst increase their future patenting in integration but not in general OE

h. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of telecom post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

ii. Inventors who switch out of diversified-with-telecom during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of diversified-with-telecom during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of diversified-with-telecom during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of diversified-with-telecom during the bubble increase their future patenting in integration but not in general OE
d. Non Star inventors (NonMOST and NonRATE) who switch out of diversified-with-telecom during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch out of diversified-with-telecom post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of diversified-with-telecom post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of diversified-with-telecom post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of diversified-with-telecom post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of diversified-with-telecom post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

iii. Inventors who switch out of diversified-without-telecom during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of diversified-without-telecom during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of diversified-without-telecom during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of diversified-without-telecom during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of diversified-without-telecom during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch out of diversified-without-telecom post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of diversified-without-telecom post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (MOST alone) inventors who switch out of diversified-without-telecom post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of diversified-without-telecom post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of diversified-without-telecom post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

iv. Inventors who switch out of academia during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of academia during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of academia during the bubble increase their future patenting in general OE but not in integration on average

c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of academia during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of academia during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch out of academia post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of academia post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of academia post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of academia post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of academia post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

v. Inventors who switch out of ‘other markets’ during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of other markets during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of other markets during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of other markets during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of other markets during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch out of ‘other markets’ post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch out of ‘other markets’ post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch out of ‘other markets’ post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch out of ‘other markets’ post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch out of ‘other markets’ post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

B6 Inventors Changing Market Applications into Specific Markets and Future Patenting

Here we will estimate:

$$Future\ Patenting_i = \beta_0 + \beta_1(\alpha_0 + \alpha_1 tech\_focus_i + \alpha_2 num\_co\_authors_i + \alpha_3 tenure_i) + \beta_2 i.market_i \#\# c.market\_change_i \#\# i.economic\_period \#\# i.inventor\_profile + \beta_3 c.market\_change_i \#\# i.OE\_portfolio_i \#\# INT\_portfolio_i + \mu$$

i. Inventors who switch into telecom during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into telecom during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into telecom during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into telecom during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch into telecom during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch into telecom post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into telecom post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into telecom post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into telecom post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch into telecom post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

ii. Inventors who switch into diversified-with-telecom during the bubble increase their future patenting in general OE but not in integration
a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into diversified-with-telecom during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into diversified-with-telecom during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into diversified-with-telecom during the bubble increase their future patenting in integration but not in general OE
d. Non Star inventors (NonMOST and NonRATE) who switch into diversified-with-telecom during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch into diversified-with-telecom post-burst increase their future patenting in general OE but not in integration
e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into diversified-with-telecom post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into diversified-with-telecom post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into diversified-

with-telecom post-burst increase their future patenting in integration but not in general OE

h. Non-Star inventors (everyone not in any of the previous Star categories) who switch into diversified-with-telecom post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

iii. Inventors who switch into diversified-without-telecom during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into diversified-without-telecom during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into diversified-without-telecom during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into diversified-without-telecom during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch into diversified-without-telecom during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch into diversified-without-telecom post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into diversified-without-telecom post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (MOST alone) inventors who switch into diversified-without-telecom post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into diversified-without-telecom post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch into diversified-without-telecom post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

iv. Inventors who switch into academia during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into academia during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into academia during the bubble increase their future patenting in general OE but not in integration on average
c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into academia during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch into academia during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch into academia post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into academia post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into academia post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into academia post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch into academia post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

v. Inventors who switch into 'other markets' during the bubble increase their future patenting in general OE but not in integration

a. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into other markets during the bubble increase their future patenting in integration as well as in general OE.
b. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into other markets during the bubble increase their future patenting in general OE but not in integration on average

c. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into other markets during the bubble increase their future patenting in integration but not in general OE
d. Non-Star inventors (everyone not in any of the previous Star categories) who switch into other markets during the bubble reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Inventors who switch into 'other markets' post-burst increase their future patenting in general OE but not in integration

e. Super Star inventors (i.e., top 1.5% of inventors by total number of patents as well as by annual patents per year pre-bubble) who switch into 'other markets' post-burst increase their future patenting in integration as well as in general OE.
f. Sustaining Star inventors (i.e., top 1.5% of inventors by total number of patents but not annual patents per year pre-bubble) who switch into 'other markets' post-burst increase their future patenting in general OE but not in integration on average
g. Evanescent Star inventors (i.e., top 1.5% of inventors by annual patents per year but not total number of patents pre-bubble) who switch into 'other markets' post-burst increase their future patenting in integration but not in general OE
h. Non-Star inventors (everyone not in any of the previous Star categories) who switch into 'other markets' post-burst reduce their future patenting in general OE as well as in integration due to the costs of moving and establishing a new line of work

Appendix 2.1: Classes and Subclasses Included in the Definition of Optoelectronics

The Fuchs Lab Optoelectronics Database created by Peter Pong uses the USPTO's classification system to identify Optoelectronics Patents, as well as the subset, Optoelectronics Integration. The table below shows the classes and subclasses that are included.

Optoelectronics Classes	
720	Dynamic Optical Information Storage and Retrieval
356	Optics: Measuring and Testing
372	Coherent Light Generators
385	Optical Waveguides
359	Optics: Systems (Including Communication) and Elements
398	Optical Communications
250/200-339 250/551	Radiant Energy - subclasses 200 through 239 for electrical circuits whose operations are controlled by means of a photocell, electrical circuits for supplying current or potential to a photocell and photocells in combination with optical means for controlling the radiant energy which illuminated the photocell; and subclass 551 for an optical signal isolator, per se.
438/24 438/25 438/27	Semiconductor Device Manufacturing: Process: Making Device Or Circuit Emissive Of Nonelectrical Signal: Packaging (e.g., with mounting, encapsulating, etc.) or treatment of packaged semiconductor: Having additional optical element (e.g., optical fiber, etc.):
353	Optics: Image Projectors
257/13, 257/21, 257/53-56, 257/59, 257/79-103, 257/113-118, 257/184-189, 257/225-234, 257/257-258, 257/290-294, 257/431-466	Active Solid-State Devices e.g. Transistors, Solid-State Diodes) – Subclasses Relevant To Optics And Light
Optoelectronics Integration	
385/014	Integrated Optical Circuit

Source: Fuchs Lab Optoelectronics Database Documentation

Appendix 2.2 Top Optoelectronics Integration And Rest Of Field Assignees By Patents Filed In Each Decade

A: Top Optoelectronic Integration Assignees by patents filed in each decade

Decade	Assignee Name	# Pats	Country	Market Application
1971 – 1980	AT T CORP	7	USA	Telecom
	HUGHES AIRCRAFT COMPANY	5	USA	Defense and Space
	THOMSON CSF	5	USA	Diversified with telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	4	USA	Other (Computing)
	CONSIGLIO NAZIONALE DELLE RICERCHE	2	ITALY	Diversified with telecom
	SIEMENS AKTIENGESELLSCHAFT	2	GERMANY	Diversified without Telecom
	TEXAS INSTRUMENTS INCORPORATED	2	USA	Other (semiconductor manufacturing)
	UNISYS CORPORATION	2	USA	Diversified with telecom
	UNITED STATES OF AMERICA ARMY	2	USA	Defense and space
	WESTINGHOUSE ELECTRIC CORP	2	USA	Diversified without Telecom
	XEROX CORPORATION	2	USA	Other (Imaging)
1981 – 1990	AT T CORP	22	USA	Telecom
	SIEMENS AKTIENGESELLSCHAFT	18	GERMANY	Diversified without Telecom
	HITACHI LTD	12	JAPAN	Diversified with telecom
	THOMSON CSF	9	USA	Diversified with telecom
	U S PHILIPS CORPORATION	8	NETHERLANDS	Diversified without telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	7	USA	Other (Computing)
	UNITED TECHNOLOGIES CORPORATION	7	USA	Diversified without Telecom
	BROTHER KOGYO KABUSHIKI KAISHA	6	JAPAN	Diversified without Telecom
	HUGHES AIRCRAFT COMPANY	5	USA	Defense and Space
	CANON KABUSHIKI KAISHA	5	JAPAN	Other (Imaging)
	MITSUBISHI DENKI KABUSHIKI KAISHA	5	JAPAN	Diversified without Telecom
	NIPPON TELEGRAPH TELEPHONE CORP	5	JAPAN	Telecom
1991 – 2000	AT&T/LUCENT TECHNOLOGIES INC	90	USA	Telecom
	NEC CORPORATION	42	JAPAN	Telecom
	FUJITSU LIMITED	39	JAPAN	Other (Computing)
	MOTOROLA INC	36	USA	Telecom

	CORNING INCORPORATED	26	USA	Diversified with telecom
	INTEL CORPORATION	22	USA	Other (Computing)
	SIEMENS AKTIENGESELLSCHAFT	20	GERMANY	Diversified without Telecom
	ROBERT BOSCH GMBH	19	GERMANY	Diversified without Telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	17	USA	Other (Computing)
2001 - 2010	INTEL CORPORATION	101	USA	Other (Computing)
	FUJITSU LIMITED	74	JAPAN	Other (Computing)
	INFINERA CORPORATION	70	USA	Telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	48	USA	Other (Computing)
	NEC CORPORATION	47	JAPAN	Telecom
	HEWLETT PACKARD DEVELOPMENT COMPANY L P	44	USA	Diversified with telecom
	SUMITOMO ELECTRIC INDUSTRIES LTD	38	JAPAN	Diversified with telecom
	CANON KABUSHIKI KAISHA	30	JAPAN	Other (imaging)
	THE FURUKAWA ELECTRIC CO LTD	28	JAPAN	Diversified with Telecom
	FUJI XEROX CO LTD	26	JAPAN	Diversified without Telecom
	FINISAR CORPORATION	26	USA	Telecom

B: Top Optoelectronic Rest Of Field Assignees By Patents Filed In Each Decade

Decade	Assignee Name	# Patents	Country	Market Application
1955 - 1960	UNITED STATES OF AMERICA ARMY	1	USA	Defense and Space
	LORAL CORPORATION	1	USA	Telecom
	RCA CORPORATION	1	USA	Diversified with telecom
1961 - 1970	UNITED STATES OF AMERICA NAVY	4	USA	Defense and Space
	AMERICAN OPTICAL CORPORATION	3	USA	Biotech
	AVCO CORPORATION	3	USA	Defense and Space
	RAYTHEON COMPANY	2	USA	Defense and Space
	WESTINGHOUSE ELECTRIC CORP	2	USA	Diversified without telecom
	AMERICAN STANDARD INC	2	USA	Other (Gen Manufacturing)
	PHILCO CORPORATION	2	USA	Diversified with Telecom
	SANDERS ASSOCIATES INC	2	USA	Defense and Space
	TECHNICAL OPERATIONS INCORPORATED	2	UNK	Unknown
1971 - 1980	UNITED STATES OF AMERICA NAVY	358	USA	Defense and Space
	AT T CORP	355	USA	Telecom
	CANON KABUSHIKI KAISHA	331	JAPAN	Other (Imaging)
	SIEMENS AKTIENGESELLSCHAFT	274	GERMANY	Diversified without telecom
	RCA CORPORATION	269	USA	Diversified with telecom
	XEROX CORPORATION	262	USA	Other (Imaging)
	UNITED STATES OF AMERICA ARMY	240	USA	Defense and Space
	U S PHILIPS CORPORATION	229	NETHERLANDS	Diversified without telecom
	OLYMPUS OPTICAL CO LTD	220	JAPAN	Diversified without telecom
	HITACHI LTD	218	JAPAN	Diversified with telecom
1981 - 1990	CANON KABUSHIKI KAISHA	1056	JAPAN	Other (Imaging)
	AT T CORP	775	USA	Telecom
	HITACHI LTD	657	JAPAN	Diversified with telecom
	U S PHILIPS CORPORATION	573	NETHERLANDS	Diversified without telecom
	OLYMPUS OPTICAL CO LTD	501	JAPAN	Diversified without Telecom
	SIEMENS AKTIENGESELLSCHAFT	481	GERMANY	Diversified without telecom

	HUGHES AIRCRAFT COMPANY	472	USA	Defense and Space
	TOSHIBA CORPORATION	470	JAPAN	Other (Computing)
	FUJI PHOTO FILM CO LTD	363	JAPAN	Other (Imaging)
1991 - 2000	CANON KABUSHIKI KAISHA	1805	JAPAN	Other (Imaging)
	LUCENT TECHNOLOGIES INC	1245	USA	Telecom
	NIKON CORPORATION	1199	JAPAN	Other (Imaging)
	NEC CORPORATION	1162	JAPAN	Telecom
	FUJITSU LIMITED	964	JAPAN	Other (Computing)
	SONY CORPORATION	945	JAPAN	Other (Computing)
	OLYMPUS OPTICAL CO LTD	878	JAPAN	Diversified without Telecom
	MATSUSHITA ELECTRIC INDUSTRIAL CO LTD	834	JAPAN	Diversified without Telecom
	HITACHI LTD	755	JAPAN	Diversified with telecom
	ASAHI KOGAKU KOGYO KABUSHIKI KAISHA	735	JAPAN	Other (Imaging)
2001 - 2010	CANON KABUSHIKI KAISHA	1884	JAPAN	Other (Imaging)
	SAMSUNG ELECTRONICS CO LTD	1629	S. KOREA	Other (Computing)
	FUJITSU LIMITED	1222	JAPAN	Other (Computing)
	SONY CORPORATION	1218	JAPAN	Other (Computing)
	SEIKO EPSON CORPORATION	1162	JAPAN	Diversified without Telecom
	HITACHI LTD	742	JAPAN	Diversified with telecom
	MATSUSHITA ELECTRIC INDUSTRIAL CO LTD	729	JAPAN	Diversified without Telecom
	AGILENT TECHNOLOGIES INC	707	USA	Diversified with telecom
	OLYMPUS CORPORATION	707	JAPAN	Diversified without Telecom
	SUMITOMO ELECTRIC INDUSTRIES LTD	682	JAPAN	Diversified with telecom

Appendix 2.3 Top Optoelectronics Integration And Rest Of Field Assignees By Patents Filed From 1955 Up To The End Each Decade

A: Top Optoelectronic Integration Assignees

Decade	Assignee Name	# Patents	Country	Market Application
1980	AT T CORP	7	USA	Telecom
	THOMSON CSF	5	USA	Diversified with telecom
	HUGHES AIRCRAFT COMPANY	5	USA	Defense and Space
	INTERNATIONAL BUSINESS MACHINES CORPORATION	4	USA	Other (Computing)
	XEROX CORPORATION	2	USA	Other (Imaging)
	SIEMENS AKTIENGESELLSCHAFT	2	GERMANY	Diversified without telecom
	TEXAS INSTRUMENTS INCORPORATED	2	USA	Other (Semiconductor Manufacturing)
	UNITED STATES OF AMERICA ARMY	2	USA	Defense and Space
	WESTINGHOUSE ELECTRIC CORP	2	USA	Diversified without telecom
	CONSIGLIO NAZIONALE DELLE RICERCHE	2	ITALY	Diversified with Telecom
	UNISYS CORPORATION	2	USA	Diversified with telecom
1990	AT T CORP	29	USA	Telecom
	SIEMENS AKTIENGESELLSCHAFT	20	GERMANY	Diversified without telecom
	THOMSON CSF	14	USA	Diversified with telecom
	HITACHI LTD	12	JAPAN	Diversified with telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	11	USA	Other (Computing)
	HUGHES AIRCRAFT COMPANY	10	USA	Defense and Space
	U S PHILIPS CORPORATION	8	NETHERLANDS	Diversified without telecom
	UNITED TECHNOLOGIES CORPORATION	7	USA	Diversified without telecom
	BROTHER KOGYO KABUSHIKI KAISHA	6	JAPAN	Diversified without telecom
2000	AT T CORP + LUCENT	119	USA	Telecom
	NEC CORPORATION	45	JAPAN	Telecom
	SIEMENS AKTIENGESELLSCHAFT	40	GERMANY	Diversified without telecom
	FUJITSU LIMITED	40	JAPAN	Other (Computing)
	MOTOROLA INC	39	USA	Telecom

	CORNING INCORPORATED	29	USA	Diversified with telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	28	USA	Other (Computing)
	HITACHI LTD	25	JAPAN	Diversified with telecom
	INTEL CORPORATION	22	USA	Other (Computing)
	THOMSON CSF	20	USA	Diversified with telecom
2010	INTEL CORPORATION	123	USA	Other (Computing)
	FUJITSU LIMITED	114	JAPAN	Other (Computing)
	NEC CORPORATION	92	JAPAN	Telecom
	AT T CORP + LUCENT	142	USA	Telecom
	INTERNATIONAL BUSINESS MACHINES CORPORATION	76	USA	Other (Computing)
	INFINERA CORPORATION	70	USA	Telecom
	MOTOROLA INC	47	USA	Telecom
	CANON KABUSHIKI KAISHA	45	JAPAN	Other (Imaging)
	SIEMENS AKTIENGESELLSCHAFT	44	GERMANY	Diversified without telecom
	CORNING INCORPORATED	44	USA	Diversified with telecom
	HEWLETT PACKARD DEVELOPMENT COMPANY L P	44	USA	Diversified with telecom

B: Top Optoelectronic Rest of Field Assignees

Decade	Assignee Name	# Patents	Country	Market Application
1960	UNITED STATES OF AMERICA ARMY	1	USA	Defense and Space
	LORAL CORPORATION	1	USA	Telecom
	RCA CORPORATION	1	USA	Diversified with telecom
1970	UNITED STATES OF AMERICA NAVY	4	USA	Defense and Space
	AVCO CORPORATION	3	USA	Defense and Space
	AMERICAN OPTICAL CORPORATION	3	USA	Biotech
	RAYTHEON COMPANY	2	USA	Defense and Space
	WESTINGHOUSE ELECTRIC CORP	2	USA	Diversified without telecom
	SANDERS ASSOCIATES INC	2	USA	Defense and Space
	TECHNICAL OPERATIONS INCORPORATED	2	UNK	Unknown
	AMERICAN STANDARD INC	2	USA	Other (Gen Manufacturing)
	PHILCO CORPORATION	2	USA	Diversified with Telecom
1980	UNITED STATES OF AMERICA NAVY	362	USA	Defense and Space
	AT T CORP	356	USA	Telecom
	CANON KABUSHIKI KAISHA	331	JAPAN	Other (Imaging)
	SIEMENS AKTIENGESELLSCHAFT	274	GERMANY	Diversified without telecom
	RCA CORPORATION	270	USA	Diversified with telecom
	XEROX CORPORATION	263	USA	Other (Imaging)
	UNITED STATES OF AMERICA ARMY	241	USA	Defense and Space
	U S PHILIPS CORPORATION	229	NETHERLANDS	Diversified without telecom
	OLYMPUS OPTICAL CO LTD	220	JAPAN	Diversified without telecom
	HITACHI LTD	218	JAPAN	Diversified with telecom
1990	CANON KABUSHIKI KAISHA	1387	JAPAN	Other (imaging)
	AT T CORP	1131	USA	Telecom
	HITACHI LTD	875	JAPAN	Diversified with telecom
	U S PHILIPS CORPORATION	802	NETHERLANDS	Diversified without telecom
	SIEMENS AKTIENGESELLSCHAFT	755	GERMANY	Diversified without telecom
	OLYMPUS OPTICAL CO LTD	721	JAPAN	Diversified without telecom

	UNITED STATES OF AMERICA NAVY	706	USA	Defense and Space
	HUGHES AIRCRAFT COMPANY	626	USA	Defense and Space
	TOSHIBA CORPORATION	544	JAPAN	Other (Computing)
	XEROX CORPORATION	509	USA	Other (Imaging)
2000	CANON KABUSHIKI KAISHA	3192	JAPAN	Other (Imaging)
	AT T + LUCENT	2952	USA	Telecom
	HITACHI LTD	1630	JAPAN	Diversified with Telecom
	NIKON CORPORATION	1601	JAPAN	Other (Imaging)
	OLYMPUS OPTICAL CO LTD	1599	JAPAN	Diversified without telecom
	NEC CORPORATION	1436	JAPAN	Telecom
	MATSUSHITA ELECTRIC INDUSTRIAL CO LTD	1170	JAPAN	Diversified without Telecom
	FUJITSU LIMITED	1163	JAPAN	Other (Computing)
	U S PHILIPS CORPORATION	1156	NETHERLANDS	Diversified without telecom
	SONY CORPORATION	1155	JAPAN	Other (Computing)
2010	CANON KABUSHIKI KAISHA	5076	JAPAN	Other (Imaging)
	AT T CORP	3517	USA	Telecom
	FUJITSU LIMITED	2385	JAPAN	Other (Computing)
	SONY CORPORATION	2373	JAPAN	Other (Computing)
	HITACHI LTD	2372	JAPAN	Diversified with Telecom
	SAMSUNG ELECTRONICS CO LTD	2184	S. KOREA	Other (Computing)
	NIKON CORPORATION	2078	JAPAN	Other (Imaging)
	MATSUSHITA ELECTRIC INDUSTRIAL CO LTD	1899	JAPAN	Diversified without Telecom
	NEC CORPORATION	1851	JAPAN	Telecom
	OLYMPUS OPTICAL CO LTD	1800	JAPAN	Diversified without telecom

Appendix 2.4 Top Optoelectronics Integration And Rest Of Field Assignees By Citations/Patent Received By End Of Each Decade

A: Top Optoelectronic Integration Assignees

Decade	Assignee Name	Cites/Pat	Country	Market Application
1980	INTERNATIONAL STANDARD ELECTRIC CORPORATION	4.0	USA	TELECOM
	TEXAS INSTRUMENTS INCORPORATED	3.5	USA	Other (Semic. Manuf.)
	TOKYO INSTITUTE OF TECHNOLOGY	3.0	JAPAN	ACADEMIA
	ENVIRONMENTAL RESEARCH INSTITUTE OF MICHIGAN	3.0	USA	Other (Environmental)
	AT T CORP	2.6	USA	Telecom
	ITT CORPORATION	2.0	USA	Telecom
	UNITED STATES OF AMERICA ARMY	2.0	USA	Defense and Space
	SIEMENS AKTIENGESELLSCHAFT	2.0	GERMANY	Diversified w/out telecom
	SHARP KABUSHIKI KAISHA	2.0	JAPAN	Diversified w/out telecom
1990	ROCKWELL INTERNATIONAL CORPORATION	23.0	USA	Defense and Space
	ITT CORPORATION	15.0	USA	Telecom
	TOKYO INSTITUTE OF TECHNOLOGY	14.0	JAPAN	Academia
	INTERNATIONAL STANDARD ELECTRIC CORPORATION	12.0	USA	TELECOM
	HONEYWELL INC	12.0	USA	Diversified w/o Telecom
	ANT NACHRICHTENTECHNIK GMBH	11.0	GERMANY	TELECOM
	CANON KABUSHIKI KAISHA	10.0	JAPAN	Other (Imaging)
	XEROX CORPORATION	9.5	USA	Other (Imaging)
	OMRON TETEISI ELECTRONICS CO	9.3	JAPAN	Diversified without telecom
	HUGHES AIRCRAFT COMPANY	8.6	USA	Defense and Space
2000	UNIVERSITY OF DELAWARE	71.0	USA	Academia
	HER MAJESTY THE QUEEN IN RIGHT OF CANADA	67.0	CANADA	Defense and Space
	AT T IPM CORP	60.0	USA	Telecom

	UNIVERSITY OF MARYLAND	38.0	USA	Academia
	UNITED STATES OF AMERICA NATIONAL AERONAUTICS AND SPACE ADMINISTRATION	35.0	USA	Defense and Space
	SPECTRA DIODE LABORATORIES INC	33.0	USA	Telecom
	MCNC	32.5	USA	TELECOM
	UNIVERSITY OF SOUTHERN CALIFORNIA	31.0	USA	Academia
	TELEFUNKEN SYSTEMTECHNIK GMBH	29.0	GERMAN Y	Diversified without Telecom
	AMP INCORPORATED	29.0	USA	Diversified with telecom
2010	HER MAJESTY THE QUEEN IN RIGHT OF CANADA	116.0	CANADA	Defense and Space
	MACRO VISION TECHNOLOGY INC	90.0	USA	Telecom
	AT T IPM CORP	86.0	USA	Telecom
	UNITED STATES OF AMERICA NATIONAL AERONAUTICS AND SPACE ADMINISTRATION	63.0	USA	Defense and Space
	SPECTRA DIODE LABORATORIES INC	57.0	USA	Telecom
	MASSASCUSETTS INSTITUTE OF TECHNOLOGY	55.0	USA	Academia
	UNIVERSITY OF MARYLAND	52.0	USA	Academia
	TELEFUNKEN SYSTEMTECHNIK GMBH	49.0	USA	Telecom
	LDT GMB H CO LASER DISPLAY TECHNOLOGIE KG	48.0	GERMAN Y	Diversified with Telecom
	UNIVERSITY OF DELAWARE	45.0	USA	Academia

B: Top Optoelectronic Rest of Field Assignees

Decade	Assignee Name	Cites/Pat	Country	Market Application
1980	REMA ELECTRONIC LTD	17.0	SWEDEN	Diversified without Telecom
	SOLERGY INC	17.0	USA	Other (Energy)
	BURRON MEDICAL PRODUCTS INC	11.0	GERMANY	Other (Biotech)
	MAINELINE SALES CO INC	11.0	USA	Other (Energy)
	LASER GRAPHIC SYSTEMS CORPORATION	11.0	USA	Unknown
	KAPTRON INC	11.0	USA	Telecom
	ZELLWEGER LTD	10.0	USA	Other (Gas Detection)
	DESERT SUNSHINE EXPOSURE TESTS INC	10.0	USA	Other (Energy)
1990	SPACE LYTE INTERNATIONAL INC	44.0	USA	Unknown
	HULSBECK FURST GMBH CO KG	39.0	GERMANY	Other (Automotive)
	BURRON MEDICAL PRODUCTS INC	37.0	GERMANY	Other (Biotech)
	UNITED STATES OF AMERICA	35.5	USA	Defense and Space
	SYNDICAT DES CONSTRUCTEURS D APPAREILS RADIO RECEPTEURS ET	34.0	FRANCE	Diversified without telecom
	SECURITY ORGANIZATION SUPREME SOS INC	33.0	USA	Diversified without telecom
	LOGE INTERPRETATION SYSTEMS INC	30.0	USA	Diversified without telecom
	ZELLWEGER LTD	30.0	USA	Other (Gas Detection)
	MAINELINE SALES CO INC	30.0	USA	Other (Energy)
2000	INSIGHT TELECAST INC	184.0	USA	Telecom
	INTERACTIVE SYSTEMS INC	157.0	USA	Other (Computing)
	VANDER CORPORATION	122.0	UNK	UNKNOWN
	TANDEM COMPUTERS INCORPORATED	116.0	USA	Diversified with Telecom
	HULSBECK FURST GMBH CO KG	111.0	GERMANY	Other (Automotive)
	LRI L P	108.0	USA	Other (Unknown)
	SPACE LYTE INTERNATIONAL INC	105.0	USA	Unknown
	CAMBRIDGE RESEARCH AND INNOVATION LIMITED	90.0	UK	Other (Venture Capital)
	ALCATEL NA NETWORK SYSTEMS CORP	88.0	FRANCE	Telecom
2010	CAMBRIDGE RESEARCH AND INNOVATION LIMITED	241.0	UK	Other (Venture Capital)

INTERACTIVE SYSTEMS INC	209.0	USA	Other (Computing)
INSIGHT TELECAST INC	208.0	USA	Telecom
VANDER CORPORATION	160.0	UNK	UNKNOWN
TANDEM COMPUTERS INCORPORATED	135.0	USA	Diversified with Telecom
LRI L P	134.0	USA	Other (Unknown)
ALCATEL NA NETWORK SYSTEMS CORP	133.0	FRANCE	Telecom
SPACE LYTE INTERNATIONAL INC	128.0	USA	Unknown
SCHOOLMAN SCIENTIFIC CORPORATION	121.0	USA	Other (Biotech)
HULSBECK FURST GMBH CO KG	116.0	GERMANY	Other (Automotive)

Bibliography

Agarwal, R. (1996). Technological activity and survival of firms. *Economics Letters, 52*(1), 101-108.

Agarwal, R., Anand, J., Bercovitz, J., & Croson, R. (2012). Spillovers across organizational architectures: The role of prior resource allocation and communication in post-acquisition coordination outcomes. *Strategic Management Journal*, *33*(6), 710-733.

Agarwal, R., Audretsch, D., & Sarkar, M. B. (2007). The process of creative construction: knowledge spillovers, entrepreneurship, and economic growth. *Strategic Entrepreneurship Journal, 1*(3-4), 263-286.

Agarwal, R., Ganco, M., & Ziedonis, R. H. (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal, 30*(13), 1349-1374.

Agrawal, A., & Henderson, R. (2002). Putting patents in context: Exploring knowledge transfer from MIT. *Management Science, 48*(1), 44-60.

Agrawal, A., Cockburn, I., & McHale, J. (2006). Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, *6*(5), 571-591.

Agrawal, A., Kapur, D., McHale, J., & Oettl, A. (2011). Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. *Journal of Urban Economics, 69*(1), 43-55.

Agrawal, A., McHale, J., & Oettl, A. (2013). Why stars matter. *University of Toronto mimeo*.

Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

Alcacer, J., & Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics*, *88*(4), 774-779.

Almeida, P., & Kogut, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management science, 45*(7), 905-917.

Almeida, P., Dokko, G., & Rosenkopf, L. (2003). Startup size and the mechanisms of external learning: increasing opportunity and decreasing ability? *Research Policy, 32*(2), 301-315.

Azoulay, P., Ding, W., & Stuart, T. (2009). The impact of academic patenting on the rate, quality and direction of (public) research output. *Journal of Industrial Economics*, *57*(4), 637-676.

Azoulay, P., Graff Zivin, J. S., & Manso, G. (2011). Incentives and creativity: evidence from the academic life sciences. *The RAND Journal of Economics*, *42*(3), 527-554.

Azoulay, P., Graff Zivin, J., & Sampat, B. (2012). The diffusion of scientific knowledge across time and space: Evidence from professional transitions for the superstars of medicine. *The Rate & Direction of Inventive Activity Revisited*, 107-155.

Azoulay, P., Graff Zivin, J., & Wang, J. (2010). Superstar extinction. *Quarterly Journal of Economics, 25,* 549-589.

Azoulay, P., Liu, C. C., & Stuart, T. E. (2009). Social influence given (partially) deliberate matching: Career imprints in the creation of academic entrepreneurs. *Harvard Business School mimeo*.

Barlevy, G. (2002). The Sullying Effect of Recessions. *The Review of Economic Studies, 69*(1), 65-96.
Bayus, B. L., & Agarwal, R. (2007). The role of pre-entry experience, entry timing, and product technology strategies in explaining firm survival. *Management Science, 53*(12), 1887-1902.
Becker, S. O., & Ichino, A. (2002). Estimation of Average Treatment Effects based on Propensity Scores. *The Stata Journal*, *2*(4), 358-377.
Berchicci, L., Tucci, C. L., & Zazzara, C. (2013). The influence of industry downturns on the propensity of product versus process innovation. *Industrial and Corporate Change*
Bowlus, A. J. (1995). Matching Workers and Jobs: Cyclical fluctuations in Match Quality. *Journal of Labor Economics, 13*(2), 335-350.
Breschi, S., & Lissoni, F. (2009). Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography, 9*(4), 439-468.
Bresnahan, T. F., & Raff, D. M. (1991). Intra-industry heterogeneity and the Great Depression: The American motor vehicles industry, 1929–1935. *The Journal of Economic History*, *51*(02), 317-331.
Brunello, G. (2009). The effect of economic downturns on apprenticeships and initial workplace training: a review of the evidence. *Journal of Empirical Research in Vocational Education and Training. 1*(2), 145-171.
Caballero, R. J. & Hammour, M. L. (1994). The Cleansing Effect of Recessions. *American Economic Review, 84*(5), 1350-1368.
Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Who leaves, where to, and why worry? employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, *33*(1), 65-87.
Carnahan, S., Agarwal, R., & Campbell, B. A. (2012). Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management Journal*, *33*(12), 1411-1430.
Choudhury, P. R. (2010). Seeking Resources or Seeking Knowledge? A Study of Mobility and Knowledge Creation Using Micro Data. *Wharton Business School mimeo*.
Cole, Jonathan R., and Stephen Cole (1972). The Ortega Hypothesis. *Science, 178*, 368-375.
Corredoira, R. A., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal*, *31*(2), 159-181.
Crespi, G. A., Geuna, A., & Nesta, L. (2007). The mobility of university inventors in Europe. *The Journal of Technology Transfer*, *32*(3), 195-215.
Davis, S. J., Haltiwanger, J. C., and Schuh S., (1996). *Job Creation and Destruction*. Cambridge, Mass.: The MIT Press
de Solla Price, Derek J. (1963). *Little Science, Big Science* New York, NY: Columbia University Press
Dokko, G., & Rosenkopf, L. (2010). Social capital for hire? Mobility of technical professionals and firm influence in wireless standards committees. *Organization Science, 21*(3), 677-695.
Eng, J. S., (2010). Fiber Optic Solutions for High-Speed Networks - U.S. Optoelectronics Industry Perspective. *Optoelectronic Industry Development Association mimeo*.
Ferry, J., (2010). U.S. Competitiveness in the Optical Industry and the Rise of Infinera. *Optoelectronic Industry Development Association mimeo*.
Field, A. J. (2003). The most technologically progressive decade of the century. *American Economic Review, 93*: 1399-1413.

Field, A. J. (2011). *A Great Leap Forward: 1930s Depression and US Economic Growth*. Yale University Press.

Fleming, L., & Marx, M. (2006). Managing Creativity in Small Worlds. *California Management Review*, *48*(4).

Fleming, L., King III, C., & Juda, A. I. (2007). Small worlds and regional innovation. *Organization Science, 18*(6), 938-954.

Fuchs, E., & Kirchain, R. (2010). Design for location? The impact of manufacturing offshore on technology competitiveness in the optoelectronics industry. *Management Science, 56*(12), 2323-2349.

Garud, R., & Rappa, M. A. (1995). On the persistence of researchers in technological development. *Industrial and Corporate Change, 4*(3), 531-554.

Geroski, P. A., & Gregg, P. (1997). *Coping with Recession: UK company performance in adversity (Vol. 38)*. Cambridge University Press

Gittell, R., and Sohl, J. (2005). Technology Centers During the Economic Downturn: What Have We Learned? *Entrepreneurship & Regional Development 17*(4), 293-312.

Giuri, P., Mariani, M., Brusoni, S., Crespi, G., Francoz, D., Gambardella, A., & Verspagen, B. (2007). Inventors and invention processes in Europe: Results from the PatVal-EU survey. *Research Policy, 36*(8), 1107-1127.

Godart, F. C., Shipilov, A. V., & Claes, K. (2013). Making the Most of the Revolving Door: The Impact of Outward Personnel Mobility Networks on Organizational Creativity. Organization *Science. 25*(2), 377-400

Goldfarb, B. D., Pfarrer, M. D., & Kirsch, D. (2005). Searching for ghosts: business survival, unmeasured entrepreneurial activity and private equity investment in the dot-com era. *Robert H. Smith School mimeo.*

Goldfarb, B., Kirsch, D., & Miller, D. A. (2007). Was there too little entry during the Dot Com Era? *Journal of Financial Economics, 86*(1), 100-144.

Greenstein, S. (2008). Chicken Little Predictions. *Micro, IEEE, 28*(6), 2-3.

Hacker, R. S. (2000). Mobility and regional economic downturns. *Journal of Regional Science, 40*(1), 45-65.

Hall, B. H. (1992). Investment and research and development at the firm level: does the source of financing matter? *National Bureau of Economic Research*, *w4096*.

Hall, B. H., & Ziedonis, R. H. (2001). The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979-1995. *RAND Journal of Economics*, 101-128.

Hao, K. Y., & Jaffe, A. B. (1993). Effect of liquidity on firms' R&D spending. *Economics of Innovation and New Technology, 2*(4), 275-282.

Hargadon, A. (1998). Firms as Knowledge Brokers: Lessons in Pursuing Continuous Innovation, *California Management Review*, *40*: 209-227.

Helpman, E. (Ed.). (1998). *General Purpose Technologies and Economic Growth*. MIT Press.

Himmelberg, C. P., and Petersen, B. C. (1994). R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries. *Review of Economics and Statistics 76*, 38-51

Hoisl, K. (2007). Tracing mobile inventors—the causality between inventor mobility and inventor productivity. *Research Policy*, *36*(5), 619-636.

Hoisl, K. (2009). Does mobility increase the productivity of inventors? *The Journal of Technology Transfer*, *34*(2), 212-225.

Hsu, D. H., & Lim, K. (2009). The Antecedents and Innovation Consequences Of Organizational Knowledge Brokering Capability. *Wharton mimeo*
Kane, A. A., Argote, L., & Levine, J. M. (2005). Knowledge transfer between groups via personnel rotation: Effects of social identity and knowledge quality. *Organizational Behavior and Human Decision Processes*, *96*(1), 56-71.
Kapoor, R., & Lim, K. (2007). The impact of acquisitions on the productivity of inventors at semiconductor firms: A synthesis of knowledge-based and incentive-based perspectives. *Academy of Management Journal*, *50*(5), 1133-1155.
Klepper, S., & Thompson, P. (2010). Disagreements and intra-industry spinoffs. *International Journal of Industrial Organization*, *28*(5), 526-538.
Lai, R., D'Amour, A., Yu, A., Sun, Y., Torvik, V., & Fleming, L. (2011). Disambiguation and co-authorship networks of the US Patent Inventor Database. *Harvard Institute for Quantitative Social Science*, Cambridge.
Lerner, J. (1996). The government as venture capitalist: The long-run effects of the SBIR program. *National Bureau of Economic Research*, *w5753*.
Levin, S. G., & Stephan, P. E. (1991). Research productivity over the life cycle: Evidence for academic scientists. *The American Economic Review*, 114-132.
Lotka, Alfred J. (1926).The Frequency Distribution of Scientific Productivity. *Journal of the Washington Academy of Sciences*, *16*, 317-323.
Marco, A. C. (2007). The dynamics of patent citations. *Economics Letters*,94(2), 290-296.
Marx, M. (2011). The Firm Strikes Back Non-compete Agreements and the Mobility of Technical Professionals. *American Sociological Review*, *76*(5), 695-712.
Marx, M., Singh, J., & Fleming, L. (2010). Regional Disadvantage? Non-Compete Agreements and Brain Drain. *INSEAD Mimeo*.
Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the Michigan non-compete experiment. *Management Science*, *55*(6), 875-889.
Miller, H., (2003). Effects of the Current Economic Downturn on the U.S. Science and Technology Workforce: Long-Term Implications. *Pan-Organizational Summit on the U.S. Science and Engineering Workforce: Meeting Summary*, 105-108.
Moore, G., 1965. Cramming More Components onto Integrated Circuits. *Electronics 38*(8):114
Mowery, D. C., & Rosenberg, N. (1991). *Technology and the pursuit of economic growth*. Cambridge University Press.
Mowery, D. C., Nelson, R. R., Sampat, B. N., & Ziedonis, A. A. (2001). The growth of patenting and licensing by US universities: an assessment of the effects of the Bayh–Dole act of 1980. *Research Policy*, *30*(1), 99-119.
Nabar, M., & Nicholas, T. (2009). Uncertainty and Innovation at the Time of the Great Depression. *Wellesley College and Harvard Business School Mimeo*.
National Research Council, 2013. *Optics and Photonics, Essential Technologies for Our Nation*. National Academies Press.
NBER, 2001. The Business-Cycle Peak of March 2001. Retrieved December 2010 from http://www.nber.org/cycles/cyclesmain.html.
NBER. NBER's Business Cycle Dating Committee. Retrieved October 2010 from http://www.nber.org/cycles/recessions.html.
OECD, (2003). After the telecommunications bubble. *OECD Economic Outlook 73*.
Oettl, A. (2012). Reconceptualizing stars: Scientist helpfulness and peer performance. *Management Science 58*(6), 1122-1140.

Oettl, A., & Agrawal, A. (2008). International labor mobility and knowledge flow externalities. *Journal of International Business Studies*, *39*(8), 1242-1260.
Paik, Y., & Woo, H. (2013). Economic Downturn and Financing Innovative Startup Companies. *Managerial and Decision Economics 35*, 114–128
Palomeras, N., & Melero, E. (2010). Markets for inventors: learning-by-hiring as a driver of mobility. *Management Science, 56*(5), 881-895.
Reagans, R., & Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science, 12*(4), 502-517.
Rosen, S. (1981). The economics of superstars. *The American Economic Review 7*1(5), 845-858.
Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science*, *49*(6), 751-766.
Shu, P. (2012). The Long-Term Impact of Business Cycles on Innovation: Evidence from the Massachusetts Institute of Technology. *MIT mimeo*
Singh, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, *51*(5), 756-770.
Singh, J. (2008). Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy*, *37*(1), 77-96.
Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science*, *57*(1), 129-150.
Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality?. *Management Science*, *56*(1), 41-56.
Song, J., Almeida, P., & Wu, G. (2001). Mobility of engineers and cross-border knowledge building: The technological catching-up case of Korean and Taiwanese semiconductor firms. *Research on Technological Innovation, Management and Policy*, *7*, 59-84.
Song, J., Almeida, P., & Wu, G. (2003). Learning–by–Hiring: When Is Mobility More Likely to Facilitate Interfirm Knowledge Transfer?. *Management Science*,*49*(4), 351-365.
Strumsky, D., Lobo, J., & van der Leeuw, S. (2012). Using patent technology codes to study technological change. *Economics of Innovation and New Technology*, *21*(3), 267-286.
Subramanian, A. M., Lim, K., & Soh, P. H. (2013). When birds of a feather don't flock together: different scientists and the roles they play in biotech R&D alliances. *Research Policy*, *42*(3), 595-612.
Trajtenberg, M., Shiff, G., & Melamed, R. (2009). The "Names Game": Harnessing Inventors, Patent Data for Economic Research. *Annales d'Economie et de Statistique*, *93-94*, 79-108.
Vusirikala, V., 2010. Drivers and Applications of Optical Technologies for Internet Data Center Operators. *Optoelectronic Industry Development Association Mimeo.*
Younge, K. A. (2012). Science and the Mobility Discount: Evidence from Initial Public Offerings. *UC Berkeley Mimeo.*
Younge, K. A., Tong, T. W., & Fleming, L. (2014). How anticipated employee mobility affects acquisition likelihood: Evidence from a natural experiment.*Strategic Management Journal*
Zucker, L. G., M. R. Darby, and M. B. Brewer (1998). Intellectual Human Capital and the Birth of U. S. Biotechnology Enterprises. *The American Economic Review 88* (1), 290-306