Bounded Exploration in Local Innovation System: The Effects of Local Industry on Academic Scientists' Research Trajectories

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Abstract

Prior research has shown that the productivity and trajectory of academic scientists are influenced by their local social and economic context, yet little is known about the relationship between individual academics and their local industry environment. This study addresses this gap by examining the impact of university-industry R&D colocation on individual academic researchers' output and the factors that affect their responsiveness to local industry environments. We explore how geographical constraints and tenure norms influence this relationship, hypothesizing that local industry presence promotes commercial and applied research, particularly for researchers with fewer geographical constraints or tenure pressures. Using a matched sample of plant biologists in the context of agricultural biotechnology, we assess the effect of proximity to industry R&D headquarters on research output and industry engagement among academics with diverse characteristics. Results show that being within 50 miles of industry R&D headquarters increased applied or commercial crop research output and local industry coauthorships, while decreasing domestic collaboration distance. In line with the argument regarding geographical constraints and tenure norms, the effects are generally more pronounced for female researchers, those with lower prior research performance, and late-career academics. Local industry collaboration seems to be a crucial pathway for exploring new research fields, particularly for less established researchers. Our findings enhance the understanding of university-industry relationships by highlighting local industry's impact on individual academics and the role of non-star researchers in connecting local industry and academia.

1 Introduction

Faced with the heightened competition for federal research funds, universities have become increasingly dependent on funding and investment from local companies, which frequently seek to develop breakthrough innovations by tapping into academic spillovers from universities in their region. In fact, many regional economies – especially those with innovative industry clusters – have been centered around this co-existence of research-intensive universities and science-based industries like pharmaceuticals, biotechnology, engineering and IT (Engel, 2015, Niosi & Zhegu, 2005, Owen-Smith et al., 2002). The codependency between industry and university in such local innovation systems have been strengthened by the industry's move away from centralized corporate research and toward relevant higher-education research entities (Arora et al., 2018).

With the recent trend of downsizing centralized corporate research, many industry giants have chosen to move closer to university campuses and engage with university scientists. A notable example is the Pharma giant Novartis' move from Basel, Switzerland to Cambridge, Massachusetts in 2002, followed by the opening of Novartis Institutes for BioMedical Research (NIBR) and the Novartis-MIT Center for Continuous Manufacturing, which were funded by a $65 million dollar investment. Another example is the ridesharing company Uber, which in 2015 established the Uber Advanced Technologies Center in Pittsburg, PA, in order to tap into research on robotics and self-driving vehicles at Carnegie Mellon University.

While many researchers have examined the bilateral nature of local industry-academia relationships in the context of a regional economy, most empirical studies have focused on the role of universities (Anselin et al., 1997, Sohn, 2020) or a select group of "star scientists" (Audretsch & Stephan, 1996, Zucker et al., 1998). Simultaneously, while ample literature has discussed how individuals in the academic incentive system respond to the emergence of pecuniary incentives (Azoulay et al., 2009, Fabrizio & Di Minin, 2008), less attention has been given specifically to individual academic engagement in the context of a local innovation system (Audretsch & Stephan, 1996, Zucker et al., 1998). This research gap prompts several questions: Does the local industry environment have an impact on the rate and direction of research at the individual level? Are there differences in how academic scientists of different types respond to changes in the local industry environment? Additionally, what mechanisms might explain why certain types of scientists are more responsive to the local environment than others?

To address this gap in the literature, we pursue two objectives. First, we aim to estimate the impact of university-industry R&D colocation on academic scientists' research output within different scientific domains, such as commercial vs. non-commercial and applied vs. basic. Second, we investigate how the effect of local industry R&D varies depending on individual researchers' characteristics. Such insights will help us understand the mechanisms that make certain types of researchers more responsive to research opportunities within the local economy.

In addressing these questions, the study illuminates the role of individual incentives in shaping academic output. The incentives of interest in this study are shaped by the costs and returns associated with pursuing research opportunities that directly or indirectly serve the local industry. They can be influenced by factors such as personal geographical constraints and career concerns, which might be a function of demographic variables such as ability, age, gender, and status (Agarwal & Ohyama, 2013, Ding et al., 2006). Geographical constraints may involve a relative lack of collaboration networks or funding sources in remote locations, as well as the inability or unwillingness to relocate to another region. Taking these factors into account, we predict that the presence of local industry R&D will disproportionately increase industry-relevant research output among university researchers with greater geographical constraints in terms of research and career opportunities. Additionally, we posit that the influence of local industry on industry-relevant research will be more pronounced for late-career researchers, who are less subject to the pressure of tenure norms that prioritize basic research.

We examine the predictions within the context of the agricultural biotechnology industry, which is suitable for studying the impact of industry on academic research given its strong presence in the scientific space. Due to the land-focused nature of agricultural research, the majority of this industry's R&D activity remains heavily concentrated near their original R&D headquarters, which were founded long before the rise of biotechnology. The locational stability of this industry R&D provides a solid anchor for identification, without concerns about the reverse causality of academic stars determining the location of industry R&D.

We obtained our sample of academic scientists from the roster of the American Society of Plant Biology. We considered only those who worked at a university in close proximity (within 50 miles) to any of five major industry R&D headquarters locations during the years these companies were active in agricultural biotechnology R&D: Monsanto – St. Louis, DuPont – Wilmington, Syngenta – Research Triangle, Pioneer – Johnston, and Dow AgroSciences – Indianapolis. Although the location of industry headquarters may be exogenous, a selection effect caused by the non-random movement of researchers into and out of those locations was a research concern. Thus, we identified the treatment effect of local industry environment by comparing treated scientists (i.e., those located within 50 miles of the five industry R&D headquarters) against a counterfactual set of scientists with a similar demographic profile and research history who were never colocated with industry during the observation period. In order to build this control group we employed multivariate matching with caliper restriction.

The regression analyses resulted in the following sets of findings. First, being located within 50 miles of an industry R&D headquarters was associated with a relative increase in applied or commercial crop research as compared to basic or non-commercial crop research. The treatment group also exhibited a significant increase in local coauthorships and a reduction in domestic collaboration distance after industry colocation, which suggests that geographical proximity resulted in more frequent interactions with local industry. Second, we find that female gender and lower prior research performance significantly increased the effect of local industry R&D on commercial-crop research output. This finding is consistent with the theory that researchers with stronger geographical constraints are more susceptible to research opportunities within the local innovation system. Relative lack of resources and higher opportunity cost of travel may incentivize these researchers to more actively exploit local industry opportunities. On the contrary, the availability of local opportunities may not be as attractive to better-positioned researchers who have been easily tapping into geographically distant opportunities. Third, we find that the effect of local industry R&D on applied research output is stronger for late-career academics who are under less pressure from tenure norms that prioritize basic research. Fourth, investigating the possible mechanisms through which local industry can shape the direction of academic research, we find that local industry collaboration seems to be the main gateway for researchers to explore new research fields. This mechanism seems to be particularly salient for researchers of lower *ex-ante* productivity.

This study contributes to the literature on university-industry relationships by shedding light on the microfoundations of local industry-driven change in academic science. Prior literature has focused primarily on how academics respond to macro-level changes in public policy and economic incentives brought by industry as a whole (Mowery & Sampat, 2005, Murray, 2010), rather than focusing on changes that happen at the local level, within specific industry clusters, such as agricultural biotechnology. This study also sheds light on the role of non-stars in bridging local industry and academia, which has not been actively investigated in the prior literature. By filling this gap in the literature, this study provides a closer investigation into the individual incentive mechanisms that operate at the regional level.

2 Literature Review and Theory

2.1 Engagement of Academic Scientists with Industry (Academic Engagement)

The enactment of the 1980 Bayh-Dole Act made it possible for universities and nonprofit research institutions to retain title to their federally-funded inventions. The ensuing institutional change brought a radical shock to the incentive system of academic researchers and resulted in the increased convergence between industry R&D and academic research (Mowery & Sampat, 2005). The ability of academic scientists to patent and license discoveries, combined with the rapid rise of science-based industries during the past few decades, has led to a vast body of research on the engagement of academic scientists in industry interactions and the commercialization of research findings (Audretsch & Stephan, 1996, Bercovitz & Feldman, 2007, Zucker et al., 1998).[1]

One such research stream investigates the consequences of academic engagement, that is, how the research agenda and productivity of academic scientists is influenced by their engagement with industry and commercialization activities (Azoulay et al., 2009, Blumenthal et al., 1986). In fact, ongoing debate exists about the extent to which industry engagement is detrimental to academic research. While existing studies have shown both positive and negative effects, the recent consensus in the literature seems to be that academic productivity and industry engagement are complementary, particularly in areas of research that simultaneously pursue scientific understandings and practical uses (Stokes, 1997). In addition, another stream of studies focuses on the antecedents of academic engagement, specifically, how various characteristics of academics, such as gender, tenure, and productivity may predict engagement in industry interactions and research commercialization (Azoulay et al., 2007, Calderini et al., 2007, D'Este & Perkmann, 2011, Ding & Choi, 2011, Ding et al., 2013). In addition to individual traits, researchers have also examined the role of social environment and organizational incentives in shaping industry engagements (Bercovitz & Feldman, 2007, Tartari et al., 2014).

A parallel body of research from the perspective of regional agglomeration has examined the consequences of industry-university engagement for the innovation economy. It is well established in this literature that geographical proximity strengthens the relationship between industry and university. Numerous studies have found that geographical proximity facilitates knowledge spillovers and technology transfer from

[1] See Perkmann et al. (2013) and Perkmann et al. (2021) for a comprehensive review of literature on the subject of academic engagement.

university to industry (Mowery & Ziedonis, 2015). Many researchers have also shown that such geographical localization of industry-academia relationships leads to stronger growth and more innovation among companies located near research-intensive universities and academic stars (Hausman, 2021, Zucker et al., 1998).

A much smaller body of research focuses on the bi-directional nature of this relationship and has shown that local industry can influence the rate and direction of academic research (Furman & MacGarvie, 2007, Sohn, 2020). However, these studies take universities as the unit of analysis and do not address how individual scientists makes their decision to engage with local industry. This study attempts to fill this gap by seeking to understand the implications of the local industry environment for the research activity of individual scientists.

2.2 Local Innovation System and the Demand- and Supply-side Dynamics of Academic Engagement

The existing literature provides two perspectives to examine the relationship between industry and academia: demand-side dynamics and supply-side dynamics. Whereas the demand-side theories examine the opportunity structure for academic scientists' industry engagement and career choices, the supply-side theories can explain the motivation and incentives for scientists to engage (Agarwal & Ohyama, 2013, Ding & Choi, 2011). The next section reviews both sides of the literature to develops a set of stylized assumption and propositions about the relationship between local industry and academic scientists.

2.2.1 Local Industry Demand for Academic Science

Industry generally engages with academic researchers to source scientific knowledge that can serve as the basis for commercially valuable products and economic profit. Many industries thrive upon a complementary relationship between basic research that enhances fundamental scientific understanding, and applied research that focuses on practical use (Agarwal & Ohyama, 2013, Rosenberg, 1982, Rosenberg & Nelson, 1994, Stokes, 1997). Notable examples can be found in the pharmaceutical, biotechnology, chemicals, and energy sectors.

American industry in the early 20th century was known for its active contribution to basic science. Since that time, basic research in corporate R&D laboratories, such as those of the Bell Company, DuPont, and

General Electric, has produced major scientific findings and breakthrough products (Nelson, 2015). During the last several decades, however, industry has become increasingly dependent upon academia for basic research for a host of causes (Arora et al., 2018). One important reason is the growth in the market for technology, which has allowed companies to easily tap into external sources of knowledge. Other reasons include the appropriability issues from narrowing firm scope, as well as the rising costs of maintaining in-house research laboratories.

This increasing industry demand for academic science reflects an industry view of basic science as an entry ticket to breakthrough innovation. Though university-based basic research may not lead to an immediate economic payoff, its open-ended and undefined nature allows industry to derive greater payoff from the research dollars it invests than it would from narrowly-defined in-house R&D (Nelson, 1971). Further, industry not only engages with academic researchers to tap into basic research for new ideas and knowledge, it also outsources applied research with clearly defined goals and objectives. Such engagement may occur in the forms of industry grants, technology transfer agreements, academic consulting, and contract research (Gulbrandsen & Smeby, 2005, Thursby et al., 2007).

Researchers have found that the geographic "reach" of university-based knowledge differs according to the channels through which it flows, that is, through nonmarket spillovers (such as patent citations) or market transactions (such as licenses), with the latter having more localized effects (Mowery & Ziedonis, 2015). Similarly, Belenzon and Schankerman (2013) revealed that citations to scientific publications are more geographically dispersed when compared to citations to patents. These findings suggest that industry collaboration and funding for basic and fundamental science can span greater geographical distances than applied and commercial research that involves technological innovation (Gittelman, 2007). Overall, this implies that industry creates a greater demand for more applied and commercial academic research within the local innovation system, whereas the demand for basic and fundamental research reaches further outside the local innovation system. Thus, when it comes to the sourcing of basic scientific knowledge, industry prioritizes the quality of ideas over the distance from which the knowledge originated. On the other hand, issues of control and coordination become more important when it comes to applied and development-focused research.

To summarize the abovementioned discussion,

Assumption 1: Industry prioritizes the quality of ideas for basic research projects, and the *quality of execution for applied research projects.*

Assumption 2: Industry demand for applied and commercial research is more geographically localized compared to basic and fundamental science.

2.2.2 Local Supply of Academic Labor to Industry Research

From a supply-side perspective, we argue that geographical constraints and academic tenure norms may shape the incentives of academic scientists to engage with local industry. The geographical scope of an academic's research activity, which is determined by the location of one's collaborators and funders, can be constrained by factors such as prominence in academia, as well as opportunity costs of travel and job move. Established scientists of higher prominence in academia are less geographically constrained in their pursuit of external research opportunities and resources, as they have developed an extensive academic collaboration network (Audretsch & Stephan, 1996). In contrast, an academic researcher's lack of visibility in the academic network may cause barriers to finding potential collaborators and resource providers across geographical distances.

The opportunity costs of travel and job mobility may also shape the strength of geographical constraints on research activity. Family responsibilities, as represented by the marital status and the presence of children, are known to disproportionately burden the economic and professional activity of women over men (Blau & Kahn, 2017, Buffington et al., 2016, Goldin et al., 2017). Such family considerations may increase the opportunity cost of travel for women, as shown in their tendency to work closer to home and less willingness to take up on travel opportunities (Catalini et al., 2020, Crane, 2007). Family responsibilities among female scientists also tend to deter them from switching jobs and moving to a new location (Fuller, 2008, Rosenfeld & Jones, 1987). As a result, female scientists may be more attentive to research opportunities that are present in the local innovation system, compared to their male peers who are more likely to actively seek geographically distant research opportunities. Similarly, Delgado et al. (2019) also provides supporting evidence that female inventors are more likely to be co-located with other members of the inventor team, and also tends to cite more geographically proximate patents.

Tenure norms also have been found to shape the incentive of academic scientists to engage with industry. Traditionally, research universities had not considered faculty members' commercialization efforts towards their merit raises, tenure, and career advancement (Sanberg et al., 2014, Siegel et al., 2003). As industry-relevant research may detract from one's efforts towards academic tenure and reputation building, academic scientists at an early stage in their career will be relatively dis-incentivized to engage in industry-relevant research. On the other hand, scientists in the later stages of their career try to cash in their academic reputation for economic return (Audretsch & Stephan, 1996).

Assumption 3 (Geographical Constraints): Academic scientists' research activity is geographically constrained by lower visibility in academia and higher opportunity costs of travel/mobility.

Assumption 4 (Tenure Norms): Academic scientists in the early career stage have an incentive to publish in basic research as opposed to applied research.

The supply- and demand-side dynamics operate in tandem to shape academic scientists' response to local industry R&D. Industry relies more heavily on local collaborations and contracts for their applied and commercial research, thus the local presence of industry R&D will disproportionately increase collaboration and funding opportunities for such type of research. The value of such opportunities is shaped by geographical constraints (*Assumption 3*) and tenure norms (*Assumption 4*). On the one hand, such opportunities would be more valuable for scientists that are subject to stronger geographical constraints. For example, scientists with a less robust academic reputation, due to their relative lack of outside funding options, may have a stronger incentive to accept external funding sources that are more applied and sponsor-oriented (Goldfarb, 2008). Female scientists, who are subject to higher cost of travel and job moves to remote locations, may also place a higher value on research topics that are likely to secure local collaborators and minimize such costs.

On the other hand, such opportunities would be more valuable for scientists that are subject to less pressure from tenure norms. As a higher priority is given to basic research before an academic scientist earns tenure, it stands to reason that the marginal value of applied research and commercial activity at the expense of basic research will be higher for younger pre-tenure academics (Boardman & Ponomariov, 2007, Geisler & Rubenstein, 1989, Thursby et al., 2007). As a result, early-career academic scientists are less likely to engage with local industry even if the opportunities are easily accessible, whereas late-career scientists have a stronger incentive to do so.

We summarize these theoretical predictions in the following set of propositions.

Proposition 1. The exposure of academic scientists to local industry R&D is associated with an *increase of research output in more industry-focused and applied areas relative to less industry-focused and basic areas.*

Proposition 2. The effect of local industry R&D on academic scientists will be stronger for less established and female ones.

Proposition 3. The effect of local industry R&D on academic scientists will be stronger for more senior ones.

3 Setting, Data and Identification

3.1 Research Setting

We conducted the empirical analysis in this study within the setting of the agricultural biotechnology industry, with a focus on plant biotechnology companies in particular. There are a number of reasons why the agricultural biotechnology industry provides a suitable setting to examine the impact of local industry co-author upon academic scientists. First, the private sector accounts for almost 40% of the entire global investment in agricultural R&D (Fuglie et al., 2011). Worldwide, many academic scientists with this research focus engage in industry collaboration, sponsored research, and patenting (Wright, 2012). Second, the agricultural industry provides a good anchor for the empirical identification, a particularly challenging task due to the endogeneity between the location and content of industry R&D and academic research (Furman & MacGarvie, 2007). Due to the land-bound nature of agricultural research, industry R&D is concentrated among a small number of anchor tenants whose location was determined during the rise of biotechnology research. This geographical fixity helps alleviate the selection effect that would arise if companies in the agricultural biotechnology industry were to choose their R&D location in pursuit of academic research.

The global agricultural biotechnology industry is dominated by a few major companies known as the "Big 6" – Monsanto, DuPont, Syngenta, Dow Agrosciences, Bayer, and BASF. These companies initially started in non-biotechnology agribusinesses, such as seed breeding, agrochemicals, and animal health (Fuglie et al., 2011). Due to a greater focus on in-house R&D instead of external sourcing, and the locational inertia of agricultural R&D, these companies did not move their R&D activities despite transitioning to new areas of R&D and relying more on academic science. As a result, the R&D headquarters of the Big 6 companies in the U.S. are located at the five places where their mother companies originated their non-biotechnology businesses: St. Louis, MO (Monsanto), Wilmington, DE (DuPont), Research Triangle, NC (Syngenta), Johnston, IA (Pioneer), and Indianapolis, IN (Dow AgroSciences). In the remainder of the paper, these locations will be referred to as the "Big 5" headquarters.

To briefly summarize the history, Monsanto's agricultural biotechnology R&D is conducted at its R&D headquarters in St. Louis, Missouri, where it began as an agrochemicals company in 1901. DuPont's agricultural biotechnology R&D is concentrated at both the DuPont Experimental Station in Delaware, and the Pioneer Hi-Bred Headquarters in Johnston, Iowa. (Pioneer is a major seed company that DuPont acquired in the late 1990s.) Syngenta has been located in Research Triangle Park, North Carolina near its mother company Ciba Geigy, which has operated its agrochemicals division there since the early 1970s. Bayer and BASF's agricultural biotechnology division also entered the Research Triangle Park, but later in the 1990s. Dow Agrosciences has been located in Indianapolis, Indiana, where Eli Lilly, the mother company of its predecessor Dow Elanco, had operated its agrochemicals division Elanco since 1954. A comprehensive overview of the evolution and corporate history of the agricultural biotechnology industry can be found in Sohn (2020), whose research uses the same empirical context as that used in this study to examine the effect of local industry R&D upon university research output.

3.2 Data

We derived the sample of academic scientists in agricultural-biotechnology-related disciplines from the membership directory of the American Society of Plant Biologists. Although this directory does not cover the entire population of scientists who have ever published in fields related to agricultural biotechnology (especially those who were active only in the early years of the industry), the left truncation is not particularly severe. The roster includes academic scientists who have exited or retired from academia, and a majority of scientists who were active during the rise of agricultural biotechnology are still active.

After drawing a random sample of individuals from the membership roster, we used publication records from the *Web of Science*, along with publicly available CVs, to construct the individual career histories. After dropping scientists that only worked at non-U.S. institutions or non-academic positions, or had zero publications in the *Web of Science*, we garnered an initial sample of 681 academic scientists. We collected information on Ph.D. degrees from the Proquest Dissertation Database and websites. In addition, we collected University-level data on annual funding from the National Science Foundation (NSF) and United States Department of Agriculture (USDA) and from the NSF Survey of Research and Development Expenditures at Universities and Colleges. Finally, we hand-collected individual NSF grant data from the NSF Award Database.

3.3 Econometrics

3.3.1 Construction of the Treated and the Control Sample

The treatment group in the sample consists of academic scientists who have ever been employed at one of the universities located within 50 miles of the "Big 5" industry R&D headquarters, during the years that these companies were actively conducting plant biotechnology R&D.[2] While industry-colocated universities remain fixed in place, individual researchers can move in and out of such institutions for various reasons, including their personal preference for industry-relevant research. Therefore, the local industry effect will capture both the treatment effect of industry R&D on the entrants and the selection effect caused by the non-random entry of researchers into those locations.

The first selection issue is an underlying preference for industry-related research on the part of the academic. Such a preference may precipitate the move of scientists, who may intentionally choose universities with local industry in order to further pursue their interest in industry-relevant research. Second, scientists may choose to move based on their individual productivity, regardless of their underlying preferences. Academics often move in due to a positive or negative trend in their productivity. For example, some may get actively recruited to another university when they have many new publications expected in the near future. Others may pre-emptively move to a lower-tier or teaching-focused university in anticipation of declining research productivity.

In order to address self-selection bias, we employed multivariate caliper matching (Cochran & Rubin, 1973, Iacus et al., 2011, Rubin, 1976) to match the treated scientists against a group of scientists with comparable pre-treatment publication histories in terms of productivity and preferences for industry-relevant research. The crucial identification assumption here is that matching on the pre-treatment publication history provides valid counterfactuals in terms of unobservables such as ability and taste for applied research.

We chose the controls based on the following set of covariates: 1) career entry year, 2) cumulative number of overall publications, 3) commercial-crop publications, 4) applied publications, and 5) industry

[2] These headquarters entered into plant biotechnology R&D between 1981 and 1989 – Monsanto, St. Louis, MO (1981); DuPont, Wilmington, DE (1981); Ciba-Geigy, Research Triangle Park, NC (1984); Pioneer Hi-Bred, Des Moines-Johnston, IA (1989); Eli Lilly (Elanco), Indianapolis, IN (1989).

co-authorships up to the year of treatment (colocation with industry R&D). The employed calipers were 4 years of career age and 25th percentiles for each type of the abovementioned publications. Matching was conducted consecutively for each treatment year without replacement. The final number of observations in the matched sample is 206 scientists (68 treated scientists and 138 control scientists).

3.3.2 Econometric Specification

The econometric specification employs a difference-in-differences estimation with varying treatment intensity for different types of individuals. To match the treated scientists with a comparable group of control scientists based on pre-treatment observables that affect research productivity, we used the multivariate caliper matching method. The identification assumption is that: 1) the treated and control scientists would have followed a common trend if not for the effect of local industry R&D, and 2) the treatment is not confounded by other events that occurred simultaneously in the same location that may have influenced the research output.

The outcome variable of interest is the publication outcome of individual scientist i at time t. The treatment variable is $Post\text{-}Colocation_{ijt}$, which equals 1 for individual scientist i who works at an industry-colocated university j during a time t when the focal company is actively conducting biotechnology R&D. The estimation equation controls for individual fixed effects, year effects, a vector of university-level controls X_{ijt}, and a suite of indicator variables to control for individual i's tenure at time t. The coefficient δ estimates the impact of industry R&D colocation on scientists at the treated universities. The vector of coefficients $\boldsymbol{\rho}$ corresponds to $\boldsymbol{W}$, a vector of time-varying and time-invariant variables such as career stage, ex-ante productivity, and gender.

$$
\begin{aligned}
Output_{ijt} = f(\epsilon_{ijt}; \alpha_i + \beta_t + \gamma X_{ijt} + \eta Tenure_{it} + \delta Post\text{-}Colocation_{ijt} \\
+ \boldsymbol{\rho} Post\text{-}Colocation_{ijt} \times \boldsymbol{W})
\end{aligned}
$$

As the dependent variable is a nonnegative count variable with skewed distribution, we use the conditional fixed-effect Poisson model with QML (quasi-maximum-likelihood) standard errors clustered at the individual level. According to Wooldridge (1997), QML ("robust") standard errors are robust to the issues of serial correlation raised by Bertrand et al. (2004).

3.4 Variables

3.4.1 Outcome Variables

We create the following variables to measure the rate and direction of academic research at the individual researcher level, with a focus on appliedness and commerciality of research.

Commercial Crop Publications. The key outcome variable of interest is an academic scientist's publication output in a given year. Commercial-crop publications are those that mention key cash crops (soybean, wheat, cotton and maize) and their scientific names (e.g. *Glycine max*, *Triticum aestivum*) in paper titles and abstracts.

Basic vs. Applied Publications. Commerciality of an academic's research output is indirectly measured in two ways. First, we measure basic and applied publication output by identifying the type of journals. Agricultural biotechnology combines the pursuit of applied, human-centered problems like crop yield with a fundamental quest for understanding of basic plant biology (Gross et al., 2014). As in Lim (2004), we define basic research journals as those that focus on the fundamental biological aspects such as general plant biology, biochemistry, microbiology and genetics. On the other hand, we define applied research journals as those that focus on specific downstream use such as crop yield, agronomy and product development. Appendix C provides detailed information on how this was coded using the *Web of Science* categories and journal names.

Industry Co-authored Publications and Patents. This *Industry Co-authorship* variable is the number of publications with at least one industry co-author that the focal researcher publishes in a given year. The variable *Patents* is the number of patent applications that the focal researcher applies for in a given year.

Local vs. Distant Industry (Backward) Citations. The variable *Local Industry Citations* is the number of publications that cite the publications by local companies (i.e., the company located within the 50-mile radius from the institution of the focal researcher) in a given year. The variable *Distant Industry Citations* is the number of publications that cite the publications by distant companies (i.e., the company located outside of the 50-mile radius from the institution of the focal researcher).

Local vs. Distant Industry Coauthorships. The variable *Local Industry Coauthorships* is the number of publications that are coauthored with local company (i.e., the company located within the 50-mile radius from the institution of the focal researcher) scientists in a given year. The variable *Distant Industry Coauthorships* is the number of publications that are coauthored with distant company (i.e., the company located outside of the 50-mile radius from the institution of the focal researcher) scientists.

Average Distance of Domestic Collaborations. For each year that an author has at least one publication, we calculated the average of the geodetic distances between the zipcode of the focal author's institution and the zipcodes of her co-authors' institutions.

Exploration of New Research Areas. Similar to the approach in Fini et al. (2021), we operationalized exploration of new research areas using the *Web of Science* journal categories. For any given year t, we counted the number of journal categories that the scientists has published for the first time in his career.

3.4.2 Explanatory Variables

Colocation with Industry R&D ("Local Industry R&D"). As mentioned in the previous section, we identified the following five locations as the loci of plant biotechnology R&D: Monsanto Headquarters in Creve Coeur, Missouri; Du Pont Experimental Station in Wilmington, Delaware; Ciba Geigy (now Syngenta)'s Agricultural Biotechnology Research Center in Research Triangle Park, North Carolina; Pioneer Hi-Bred (now part of Du Pont) Headquarters in Johnston, Iowa; DowElanco (now Dow Agrosciences) Headquarters in Indianapolis, Indiana. We identified the exact location of the main R&D headquarters by cross-checking the Directory of American Research and Technology and the author addresses in company publications.

Universities within a 50-mile radius of these locations are considered to be geographically proximate to, that is, colocated with, industrial R&D, as suggested in prior literature (Adams, 2002, Furman & MacGarvie, 2009, Sohn, 2020). An academic researcher is considered to be treated if he is present at a university located within a 50-mile radius from the anchor tenants that are actively pursuing biotechnology R&D.

Individual Characteristics. To examine how individual characteristics moderate the impact of local industry R&D upon colocated scientists, we employ the following set of variables: (1) whether an individual is ranked within top 25% of research productivity, as measured by the stock of publications at the time of treatment, compared to his cohorts who obtained Ph.D degrees in the same year, (2) whether an individual is female (inferred from names and photos), and (3) career stage (early-career, mid-career and late-career).

The career stages are defined by using the number of years since the receipt of a Ph.D degree (or the year of first publication if the former information is unavailable). The "early-career" stage is defined by the career age of 12 years or less, the "mid-career" stage is between 13 and 24 years, and the "late-career" stage is greater than 24 years. The cut-offs represent the 33rd and 66th percentiles of the career age for researchers in the post-treatment phase. Essentially, early-career researchers mostly include postdoctoral researchers and assistant professors who are untenured or within several years of receiving tenure. Mid-career and late-career researchers mostly include tenured associate and full professors.

3.4.3 Control Variables

As the institutional attributes of universities may influence the rate and direction of individual research regardless of individual constraints and incentives, a number of university-level controls are included in all regressions. First, we control for the research strength of the university (the top 25% in terms of NSF funding) and agricultural focus (land-grant status). We use the pre-1980 ranking because the level of NSF funding for a university may be endogenously shaped by the local industry's involvement in biotechnology after 1980 and onwards. Second, the existence of Agricultural Research Service Experimental Research Station are included as a separate variable on top of USDA funding and land-grant status, as it provides university academics with preferential access to government infrastructure. Third, commercial orientation of a university, proxied by the early (pre-1980) adoption of technology transfer office, may also influence an individual's decision to engage in industry-relevant research and thus is also controlled for. Universities with higher pre-existing commercial orientation are likely to exhibit subsequent development in industry boundary-spanning institutions such as technology transfer office, incubators, science parks and thus lower the cost of (and increase the returns to) their researchers shifting into industry-relevant research compared to the counterparts.

Finally, life cycle effects are controlled for by including career age indicator variables (binned in 5 year intervals). Calendar year effects are included in all regressions, and Agricultural Research Station (ARS) Region fixed effects are also included to control for the effect of the regional economy other than the existence of the anchor tenants.

4 Results and Discussion

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the matched sample for the entire observation period, whereas Table 2 provides details on the covariate balance of the matched sample during the pre-treatment period.

This table shows that the coarsened-exact-matched sample satisfies the identification assumption that industry colocation is not correlated with individual characteristics such as gender and ability (albeit limited to observables) that may be correlated with research productivity and taste for industry-relevance and commercializability.

Insert Table 1, 2 about here

4.2 Geographical Constraints

Prior to conducting the main analysis of the matched sample, we examine the full sample to identify the types of scientists that are subject to stronger geographical constraints. We examine the strength of geographical constraints by using the following proxies: job moves, the size of coauthorship network, and average collaboration distance (for domestic co-authorships only). The assumption is that stronger geographical constraints would manifest as lower job mobility, smaller coauthorship network and smaller collaboration distances. Appendix Section B provides a set of regression analyses that explore such assumptions.

Appendix Table B.2 examines which types of researchers are more likely to switch jobs by regressing job moves on a suite of researcher characteristics. The analysis controls for the hiring institution's characteristics and finds that female and senior scientists are less likely to switch. The difficulty or unwillingness to switch jobs may encourage these scientists to focus on research areas in higher demand within the local innovation ecosystem. Additionally, Appendix Table B.3 shows that female researchers have a smaller coauthorship network compared to male counterparts, after controlling for research productivity and career age which can increase the network size.

Lastly, Appendix Table B.4 examines the relationship between researcher characteristics and the average distance of domestic collaborations. The analysis shows that lower productivity is associated with smaller collaboration distances, and no significant effects of gender or seniority are detected. In Column (2), the analysis includes the number of years spent at the current institution and finds that longer tenure at the institution significantly reduces the average collaboration distance. This suggests that while gender alone may not determine the geographical scope of collaboration, the lower inclination of female scientists to switch jobs and longer tenure at the institution may indirectly influence the extent of geographical localization.

4.3 Effect of Local Industry R&D

Table 3 examines the effect of local industry R&D upon academic scientists' publication output in different areas of research. Researcher i who is present at a university j located within 50 miles from "the Big 5" R&D headquarters in a given year t after the industry entry into plant biotechnology R&D is assigned a value of 1 for the dummy $Post\text{-}Colocation_{ijt}$. The regressions control for the characteristics of the university employers that may be confounded with the effect of industry colocation. Fixed effects Poisson regression estimates are reported, and all models include researcher-level fixed effects, calendar year effects, state fixed effects and tenure fixed effects (binned in 5 year intervals). Robust standard errors are clustered at the researcher level.

Model (1) of Table 3 shows that colocation with industry R&D resulted in about a 17% increase in an academic's overall publication output. The effect becomes much more substantial if we focus on areas of research that are closely related to industry R&D. While the effect of industry colocation on commercial crop publication is only mildly significant (p-value: 0.084), the effect on applied publications is substantial and positively significant. The entry of industry R&D increases the treated scientists' number of commercial crop-related publications by about 44%, and applied publications by about 134%. The average number of applied publications by the control scientists is 0.30 per year. This means that holding other variables at the mean value, the treated incumbent scientists produce about 0.40 more applied publications per year compared to the controls. The non-significance of the treatment effect on the research output of academic scientists in less industry-relevant fields as shown in Columns 3 and 5, show that the effect is unlikely to be driven by the general productivity increase of researchers at the treated universities. Rather, the results of Table 3 suggest that treated scientists exhibited a within-individual shift in research trajectory towards more industry-focused research.

Table 4 examines how the effect of local industry differs by the duration of time a researcher has spent at the industry-colocated institutions. Across all specifications, we find that the effect size continues to increase over time. This suggests that the positive effect of local industry is unlikely to have been driven by the movement of scientists in anticipation of a transient increase in productivity. Rather, it seems plausible that the effect of local industry intensified as the researcher built a stronger network within the local innovation system.

Table 5 further explores this claim by looking into the temporal effect of industry colocation on different measures of industry engagement. Columns 1 and 2 use industry-citing publications as the dependent variable. We find that industry colocation induces academics to cite more industry publications. The effect size for *local industry citations* (i.e. academics citing companies located within 50 miles from their institutions) is significantly greater than the effect for *other industry citations*, in which academics cite companies that are located outside of the 50-mile radius. The effects on local industry citatiosn and coauthorships are not significant between 0 to 4 years from treatment, which suggests that treated academics did not select into the industry location in anticipation of engaging with local industry right away. Overall, these findings show that the local presence of industry R&D inspired academics to become more interested in industry research over time.

Columns 3 and 4 use industry coauthorships as the dependent variable. We note that only a small subset of researchers in our matched sample published industry-coauthored publications. Among 206 researchers, only 24 engaged in local industry coauthorships, and 50 engaged in distant industry coauthorships. Thus, we could not use researcher fixed effects in the specifications specifications for Columns 3 and 4, and instead focus on uncovering the between-researcher differences. We find that academics that are colocated with industry researchers are significantly more likely to coauthor with them. This result is consistent with the finding in prior studies which show that coauthorships are more geographically localized compared to citations (Mowery & Ziedonis, 2015, Sohn, 2020).

Columns 5 and 6 explore other outcomes that may be indirectly influenced by local industry relationships. Column 5 shows that industry colocation did not result in a significant increase in patenting output. Column 6 shows that the average distance of domestic collaborations, as measured by the average distance between the focal researcher and his domestic coauthors, decreased significantly from 5 years onward, during which the local industry citations and coauthorships also increased. Appendix Table D.3 suggests that the reduction in collaboration distance may have been driven by the disproportionate increase in local publications, defined as publications that are either solo-authored or co-authored with local collaborators.

Insert Table 3, 4 and 5 about here

Tables 6 and 7 shed light on the role of geographical constraints and tenure norms by investigating how researcher characteristics moderate the effect of industry colocation. The theoretical prediction is that the effect of local industry will be greater among scientists who are subject to greater geographical constraints and weaker tenure norms, that is, scientists with less ex-ante productivity, female scientists, and senior scientists. We expect that the effect of industry colocation on applied and development-focused research will be stronger for these types of scientists than other types.

Column 1 of Table 6 examines if any of the demographic features mentioned above can meaningfully moderate the effect of industry colocation on overall research output. None of the interaction terms was positive and significant, which means that the demographic features did not significantly enhance the effect of industry colocation on overall productivity. However, columns 2 through 5 show that the interaction effects were greater in magnitude when we focused on research output that are more directly tied to industry relations.

Columns 2 and 3 examine the moderating effect of demographic features on different types of publication output. Column 2 shows that among industry-colocated researchers, those with lower ex-ante productivity and female gender showed a greater increase in commercial-crop publication output as a result of the treatment, in comparison to their counterparts of higher ex-ante productivity or male gender. Column 3 shows that industry-colocated researchers with higher career age (13 years or more since the receipt of Ph.D) experienced a significantly greater increase in applied research output.[3] This implies that most significant determinant for applied research for applied research may be the tenure norms that encourage untenured faculty to prioritize basic research. On the other hand, geographical constraints, which may be more pronounced for less prolific or female scientists, could determine how one responds to local opportunities in commercial-crop research.

Columns 4 and 5 focus on industry-coauthored and local industry-citing publications as dependent variables, respectively. The limited number of local industry coauthorships (i.e., publications coauthored with an industry researcher working in the vicinity of a treated academic scientist) precluded an estimation that incorporated both interaction terms and researcher fixed effects. Thus, all industry-coauthored publications, which include both local and distant industry coauthorships, were used as the dependent variable. While local industry coauthorships provide as a more accurate representation of geographically localized relationships, collaborations with local industry researchers may also indirectly encourage distant industry coauthorships. The effect of industry colocation on industry coauthorships is significantly stronger for academics of lower ex-ante productivity and greater career age. When examining local industry-citing

[3] Supplementary analysis indicates that this pattern is not present when non-commercial-crop or basic publications are used as the outcome variable.

publications, the interaction effect was only statistically significant for mid-career scientists; however, the interactions for female and late-career scientists were both positive in direction. Column 6 examines the relationship between different types of the treated scientists and the average collaboration distance. The interaction terms are not statistically significant but negative in direction, which is consistent with the idea that industry-colocated scientists of the abovementioned characteristics may experience a greater geographical localization of domestic collaborations.

Before interpreting the results, it is important to acknowledge the issue of limited statistical power in our analysis. The study's sample size is relatively small, and employing interaction effects to further divide the treatment group reduces the statistical power for variables like gender – only 16 out of 68 treated scientists are female. Due to these limitations, detecting a statistically significant effect for many variables may be challenging, even if such an effect exists. Alternatively, some significant findings might be driven by the random idiosyncrasies of the groups. Further research is required to fully comprehend the mechanisms underlying the differences between gender or career age. Consequently, the ensuing discussion should be considered an attempt to understand the general pattern in the results and offer a plausible interpretation, rather than a definitive statement.

Overall, these results are generally consistent with the theoretical predictions about the roles of geographical constraints and academic tenure norms. A notable finding is that the demographic features that mattered for the increase in commercial research output were different from the ones that mattered for applied research output. When it comes to research of higher commercial potential, it could be that geographical proximity to industry acts as a primary binding constraint because contractual relationships around research commercialization tend to be geographically localized. Less established academics are less likely to be pursued by industry for commercial research over geographical distance, thus industry colocation may significantly boost the chances of collaboration. In contrast, those with less ex-ante geographical constraints may be less likely to find industry colocation to provide a significant change to one's the opportunity for collaboration.

In summary, we find that local industry R&D induces academics to become more productive in industry-relevant areas of research. When comparing different types of academics in the treatment group, those with lower ex-ante productivity and higher career age were the ones to drive the local industry effect. These types of scientists experienced a greater increase in the number of industry coauthorships, as well as commercial and applied publication output.

Prior research has claimed that industry engagement provide academic scientists more opportunities for exploration into unanticipated experiments and questions (Evans, 2010, Fini et al., 2021). We expect this effect to be stronger for treated scientists with stronger geographical constraints, as limitations in the geographical reach of their collaboration network increases the relative importance of research opportunities within the local innovation system. It is less clear if industry exposure would induce late-career academics to explore more new topics and areas compared to junior academics. On the one hand, given the pressing need to achieve academic tenure and establish one's status in academia, early-career scientists may have less bandwidth or risk tolerance to embark on new research trajectories related to applied and commercial topics. Established scientists with tenure may be free from career concerns and thus be more open to explore industry-relevant and applied research. On the other hand, one may expect career age to dampen a scientist's propensity to explore new paths. Recent empirical studies have found some evidence to support the longstanding claim that creativity and exploration declines monotonically with age, suggesting that scientists may explore less as they get older (Kaltenberg et al., 2021, Packalen & Bhattacharya, 2019).

Table 7 investigates this conjecture by looking at whether local industry exposure indeed led to a substantial shift in one's research trajectory and for which types of scientists. Column 1 shows the effect of industry colocation on exploration of new research topics, as measured by one's first-time publications in new *Web of Science* journal categories in a given year. We found that treated scientists are in the bottom 75% of ex-ante productivity are more likely to engage in new exploration. This finding is consistent with the assumption that scientists who are less invested in pre-existing research pipelines may have lower opportunity costs for exploring new topics.

It is puzzling that female scientists in the treated group exhibited neither a significant increase in exploratory behavior nor industry collaboration, yet experienced a significant gain in commercial-crop research output. A possible conjecture is that female researchers were influenced by the increased spillovers of industry-relevant research in the local innovation system, rather than a direct engagement in industry collaborations and funding. Also, the relative lack of exploration suggests that female researchers strengthened and extended their line of research in the context of commercial crops as a result of such exposure, rather than actively moving across new research fields.

Insert Table 6, 7 about here

4.4 Additional Analysis and Robustness Checks

Since the use of a counterfactual group does not completely eliminate the selection effect of non-random movement, we examined the implications of researcher mobility by separating the treated scientists into three categories: (1) incumbent scientists who entered industry colocated universities at least 3 years prior to the local company's entry into biotechnology R&D (i.e., local industry shock), (2) entrant scientists who self-selected into these colocated universities shortly before or after the local industry shock, and (3) departing scientists who left these colocated universities after the local industry shock. We separately estimated the treatment effect upon each category of researcher and examined the implications of researcher mobility. While the magnitude of the effect is larger for the incumbent treated scientists, it does not seem that the effect of local industry effect is statistically different between the incumbent and entrant group.

5 Conclusion

Building upon the literature on geography of science and academic norms, we investigate how different types of researchers vary in their responses to the local industry environment. we propose that exposure to local industry R&D provokes more commercial and applied research among academic scientists with more limitations in geographic reach. We also propose that late-career scientists under weaker tenure pressure are more likely to respond to research opportunities created by the local industry. We find general support for this argument using a matched sample of plant biologists in the context of agricultural biotechnology research. Being located within 50 miles from major industry R&D locations increased academic scientists' commercial and applied research output, compared to their non-industry-colocated controls. As predicted, we find that this increase is primarily seen among less productive, female, and late-career researchers whose research activity is more geographically bounded and who are less likely to switch institutions. In particular, treated researchers with lower ex-ante productivity experienced a relative increase of exploration into new research areas, consistent with the argument that the local industry environment provides a low-cost opportunity for innovation and exploration. Among different types of industry engagement, local coauthorship ties partially mediated this relationship, consistent with the prior studies that find industry collaboration to increase academic scientists' exploration.

The findings of this study suggest that local industry can provide new research opportunities for those academic scientists who are relatively disadvantaged in the academic community, including female researchers and less productive researchers. At the same time, to the extent that academic tenure and evaluation systems reward faculty for more basic research, increased engagement with local industry may not be in their best interests, especially for their long-term career. From the perspective of university administrators, this study suggests that facilitating local interactions between industry and academia may be a way to stimulate research output and novel exploration among researchers. Alternatively, alleviation of geographical frictions may help to ensure an optimal distribution of research efforts according to one's true interests and abilities.

This paper makes a novel contribution to the stream of literature on antecedents of academic engagement by shedding light upon the role of individual incentives and constraints. At the same time, this paper adds onto the stream of literature on consequences of academic engagement by examining the evolution of individual research agenda in response to the local industry environment.

This study has several limitations. Its matching strategy does not completely eliminate the selection effect of unobservables. We acknowledge, then, that the contribution of this study is not in providing a precise measure of a treatment effect, but rather, in capturing and enhancing our understanding of individual variation in a treatment effect. Nor does this study clearly address the role of organizational incentives, such as a designated technology transfer office that lowers the cost of commercialization efforts, or a tenure policy that rewards research of practical relevance and incentivizes university researchers to engage more actively in industry-relevant work. Given the small number of universities in the treated sample, it is difficult to reach a robust conclusion about the role of university characteristics. Further, because this analysis concerns only the agricultural biotechnology industry, the unique features of that industry may limit the external validity of the findings. More investigation is needed to generalize and extend the findings to other industry settings.

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Table 1: Summary Statistics

	Mean	SD	Min	Max
Year	1,996.57	8.89	1,972.00	2,009.00
Female	0.21	0.41	0.00	1.00
Tenure	13.00	9.40	0.00	47.00
Year of Ph.D	1,983.57	10.26	1,960.00	2,004.00
All Publications	2.44	2.60	0.00	23.00
Commercial-crop Publications	0.45	1.06	0.00	12.00
Non-commercial-crop Publications	1.99	2.35	0.00	23.00
Applied Publications	0.30	0.77	0.00	8.00
Basic Publications	2.05	2.31	0.00	21.00
Company Coauthorships	0.09	0.37	0.00	4.00
Local Industry Citations	0.15	0.55	0.00	7.00
Distant Industry Citations	0.41	0.90	0.00	10.00
Local Industry Coauthorships	0.01	0.14	0.00	4.00
Local Industry Coauthorships	0.04	0.30	0.00	5.00
Average Collaboration Distance (Domestic)	857.15	660.32	0.00	4,297.47
Time-Varying Observations (4,231 Person-Year)				

Table 2: T-Test of Treated Scientists and Control Scientists' Pre-Treatment Characteristics

Variables	Treated	Control	Dif	T-stat(P-value)
Year of Ph.D	1979.19(1.46)	1979.06(1.47)	0.13(2.88)	0.05(0.963)
Female	0.22(0.07)	0.13(0.04)	0.09(0.08)	1.21(0.228)
Top Ph.D	0.64(0.08)	0.71(0.06)	-0.07(0.10)	-0.76(0.447)
All Publications	1.96(0.15)	1.93(0.16)	0.03(0.29)	0.12(0.908)
Commercial-crop Publications	0.33(0.06)	0.32(0.05)	0.01(0.10)	0.08(0.937)
Non-commercial-crop Publications	1.63(0.16)	1.61(0.16)	0.03(0.29)	0.09(0.930)
Applied Publications	0.10(0.02)	0.13(0.03)	-0.03(0.05)	-0.62(0.538)
Basic Publications	1.77(0.15)	1.75(0.15)	0.02(0.28)	0.07(0.944)
Company Coauthorships	0.04(0.01)	0.09(0.04)	-0.05(0.05)	-0.88(0.380)
Patents	0.04(0.03)	0.01(0.00)	0.03(0.03)	1.01(0.316)
No. of Scientists	68	138		

Table 3: The Effect of Industry R&D Colocation: Research Productivity in Different Fields of Research

	DV = Publication Output				
	(1)	(2)	(3)	(4)	(5)
	All	Commercial Crop	Non-Commercial Crop	Applied	Basic
Post-Colocation	0.161**	0.368*	0.099	0.852***	0.119
	(0.081)	(0.213)	(0.089)	(0.291)	(0.080)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Obs	3796	3063	3778	3205	3791
No. of Researchers	206	152	205	160	205
Log Likelihood	-6884.87	-2585.96	-6185.18	-1876.46	-6359.97

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: The Temporal Effect of Industry R&D Colocation

	DV = Publication Output				
	(1)	(2)	(3)	(4)	(5)
	All	Commercial Crop	Non-Commercial Crop	Applied	Basic
Post-Colocation	0.085	0.334	0.003	0.675**	0.044
× 0-4 years from treatment	(0.080)	(0.206)	(0.096)	(0.325)	(0.084)
Post-Colocation	0.162	0.329	0.108	0.729**	0.150
× 5-9 years from treatment	(0.104)	(0.245)	(0.106)	(0.331)	(0.103)
Post-Colocation	0.255**	0.470*	0.209	1.218***	0.178
× 10+ years from treatment	(0.123)	(0.273)	(0.136)	(0.334)	(0.119)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Obs	3796	3063	3778	3205	3791
No. of Researchers	206	152	205	160	205
Log Likelihood	-6880.65	-2585.09	-6180.43	-1870.30	-6357.72

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: The Effect of Industry R&D Colocation: Industry Citations, Coauthorship and Patenting

	(1)	(2)	(3)	(4)	(5)	(6)
	Local Industry Citations	Other Industry Citations	Local Industry Coauthorships	Other Industry Coauthorships	Patents	Average Collaboration Distance (Domestic)
Post-Colocation	0.649	0.036	1.106	-0.005	-0.270	-0.099
$\times$ 0-4 years from treatment	(0.446)	(0.234)	(0.964)	(0.625)	(0.732)	(0.136)
Post-Colocation	1.462***	0.478*	3.033***	0.330	0.040	-0.305***
$\times$ 5-9 years from treatment	(0.496)	(0.253)	(0.788)	(0.789)	(0.840)	(0.108)
Post-Colocation	1.167**	0.355	3.030***	-0.088	0.232	-0.236*
$\times$ 10+ years from treatment	(0.585)	(0.266)	(1.121)	(0.799)	(0.989)	(0.136)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES	YES
Researcher FE	YES	YES	NO	NO	YES	YES
Tenure FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Obs	2348	3169	3796	3796	1361	1804
No. of Researchers	116	168	206	206	68	187
Log Likelihood	-978.86	-2173.18	-195.25	-526.19	-507.09	-364078.70

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: The Effect of Industry R&D Colocation: Research Productivity in Different Types of Research

	DV = Publication Output					
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Commercial Crop	Applied	Industry-Coauthored	Local Industry-Citing	Log of Average Collaboration Distance
Post-Colocation	-0.056	-0.460	-0.252	-0.842	0.801	0.242
	(0.122)	(0.403)	(0.546)	(0.552)	(0.798)	(0.525)
Post-Colocation	0.163	0.841**	0.596	0.969**	-0.394	-0.172
× Not Top 25% Publication	(0.127)	(0.427)	(0.650)	(0.481)	(0.843)	(0.521)
Post-Colocation	0.107	1.030***	0.660	0.458	1.172	-1.114*
× Female	(0.174)	(0.343)	(0.550)	(0.970)	(0.910)	(0.616)
Post-Colocation	0.105	0.129	0.519**	0.658*	0.894***	-0.034
× Mid-Career	(0.101)	(0.217)	(0.206)	(0.388)	(0.311)	(0.283)
Post-Colocation	0.114	-0.310	0.910***	1.205**	0.363	-0.200
× Late-Career	(0.152)	(0.335)	(0.350)	(0.473)	(0.523)	(0.514)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES
Obs	3796	3063	3205	2186	2348	1162
No. of Researchers	206	152	160	104	116	194
Log Likelihood	-6881.86	-2574.78	-1868.46	-682.49	-975.12	-2038.47

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses for Models (1)-(5). OLS regression coefficients for Model (6). Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7: The Effect of Industry R&D Colocation: Entry into New Research Field

	DV = Entry into New Research Field				
	(1)	(2)	(3)	(4)	(5)
Post-Colocation	-0.510	-0.499	-0.484	-0.520	-0.466
	(0.327)	(0.303)	(0.383)	(0.331)	(0.349)
Post-Colocation	0.626**	0.395	0.659*	0.582*	0.385
× Not Top 25% Publication	(0.307)	(0.273)	(0.341)	(0.336)	(0.331)
Post-Colocation	-0.082	0.104	-0.101	-0.106	0.028
× Female	(0.354)	(0.355)	(0.389)	(0.357)	(0.416)
Post-Colocation	0.222	0.162	0.222	0.219	0.158
× Mid-Career	(0.234)	(0.240)	(0.234)	(0.235)	(0.240)
Post-Colocation	0.198	0.144	0.193	0.193	0.129
× Late-Career	(0.338)	(0.349)	(0.336)	(0.339)	(0.348)
Post-Colocation		0.791**			0.795**
× Coauthored with Local Company		(0.361)			(0.366)
Post-Colocation			-0.065		-0.135
× Cited Local Company			(0.398)		(0.410)
Post-Colocation				0.081	0.139
× Had a Patent				(0.314)	(0.348)
Obs	1479	1479	1479	1479	1479
No. of Researchers	96	96	96	96	96
Log Likelihood	-1367.31	-1362.56	-1367.29	-1367.25	-1362.39

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendices

Appendix A Multivariate Caliper Matching

The literature provides different ways of constructing matches. By utilizing a distinct "tuning parameter" (i.e. caliper) per variable instead of orthogonalizing the parameters (as in propensity score or mahalanobis distance), imbalance in the means, moments, nonlinearities, and the full multivariate distribution of the treated and control groups may be improved, without hurting maximum imbalance on other variables (Iacus et al., 2011). Coarsened exact matching is a widely used matching method which has such benefit (called "Monotonic Imbalance Bounding" by Iacus et al. (2011)). While coarsened exact matching has the advantage of maximizing covariate balance, it is subject to the curse of dimensionality when multiple covariates are used for matching and the sample size is limited. The loss of unmatched observations due to stringent stratification may lead to an increased bias. Using pre-defined calipers of covariate distance for each distinct covariate, instead of pre-defined strata cut-offs, can minimize the loss of observations without sacrificing the benefit of Monotonic Imbalance Bounding.

For example, assume that coarsened exact matching requires us to use multiple covariates that each measure different types of publication output. The covariates would be binned using cutoffs at 25th, 50th and 75th percentile. There is a treated subject with three different covariates output at 26th, 26th and 76th percentile, respectively. The covariate values of the closest match to this subject are at the 27th, 28th and 74th percentile. Since the third variable does not belong to the 75th and above percentile, CEM would fail to identify this case as a valid control. Employing nearest neighbor matching with caliper size of 25th percentiles would avoid losing an observation, while achieving the covariate balance that coarsened exact matching aims to pursue.

Appendix B Supplementary Information on Geographical Constraints

Figure B.1: Kernel Density Plot of Average Coauthorship Distance by Researcher Productivity

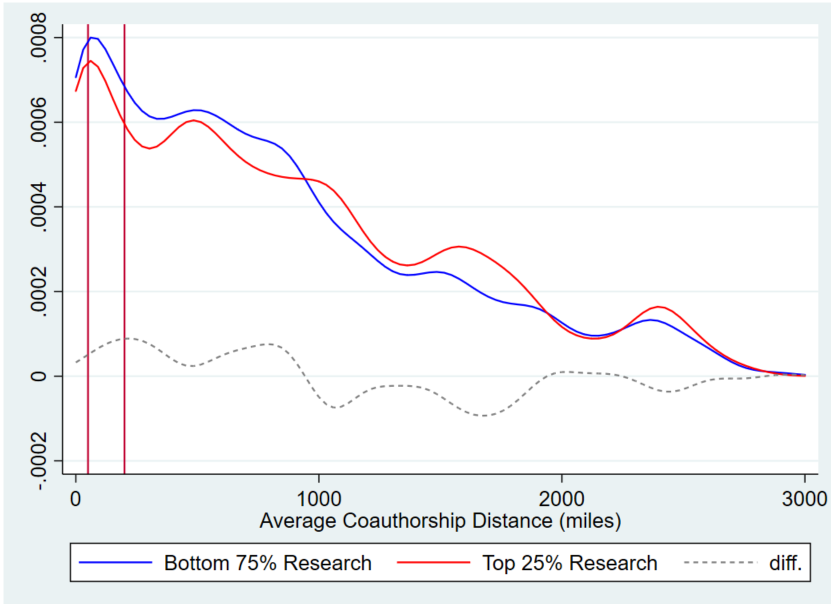

Figure B.2: Kernel Density Plot of Average Coauthorship Distance by Researcher Gender

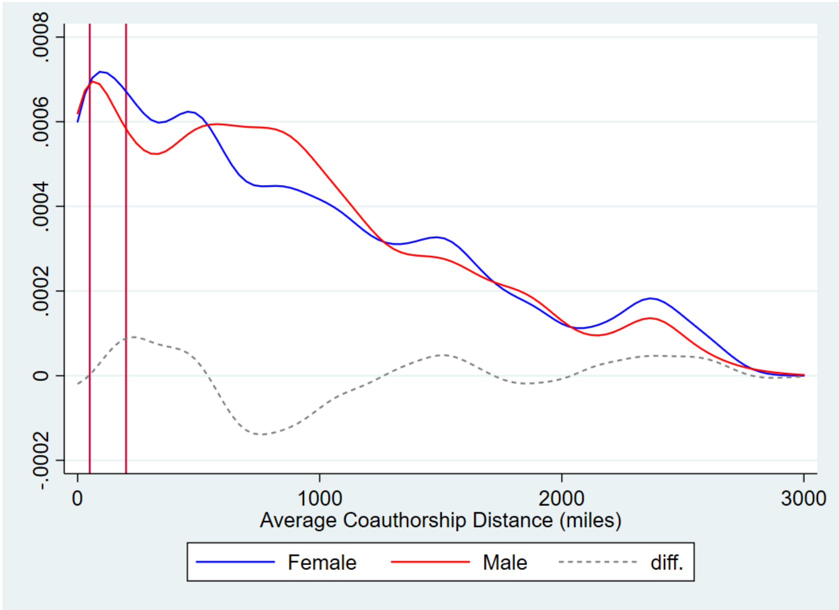

Figure B.3: Kernel Density Plot of Average Coauthorship Distance by Researcher Career Age

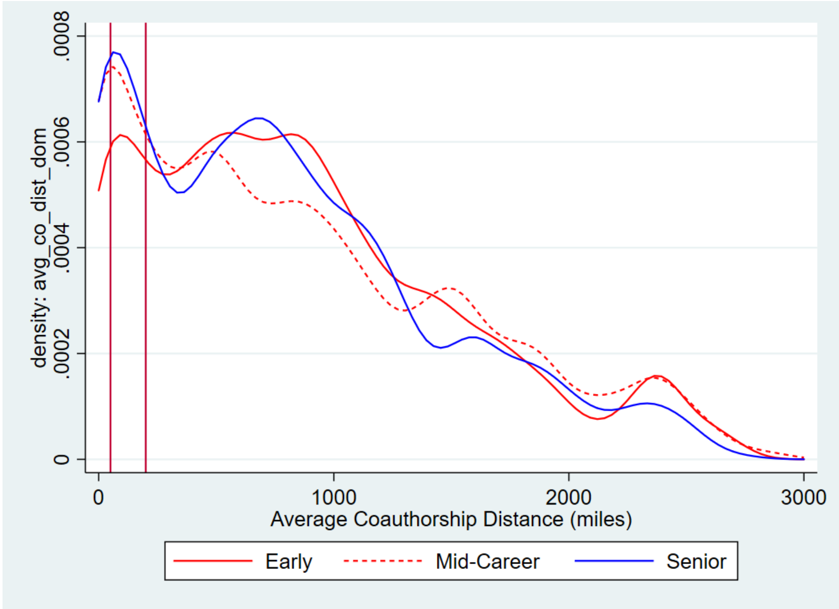

Table B.1: The Average Collaboration Distance for Different Types of Academic Publications (Domestic Publications Only)

	DV = Log of Collaboration Distance	
	(1)	(2)
Applied	-0.168***	-0.153***
	(0.030)	(0.030)
Industry Coauthorship	-0.129	-0.113
	(0.084)	(0.101)
Commercial Crop	-0.042	-0.056
	(0.035)	(0.035)
Applied $\times$ Industry		-0.382*
		(0.202)
Commercial Crop $\times$ Industry		0.284
		(0.186)
Year FE	YES	YES
Collab. Size FE	YES	YES
Obs	15373	15373
Adjusted R2	0.78	0.78

Notes: OLS regression coefficients with robust standard errors. Year FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B.2: The Relationship between Researcher Characteristics and Mobility

	DV = Job Move	
	(1) Individual Characteristics	(2) Individual + Univ. Characteristics
Research Productivity (Baseline=4th)		
1st Quartile	0.394**	0.490***
	(0.155)	(0.152)
2nd Quartile	0.123	0.148
	(0.165)	(0.157)
3rd Quartile	0.047	-0.010
	(0.163)	(0.176)
Career Age (Baseline=0-4 years since Ph.D)		
5-9 years	-0.666***	-0.834***
	(0.137)	(0.152)
10-14 years	-1.340***	-1.473***
	(0.164)	(0.171)
15-19 years	-1.700***	-2.077***
	(0.202)	(0.235)
20+ years	-1.975***	-2.689***
	(0.269)	(0.209)
Female	0.088	-0.274**
	(0.179)	(0.123)
Land-grant		-0.409***
		(0.155)
Early TTO		-0.009
		(0.126)
Genetic Dept.		0.173
		(0.132)
Major Ag. Station		0.113
		(0.184)
Top 25% Univ		0.034
		(0.243)
Year FE	YES	YES
Region FE	YES	YES
Obs	6757	5987
No. of Researchers	414	388
Log Likelihood	-1534.91	-1124.48

Notes: Logit regression coefficients with robust standard errors clustered at the researcher level in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B.3: The Relationship between Researcher Characteristics and the Number of Coauthoring Institutions

	DV = No. of Unique Coauthoring Institutions	
	(1) Individual Characteristics	(2) Individual + Univ. Characteristics
Research Productivity (Baseline=4th)		
1st Quartile	-0.754*** (0.085)	-0.659*** (0.091)
2nd Quartile	-0.552*** (0.079)	-0.468*** (0.078)
3rd Quartile	-0.340*** (0.070)	-0.309*** (0.072)
Career Age (Baseline=0-4 years since Ph.D)		
5-9 years	0.153** (0.061)	0.116* (0.065)
10-14 years	0.317*** (0.077)	0.253*** (0.081)
15-19 years	0.550*** (0.088)	0.464*** (0.089)
20+ years	0.593*** (0.078)	0.506*** (0.079)
Female	-0.073 (0.082)	-0.162** (0.080)
Land-grant		-0.147* (0.086)
Early TTO		0.124* (0.074)
Genetic Dept.		-0.080 (0.062)
Major Ag. Station		-0.027 (0.088)
Top 25% Univ		0.011 (0.118)
Year FE	YES	YES
Region FE	YES	YES
Obs	5737	5197
No. of Researchers	412	384
Log Likelihood	-16398.16	-14636.34

Notes: Poisson regression coefficients with robust standard errors clustered at the researcher level in parentheses.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table B.4: The Relationship between Researcher Characteristics and the Average Collaboration Distance

	DV = Log of Collaboration Distance	
	(1) Individual + Univ. Characteristics	(2) + Duration at Current Institution
Research Productivity (Baseline=4th)		
1st Quartile	-0.449***	-0.488***
	(0.163)	(0.163)
2nd Quartile	-0.266**	-0.269**
	(0.113)	(0.114)
3rd Quartile	-0.107	-0.102
	(0.105)	(0.105)
Career Age (Baseline=0-4 years since Ph.D)		
5-9 years	-0.014	0.024
	(0.140)	(0.138)
10-14 years	-0.130	0.037
	(0.149)	(0.156)
15-19 years	-0.169	0.093
	(0.161)	(0.180)
20+ years	-0.202	0.169
	(0.142)	(0.164)
Female	-0.009	-0.006
	(0.111)	(0.112)
Land-grant	-0.317**	-0.325**
	(0.126)	(0.126)
Early TTO	-0.143	-0.100
	(0.132)	(0.133)
Genetic Dept.	0.014	0.001
	(0.103)	(0.103)
Major Ag. Station	0.353**	0.347**
	(0.151)	(0.150)
Top 25% Univ	0.319**	0.347**
	(0.151)	(0.153)
Years at Current Institution (Baseline=0-4 years)		
5-9 Years		-0.229**
		(0.102)
10-19 Years		-0.411***
		(0.123)
20+ Years		-0.575***
		(0.170)
Obs	3137	3137
R^2	0.05	0.06

Notes: OLS regression coefficients with robust standard errors clustered at the researcher level in parentheses. Year and Region FE included. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix C Supplementary Information on Publication

Web of Science assigns multiple categories to each journal, and we utilize these journal categories to distinguish between basic and applied research journals. The journal categories used to identify "Applied Research" include: Agricultural Economics; Agricultural Engineering; Agricultural Dairy & Animal Science; Agriculture, Multidisciplinary; Agronomy; Biotechnology & Applied Microbiology; Chemistry, Applied; Chemistry, Medicinal; Food Science & Technology; Nutrition & Dietetics; Horticulture; Soil Science. The journal categories used to identify "Basic Research" include: Biochemistry & Molecular Biology; Biology; Biophysics; Cell Biology; Developmental Biology; Ecology; Evolutionary Biology; Genetics & Heredity; Microbiology; Multidisciplinary Sciences; Plant Sciences; Virology.

Many journals are mapped to multiple *Web of Science* categories and may include a category associated with the Applied Research group as well as another associated with the Basic Research group. In such cases, the journal will be counted for both Applied and Basic Research groups. Table B.5 displays the most common categories in the Applied and Basic Categories. Plant Science also ranks highly in the Applied WoS categories since it is often assigned alongside Agronomy.

In other cases, some journals were manually identified and added to each group after examining the titles and objectives. For example, journals with titles that contain keywords of strong applied orientation like "product", "pharma", "industry", "transgenic" were added to the Applied group, regardless of the Web of Science categories.

Table B.5: Applied and Basic Web of Science Journal Categories

Applied WoS Categories	Freq.	Percent	Cum.	Basic WoS Categories
Biotechnology & Applied Microbiology	1,327	15.34	Plant Sciences	12,080
Horticulture	1,281	14.81	Biochemistry & Molecular Biology	6,862
Agronomy	1,239	14.32	Cell Biology	3,765
Plant Sciences	1,198	13.85	Multidisciplinary Sciences	1,751
Biochemistry & Molecular Biology	633	7.32	Genetics & Heredity	1,411
Genetics & Heredity	576	6.66	Biophysics	1,293
Food Science & Technology	450	5.2	Biology	636
Chemistry, Applied	293	3.39	Developmental Biology	518
Agriculture, Multidisciplinary	206	2.38	Microbiology	492
Biochemical Research Methods	178	2.06	Virology	363
Microbiology	103	1.19	Ecology	308
Soil Science	100	1.16	Biochemical Research Methods	218
Chemistry, Organic	91	1.05	Evolutionary Biology	164
Agricultural Engineering	85	0.98	Environmental Sciences	110
Agriculture, Dairy & Animal Science	79	0.91	Physiology	110
Nutrition & Dietetics	61	0.71	Marine & Freshwater Biology	83
Pharmacology & Pharmacy	48	0.55	Chemistry, Analytical	66
Mathematical & Computational Biology	47	0.54	Entomology	52

Appendix D Supplementary Analysis & Robustness Tests

Table D.1: Pairwise Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) All Pubs.	1.00							
(2) Com. Crop Pubs.	0.44***	1.00						
(3) Applied Pubs.	0.45***	0.34***	1.00					
(4) Treated	0.06***	0.02	-0.03*	1.00				
(5) Post-Colocation	0.11***	0.08***	0.03*	0.65***	1.00			
(6) Female	-0.05**	-0.04**	-0.05***	-0.01	-0.01	1.00		
(7) Top 25% in Pub	0.05***	-0.01	-0.04**	0.14***	0.13***	-0.03*	1.00	
(8) Career Age	0.25***	0.15***	0.14***	0.10***	0.29***	-0.13***	0.02	1.00

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table D.2: The Effect of Industry R&D Colocation: Incumbents, Entrants and Leavers

	DV = Publication Output				
	(1)	(2)	(3)	(4)	(5)
	All	Commercial Crop	Non-Commercial Crop	Applied	Basic
Post-Colocation	0.247^{*}	0.662^{**}	0.087	0.883^{**}	0.178
× Incumbent	(0.128)	(0.301)	(0.152)	(0.360)	(0.120)
Post-Colocation	0.117	0.196	0.113	0.722^{**}	0.098
× Entrant	(0.094)	(0.237)	(0.100)	(0.285)	(0.103)
Post-Departure	0.310^{*}	0.157	0.347^{**}	-0.090	0.315
	(0.159)	(0.451)	(0.159)	(0.421)	(0.214)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Obs	3796	3063	3778	3205	3791
No. of Researchers	206	152	205	160	205
Log Likelihood	-6880.13	-2582.94	-6181.20	-1876.10	-6356.36

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table D.3: The Effect of Industry R&D Colocation: Local vs. Distance Collaborations

	DV = Publication Output		
	(1)	(2)	(3)
	Local Publication	Non-local Publications	Average Collaboration Distance (Domestic)
Post-Colocation	0.331***	-0.220*	-0.099
× 0-4 years from treatment	(0.117)	(0.134)	(0.136)
Post-Colocation	0.556***	-0.364**	-0.305***
× 5-9 years from treatment	(0.139)	(0.156)	(0.108)
Post-Colocation	0.479***	-0.075	-0.236*
× 10+ years from treatment	(0.132)	(0.196)	(0.136)
Univ. Controls	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES
Researcher FE	YES	YES	YES
Tenure FE	YES	YES	YES
Region FE	YES	YES	YES
Obs	3756	3714	1804
No. of Researchers	201	198	187
Log Likelihood	-5494.37	-4754.37	-364078.70

Notes: Poisson regression coefficients with QML robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table D.4: The Effect of Industry R&D Colocation: Research Productivity in Different Types of Research (Negative Binomial)

	DV = Publication Output						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Industry-Citing	Industry-Coauthored	Commercial Crop	Non-Commercial Crop	Applied	Basic
Post-Colocation	-0.033	0.065	-0.741	-0.489*	0.057	-0.342	0.004
	(0.124)	(0.275)	(0.737)	(0.294)	(0.136)	(0.516)	(0.129)
Post-Colocation × Not Top 25% Publication	0.052	0.305	0.822	0.716**	-0.119	0.599	0.021
	(0.120)	(0.283)	(0.726)	(0.301)	(0.130)	(0.516)	(0.125)
Post-Colocation × Female	0.217	0.357	0.153	1.116***	-0.014	0.691	0.201
	(0.135)	(0.349)	(1.024)	(0.326)	(0.149)	(0.557)	(0.142)
Post-Colocation × Mid-Career	0.077	0.303**	0.629*	0.156	0.076	0.491**	0.030
	(0.068)	(0.128)	(0.343)	(0.146)	(0.077)	(0.195)	(0.073)
Post-Colocation × Late-Career	0.147	-0.006	1.109**	-0.215	0.239**	0.804***	0.033
	(0.095)	(0.201)	(0.518)	(0.210)	(0.105)	(0.282)	(0.103)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES
Obs	3796	3387	2186	3063	3778	3205	3791
No. of Researchers	206	181	104	152	205	160	205
Log Likelihood	-6769.26	-2709.70	-677.02	-2524.84	-6093.44	-1851.41	-6273.84

Notes: Conditional Fixed Effects Negative Binomial regression coefficients with OIM standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table D.5: The Effect of Industry R&D Colocation: Research Productivity in Different Types of Research (OLS with Logged DV)

	DV = Publication Output						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Industry-Citing	Industry-Coauthored	Commercial Crop	Non-Commercial Crop	Applied	Basic
Post-Colocation	-0.014	-0.004	-0.054*	-0.070	0.057	-0.032	0.013
	(0.097)	(0.092)	(0.028)	(0.078)	(0.106)	(0.055)	(0.095)
Post-Colocation	-0.019	0.091	0.050*	0.157*	-0.137	0.050	-0.042
× Not Top 25% Publication	(0.091)	(0.098)	(0.027)	(0.085)	(0.097)	(0.063)	(0.086)
Post-Colocation	0.155	-0.024	0.016	0.221***	-0.021	-0.017	0.132
× Female	(0.097)	(0.098)	(0.027)	(0.073)	(0.108)	(0.067)	(0.091)
Post-Colocation	0.066	0.128**	0.045	0.042	0.067	0.065*	0.039
× Mid-Career	(0.072)	(0.060)	(0.030)	(0.052)	(0.075)	(0.034)	(0.074)
Post-Colocation	0.164	0.056	0.051**	-0.037	0.196	0.127	0.090
× Late-Career	(0.131)	(0.093)	(0.024)	(0.094)	(0.128)	(0.079)	(0.122)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES
Obs	3796	3796	3796	3796	3796	3796	3796
No. of Researchers	206	206	206	206	206	206	206
Log Likelihood	-2890.75	-1710.84	1123.67	-1538.41	-2840.03	-901.77	-2841.68

Notes: Fixed Effects OLS regression coefficients with robust standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table D.6: The Effect of Industry R&D Colocation: Research Productivity in Different Types of Research (with ARS Region × Post-Entry)

	DV = Publication Output						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Industry-Citing	Industry-Coauthored	Commercial Crop	Non-Commercial Crop	Applied	Basic
Post-Colocation	-0.047	-0.066	-0.637	-0.240	0.016	-0.454	0.035
	(0.157)	(0.359)	(0.680)	(0.420)	(0.172)	(0.588)	(0.157)
Post-Colocation	0.192	0.584**	1.089*	0.905**	0.014	0.685	0.143
× Not Top 25% Publication	(0.141)	(0.298)	(0.580)	(0.421)	(0.141)	(0.679)	(0.133)
Post-Colocation	0.177	0.682	0.829	0.989***	-0.071	0.863	0.159
× Female	(0.178)	(0.429)	(1.138)	(0.379)	(0.201)	(0.591)	(0.183)
Post-Colocation	0.090	0.300*	0.633*	0.139	0.077	0.505**	0.037
× Mid-Career	(0.103)	(0.164)	(0.383)	(0.217)	(0.123)	(0.211)	(0.112)
Post-Colocation	0.085	-0.058	1.069**	-0.296	0.201	0.921***	-0.040
× Late-Career	(0.155)	(0.251)	(0.486)	(0.330)	(0.170)	(0.351)	(0.164)
Univ. Controls	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*	*incl.*
Year FE	YES	YES	YES	YES	YES	YES	YES
Researcher FE	YES	YES	YES	YES	YES	YES	YES
Tenure FE	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES
Obs	3796	3387	2186	3063	3778	3205	3791
No. of Researchers	206	181	104	152	205	160	205
Log Likelihood	-6867.31	-2718.84	-675.14	-2559.61	-6162.06	-1865.57	-6345.31

Notes: Conditional Fixed Effects Negative Binomial regression coefficients with OIM standard errors clustered at the researcher level in parentheses. Year FE, Tenure FE and ARS (Agricultural Research Station) Region FE included in all models. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$