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ABSTRACT

We draw on a recombinant view of innovation, where being in a new location and/or multiple locations leads to exposure to novel combinations of ideas that increase the creativity of top scientists. Using a rich, unique dataset we helped assemble, we estimate the empirical relationship between being in a new location and/or multiple locations and the expected interval before an eventual Nobel laureate (ENL) commences their prize-winning work. We find that being in a new location and in multiple locations are substantially and significantly associated with a shorter expected interval before ENLs commence their prize-winning work.

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1 Introduction

Interest in knowledge spillovers is widespread in economics and other disciplines (among non-economists, see Moore (1966); Zuckerman (1977); and Larsson (2002)). Within economics, knowledge spillovers are crucial for understanding economic growth, urban agglomeration, and international trade (Romer (1986); Lucas (1988); Glaeser, Kallal, Scheinkman, and Schleifer (1992); and Krugman (1991)). Researchers using microdata have recently studied the effects of exposure to more and/or better colleagues on the quantity or quality of contemporaneous scientific publications. (See Azoulay, Graff-Zivin, and Wang (2010), Waldinger (2010, 2012); Borjas and Doran (2012, 2015).)

We diverge from the existing microdata studies by considering a different mechanism for knowledge spillovers among scientists as well as a different means of measuring productivity. We use a rich dataset that we helped to build to estimate a model based on a recombinant view of innovation. This view emphasizes the impact of novel and important combinations of ideas for generating the insights behind important contributions. Crucially, we highlight the importance of top scientists being exposed to a wide range of disparate ideas. We investigate two critical avenues of being exposed to the most novel and insightful combinations of ideas: (i) when people move to a new location where they are more likely to be exposed to a new set of ideas for the first time; and (ii) when people span multiple locations, which can capture "arbitraging" ideas across different places.

We focus on Nobel laureates in chemistry, medicine, and physics from 1901 to 2003 to obtain the necessary data for our study[1]. Our dataset has high-frequency biographical data,

[1] We exclude Nobel laureates in economics because the economics prize started only in 1969. Hence, there is much less data on economists than on researchers in chemistry, medicine, and physics.

including laureates' locations in each year. Moreover, we know when each scientist started the research that will eventually garner them the Nobel prize. We hypothesize that exposure to new and different ideas is likely to be more important at the outset of a scientist's research program. Our results are drawn from over a century of data and many countries and hence are not based on only one episode in one country.

Because hazard function parameters are difficult to interpret beyond their sign and significance, we focus on the effect of being in a new location and/or multiple locations on the expected interval before the eventual Nobel laureates (ENL) commence their prize-winning work. We acknowledge that our new location and multiple location variables of interest are choice variables; thus, readers may wish to treat our parameter estimates as non-causal. On the other hand, assuming that productivity differences among the scientists who eventually win a Nobel prize, conditional on the quality of their colleagues, are not correlated with the propensity to switch locations or have be in locations, our estimates will have a causal interpretation. This assumption is, of course, much weaker than one where productivity differences among all scientists are not correlated with the propensity to switch locations or have multiple locations. To our knowledge, no work has focused specifically on estimating models of knowledge spillovers drawing directly on the logic of recombinant innovation. Hence, we hope that our estimates will be helpful under either interpretation.

The parallel literature on the effect of colleagues on a scientist's productivity is relatively mixed in terms of identifying assumptions, external validity, and consistent estimation. Borjas and Doran (2012) consider the effect of Jewish mathematicians migrating from Russia to the U.S. on American mathematicians in the post-1992 era. The treatment effect consists of the exposure of American mathematicians to Jewish mathematicians from the

Soviet Union. American mathematicians working in the same areas as the émigrés now face more competition than before in terms of finding and keeping a job and publishing in American journals. However, this effect should be much smaller for American mathematicians working in areas where Russian mathematicians are weaker. Borjas and Doran use a parametric model to decompose the treatment effect of the Jewish mathematicians into an idea spillover effect and a competition effect.

Borjas and Doran (2015) consider the effect of this emigration on mathematicians who remained in Russia. While these mathematicians have lost the benefit of spillovers from the emigrating mathematicians, they now face reduced competition in finding and keeping a job and publishing in Russian journals. Again, Borjas and Doran use a parametric model to separately estimate the opposing effects. One potential limitation of this study is that it may be problematic to extrapolate results for Russia from the period right after the fall of the Soviet Union to other periods and countries.

Waldinger (2012) estimates spillover effects on the remaining German scientists from the expulsion of Jewish scientists in the 1930s.[2] However, by Borjas and Doran's logic, he estimates a treatment effect that captures the impact of a loss of spillovers and a decrease in competition among the remaining scientists, not a pure spillover effect. Further, one would have to be careful in extrapolating results for Nazi Germany just before the Second World War to other situations.

Azoulay, Graff-Zivin, and Wang (2010) measure the effect on a scholar of the death of a superstar co-author, as opposed to having a superstar co-author who does not die. They

[2] In a fascinating companion article, Waldinger (2010) examines the effect of the expulsions of Jewish scientists on graduate students and finds large negative effects. This effect could reflect both the decline in faculty quality and increased competition among graduate students.

note that the superstar deaths cannot be treated as if they occur randomly, as there appears to be selection regarding who works with a superstar who dies. For example, older superstars are likely to die more often than younger superstars, and better co-authors may prefer working with younger superstars. They address this selection issue using a version of propensity score matching called "Coarsened Exact Matching," proposed by Iacus, King, and Porro (2012), with a reasonable set of conditioning variables. They use choice-based sampling to reduce their computational burden (but do not correct their estimation approach for choice-based sampling (Heckman and Todd, 2009)).

In our study, we find that being in a new location and/or having multiple locations are significantly (and substantially) associated with shorter expected intervals before the *commencement* of Nobel work. Always being in multiple locations, as opposed to never being in multiple locations, is associated with a shorter expected interval before the *commencement* of Nobel work by a statistically significant 2.50 years on a base duration of 10.57 years. Moving to a new location every two years, as opposed to never moving to a new location, is associated with a shorter expected interval before the *commencement* of Nobel work by a statistically significant 2.0 years.

Our focus on Nobel laureates should not be viewed as an assumption that they are the most important innovators in their fields. Instead, we view them as a group of people who have made significant contributions and perhaps the only systematic group for whom the data necessary to estimate our model are available. At the same time, especially in the case of innovation, we believe that spillovers among the right tail of the innovator distribution are particularly important to understand and quantify.

The outline of the paper is as follows. Section 2 presents our econometric framework.

Section 3 describes our longitudinal data on ENLs. Here, we have a detailed discussion of how we determine the date that a scientist commenced her Nobel work. Finally, in this section, we provide summary statistics for this sample. We present our empirical results in Section 4 and spend some time interpreting them. Section 5 concludes.

2 Empirical Specification, Identifying Assumptions, and Estimation Approach

2.1 Specification of the Hazard Functions for Commencing Prize-Winning Work

Our empirical strategy is predicated on knowing when scientists commenced their prize-winning work. (In Section 4, we discuss how we determine this start date for each scientist. The starting point for our approach is a duration model in which we specify the relevant hazard function, i.e., the probability of leaving state *j* in period *t*, conditional on not leaving the state in the previous *t–1* periods.[3] Since we have annual data, we use a discrete-time hazard model to determine the probability that individual *i*, who *started* their career in calendar year τ_i, *commences* their Nobel work *t* years later:

$$\begin{aligned}\lambda_i(t \mid \theta_i) &= \frac{1}{1+\exp\{-h(t)-\alpha_1 NL_i(\tau_i+t)-\alpha_2 ML_i(\tau_i+t)-\mu CQ_i(\tau_i+t)-\phi ICQ_i - X_i\beta - g(\tau_i+t)-\theta_i\}} \\ &= \frac{1}{1+\exp\{-h(t)-Z_i(\tau_i+t)'\delta-\theta_i\}},\end{aligned} \tag{1}$$

where we use more compact notation in the second line of (1). Further, $NL_i(\tau_i+t)$ is a dummy variable coded one if the scientist is in a new location (one that they have not been in within a certain number of years) in the calendar year τ_i+t and zero otherwise, while

[3] Among the many papers estimating standard duration models, see Ham and Rea (1987), McCall (1996), and Baker and Rea (1998). These papers do not have to deal with the type of selection issues we encounter here.

$ML_i(\tau_i + t)$ is a dummy variable coded one if the scientist is in more than one location (each for roughly a month or longer) in the calendar year $\tau_i + t$ and zero otherwise. Further, $CQ_i(\tau_i + t)$ denotes colleague quality in the calendar year $\tau_i + t$ and ICQ_i captures colleague quality in their first job after leaving graduate school. Moreover, $h(t)$ denotes duration dependence, X_i denotes field dummies, and $g(\tau_i + t)$ captures a trend in calendar time, which we specify as a quadratic function. Finally, θ_i denotes a permanent unobserved (at least to current researchers and the econometrician) productivity term, where a larger θ_i indicates a more productive scientist with a larger hazard function. In the absence of unobserved heterogeneity, it is constant across scientists and becomes the intercept term.

Our focus is on estimating α_1 and α_2, the coefficients on $NL_i(\tau_i + t)$ and $ML_i(\tau_i + t)$, respectively. We include $CQ_i(\tau_i + t)$ for several reasons. First, it allows us to abstract from the effect of being exposed to very high-quality colleagues when a scientist moves to a new location or takes on an additional position and is, therefore, in more than one location. We also view it as controlling for heterogeneity in scientist quality, since, if all else were held equal, better scientists would be in better departments. However, we do not try to estimate the impact of having better colleagues on the time it takes to start a Nobel Prize-winning work.[4] We also consider the impact of having high-caliber colleagues in the first year after graduate school to account for the possibility that a strong academic start affects the hazard function across the researcher's career.

We will estimate the parameters of this hazard function by maximum likelihood.

[4] One issue that comes up here is that scientists may win the Prize with their colleagues. Since we only use it to control for scientist heterogeneity, we did not deal with this issue.

Consider first a sample of all scientists, where only a few will eventually win a Nobel prize. A scientist who did Nobel prize-winning work at duration t_i^* will contribute to the likelihood

$$Pr(t_i^*) = f(t_i^*) = \int_{\theta_i} f(t_i^* | \theta_i) dG(\theta_i)$$

$$= \int_{\theta_i} \frac{1}{1 + exp\{-h(t_i^*) - Z_i(\tau_i + t_i^*)'\delta - \theta_i\}}$$

$$, \qquad \prod_{r=1}^{t_i^*-1} \left[1 - \left(\frac{1}{1+exp\{-h(r)-Z_i(\tau_i+r)'\delta-\theta_i\}}\right)\right] dG(\theta_i) \qquad (2)$$

where $G(\theta_i)$ is the distribution function for θ_i across all scientists.

Now consider a scientist who does not do Nobel prize-winning work. Assume that scientists are followed until they turn 70 if that occurs before 2003, and followed until 2003 if that occurs before they turn 70. Let these two events occur at durations $\overline{t}_{70i}$ and $\overline{t}_{03i}$ respectively. For a non-ENL who turns 70 before 2003, the contribution to the likelihood is

$$S(\overline{t}_{70i}) = S(\overline{t}_{70i} \mid \theta_i) dG(\theta_i) = \int_{\theta_i} \prod_{r=1}^{\overline{t}_{70i}} \left[1 - \left(\frac{1}{1 + \exp\{-h(r) - Z_i(\tau_i + r)'\delta - \theta_i\}}\right)\right] dG(\theta_i). \qquad (3)$$

The contribution to the likelihood of a non-ENL who is younger than 70 in 2003 is

$$S(\overline{t}_{03i}) = S(\overline{t}_{03i} \mid \theta_i) dG(\theta_i) = \int_{\theta_i} \prod_{r=1}^{\overline{t}_{03i}} \left[1 - \left(\frac{1}{1 + \exp\{-h(r) - Z_i(\tau_i + r)'\delta - \theta_i\}}\right)\right] dG(\theta_i). \qquad (4)$$

In such a model, $Z_i(\tau_i + r)'$ is assumed independent of θ_i across all scientists. Since $Z_i(\tau_i + r)'$ contains variables like new locations, multiple affiliations, and colleague quality, it is much more plausible that $Z_i(\tau_i + r)$ and θ_i are positively correlated in a sample of all scientists.

Let $NP_i = 1$ if a scientist does ENL work and let $NP_i = 0$ otherwise. The overall likelihood for a random sample of all scientists is

$$L = \prod_{i \in NP_i = 1} f(t_i^*) \prod_{i \in NP_i = 0} S(\overline{t}_{70i}), \tag{5}$$

for someone who turns 70 before 2003.[5]

2.2 Controlling for Selection Bias in Estimation for a Sample that Only Contains Eventual Prize Winners

We will use a selected sample, which contains only ENLs, and hence, we must adjust for this selection in estimation.[6] The standard way of adjusting for this selection is first to define the probability of being an ENL. For someone who turns 70 before 2003, we have[7]

$$\begin{aligned}\Pr(NP_i = 1) &= 1 - \int_{\theta_i} \prod_{r=1}^{\overline{t}_{70i}} \left[1 - \left(\frac{1}{1 + \exp\left\{-h(r) - Z_i(\tau_i + r)'\delta - \theta_i\right\}} \right) \right] dG(\theta_i) \\ &= 1 - \int_{\theta_i} S(\overline{t}_{70i} \mid \theta)\, dG(\theta_i) = 1 - S(\overline{t}_{70i}).\end{aligned} \tag{6}$$

We need the conditional contribution to the likelihood for each of the scientists who are ENLs. We proceed as follows. Note that

$$\Pr(t_i \mid NP_i = 1) \quad = \frac{\Pr(t_i, NP_i = 1)}{\Pr(NP_i = 1)} \quad . \tag{7}$$

Consider the numerator in (7)

$$\Pr(t_i, NP_i = 1) = \Pr(NP_i = 1 \mid t_i) * \Pr(t_i) = \Pr(t_i)\,, \tag{8}$$

since

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[5] The contribution for someone who is younger than 70 in 2003 is analogous, and for expositional ease we will leave this case implicit here and in what follows.

[6] Examples of duration studies that control for selection are Ham and LaLonde [1996], Eberwein, Ham, and LaLonde [1997], Ham, L, I and Shore-Sheppard (2016), Ba et al. [2017] and Fitzenberger, Osikominu, and Paul [2022].

[7] Again, the contribution for someone who is younger than 70 in 2003 is analogous.

$\Pr(NP_i = 1 | t_i) = 1$ for those in our sample. Hence,

$$\Pr(t_i \mid NP_i = 1) = \frac{\Pr(t_i)}{\Pr(NP_i = 1)} , \tag{9}$$

where $\Pr(NP_i = 1)$ is given in (6) and $\Pr(t_i) = f(t_i^*)$ is given by (2). For what follows, it is important to note that (9) involves integrating over the unobserved heterogeneity in the numerator and denominator separately. Therefore, the likelihood function for estimation is

$$L = \prod_{i \in NP_i = 1} \tilde{f}(t_i^*), \text{ where } \tilde{f}(t_i^*) = f(t_i^*)/(1 - S(\overline{t}_{70i})). \tag{10}$$

However, maximizing (10) will produce consistent estimates only under the very unrealistic assumption that the unobserved heterogeneity is independent of the explanatory variables among all scientists. We propose the following approach. First, note that

$$\begin{aligned}
Pr(t|NP_i = 1) &= \int_{\theta_i} Pr(t, \theta_i | NP_i = 1) \quad d\theta_i \\
&= \int_{\theta} \frac{Pr(t, \theta_i, NP_i = 1)}{Pr(NP_i = 1)} \; d\theta_i \\
&= \frac{1}{Pr(NP_i = 1)} \int_{\theta_i} Pr(t|\theta_i, NP_i = 1) \; Pr(\theta_i|NP_i = 1) \; Pr(NP_i = 1) \, d\theta_i \\
&= \frac{Pr(NP_i = 1)}{Pr(NP_i = 1)} \int_{\theta_i} Pr(t|\theta_i, NP_i = 1) \; Pr(\theta_i|NP_i = 1) \, d\theta_i \\
&= \int_{\theta_i} Pr(t|\theta_i, NP_i = 1) \; Pr(\theta_i|NP_i = 1) \, d\theta_i \,.
\end{aligned} \tag{11}$$

We will use the last line of (11) to obtain our estimates. Specifically, we parameterize the distribution of θ_i among the ENLs as $\tilde{G}(\theta_i) = \Pr(\theta_i \mid NP_i = 1)$. We model $\tilde{G}(\theta_i)$ as a finite mixture (Heckman and Singer (1984)). Thus the contribution to the likelihood implied by the last line of (11) for individual *i* is

$$L_i = \int_{\theta_i} \tilde{f}(t_i^* \mid \theta_i) d\tilde{G}(\theta_i) = \int_{\theta_i} f(t_i^* \mid \theta_i)(Pr(NP_i = 1)^{-1} d\tilde{G}(\theta_i)$$

$$= \int_{\theta_i} \left[\frac{1}{1+\exp\left\{-h(t_i^*) - Z_i(\tau_i + t_i^*)'\delta - \theta_i\right\}} \right] \prod_{r=1}^{t_i^*-1} \left[1 - \left(\frac{1}{1+\exp\left\{-h(r) - Z_i(\tau_i + r)'\delta - \theta_i\right\}} \right) \right]$$

$$\left[1 - \left(\prod_{r=1}^{\overline{t}_{70i}} \left[1 - \left(\frac{1}{1+\exp\left\{-h(r) - Z_i(\tau_i + r)'\delta - \theta_i\right\}} \right) \right] \right) \right]^{-1} d\tilde{G}(\theta_i).$$

(12)

For this approach to produce causal estimates for the effect of new locations and multiple locations, it must be true that among the ENLs, the unobserved heterogeneity in terms of productivity is independent of the new location and multiple location variables, conditional on colleague quality.[8] Here we would note the problems in ranking ENLs by quality, since, e.g., many economists would be uncomfortable with ranking Nobel Prize-winners in Economics based on quality. It may be true that in the case of a few winners, such a ranking seems sensible, but we believe that conditioning on colleague quality will diminish the problem among these outliers. Further, we would expect all eventual prize winners to receive many offers of new positions and additional appointments. But one could argue that while the differences among prize winners will be much smaller than the differences among all scientists, there will still be some differences; moreover, the very best ENLs will have better opportunities and are hence more likely to assume a new position or an additional affiliation. Under this interpretation, it is better to treat our estimated coefficients for a new location or multiple locations as reduced-form estimates. Since this is the first paper to explore knowledge spillovers from a recombinant innovation perspective, readers should make their own interpretation of the coefficients. Our paper is informative under either interpretation.

[8] To the best of our knowledge, this approach is original to this paper.

Finally, we obtain standard errors for our parameter estimates using the Information Matrix. When constructing the variance-covariance matrix of the parameter estimates, some may wish to do the equivalent of clustering standard errors by, e.g., metropolitan regions, as in a regression model. The problem with this in a duration model is that one must fully control for any heterogeneity in estimation (Elbers and Ridder 1982) to obtain consistent estimates. If there is correlation across the unobserved heterogeneity for scientists in the same metropolitan error but one does not account for it in estimation, the parameter estimates will be inconsistent.

Because the estimated hazard function coefficients can be difficult to interpret, we also use these coefficients to calculate the counterfactual effect of changing an independent variable on the expected interval before the scientist commences their prize-winning work. Formally, the expected duration among the ENLs is

$$ED_i = \int_{\theta_i} \left(\sum_{r=1}^{\infty} r \, \tilde{f}\left(r \middle| \theta_i\right) \right) d\tilde{G}(\theta_i), \tag{13}$$

where $\tilde{f}\left(r \middle| \theta_i\right) = f(t_i^* \mid \theta_i)/(1 - S(\overline{t}_{70i} \mid \theta_i))$. Since we can observe individuals only until $\overline{t}_{70i}$ (which is determined by year of birth), we instead calculate a modified expected duration to conduct our counterfactuals

$$ED_i^{\text{mod}} = \int_{\theta_i} \left(\sum_{r=1}^{\overline{t}_{70i}} r\tilde{f}\left(r \middle| \theta_i\right) \right) d\tilde{G}(\theta_i). \tag{14}$$

To estimate the effect of having multiple affiliations each year on the average expected duration before the commencement of prize-winning work, we calculate (14) for each scientist in two polar cases: (i) where the scientist has multiple affiliations in each year; and (ii) where the scientist has only one affiliation in each year. We take the average of the quantities in (i) and (ii) across our sample and then take the difference in these averages. We use a similar procedure assuming each scientist has, for example, a new location every five years versus never having a new location.[9]

3. A Unique Data Set on Top Scientists' Productivity

3.1 When Do Nobel Prize Winners Start Their Work?

A crucial component of our work is our ability to identify when each ENL commenced the work that will eventually garner them the Nobel prize. We rely on the rich biographical information on the laureates in the Nobel autobiographies, the statements of the Nobel Committees, and other sources. We define the *commencement* of their Nobel prize-winning work by when they embarked on the broad research agenda that will ultimately lead to the contribution cited by the Nobel committee in awarding the prize.[10] Alternatively, we could focus on when each ENL began the specific work for which they received the prize. However, many (but not all) prize-winning contributions are the consequence of long periods of research on a particular topic. Focusing on when each ENL began the specific work for which they won the prize would effectively ignore the original idea generation and the body of research that brought them to the point of being able to do the specific work.

3.2 Assembling Our Detailed Academic Histories on Eventual Prize Winners

Our data on when scientists *commenced* their Nobel prize-winning work are drawn from Jones and

[9] Obtaining standard errors for these counterfactuals is straightforward, as the delta method can be used because the difference in the expected truncated durations is a differentiable function of the parameters with non-zero, bounded derivatives. Interestingly, the only other studies we know of that calculate such counterfactual effects and their (correct) standard errors are Ham, Li, and Shore-Sheppard (2016), Ba et al. (2017), and Fitzenberger, Osikominu, and Paul (2022).

[10] Nobel Prizes in the natural sciences are typically awarded for specific contributions, with the Nobel committee often pointing to a specific paper or papers. A small number of (the most distinguished) laureates make more than one contribution that might well qualify for a Nobel Prize. Very few people are awarded more than one Nobel Prize (and we drop any subsequent prizes awarded to one person). Thus, our estimates focus on whichever work was cited by the Nobel committee, which is typically the first prize-worthy contribution.

Weinberg (2011), which builds on the valuable contribution of Stephan and Levin (1993). We then added data on the location(s) of each Nobel laureate in each year of their career to this data set. From this information, we were able to determine for each year whether an ENL was in a new location (for the first time in, for instance, five years), in multiple locations, and the number of ENLs in their metropolitan area in a given year.

Our data contain a range of other background information, including the years of any bachelor's, master's, or doctoral work. We define the beginning of laureate *i*'s career, τ_i, as occurring three years before the receipt of her first doctorate or highest degree. We use this measure as during the early years of the sample, not all Nobel laureates received doctorates. Meanwhile, some laureates, especially those in medicine or those trained in Germany, have two doctorates. For these laureates, the year of the first doctorate was used.

We use the number of ENLs in a given metropolitan area each year to measure the colleague quality variable in that year. Of course, this is a noisy measure of colleague quality. However, we know of no other measure of colleague quality in the literature; as such, a measure would require us to measure academic quality in the respective discipline in each metropolitan area for over 100 years. We view the latter as a heroic undertaking.

To implement our approach, we must calculate the number of laureates in each city yearly. Since we know the cities in which our laureates live each year, we can calculate the total number of current or future laureates in field *f* in city c in year *t*, N_{fct}. For each laureate i in each year *t*, we then identify the set of cities in which they are located in year *t*, C_{it}.[11] We then take the sum of the number of laureates in *i*'s field across all the cities that *i* is in year *t*, i.e., $N_{it} = \sum_{c \in C_{it}} N_{fct}$.

[11] Throughout our paper, metropolitan areas, not institutions, are the units of analysis. Hence, a laureate who has more than one affiliation in a particular metropolitan area or city is counted only once.

Summing laureates across cities, as opposed to weighing them by the fraction of time spent in each city, assumes that ideas can be transferred in a relatively short period of time. In other words, we assume that splitting time across multiple cities does not reduce the quantity of spillovers that can occur in any one city.[12] Below, we obtain a significant coefficient on this variable, which suggests that our measure is not so noisy as to be uninformative.

3.3 Descriptive Statistics for our Eventual Nobel Laureates

This section describes some of the features of our sample which readers may find interesting and may help with the interpretation of our estimates. Figure 1 shows for each of our three fields the average time to beginning work from the beginning of their career (defined as three years before the receipt of their highest degree) across three time periods: graduation before 1918, graduation between 1918 and 1945 (inclusive), and graduation after 1945. Overall, the mean times to begin are fairly tightly clustered, ranging from 7.6 years for Medicine in the most recent period to 11.3 years for Physics in the earliest period. There are some time patterns within fields. In the case of Chemistry, the average time to begin is remarkably similar in the first two periods at around 9.3 years. It rises by about 10% to 10.3 years in our last period. In Medicine, the average duration in our first two periods is around 9.9 years, while it drops by about a quarter in our last period to 7.6 years. For physics, the average duration is about 11.3 years in our first period before falling to around 9.4 years in the last two periods (Jones and Weinberg (2011) argue that the quantum revolution reduced the time to doing Nobel work in physics).

Figure 2 provides the distribution of spell lengths across the three time periods when the

[12] Our measure, based on summing laureates across cities, as opposed to the alternative measure of prorating them by city, is conservative in that it will tend to diminish the estimated coefficient on the multiple locations. This occurs because our measure is more positively correlated with the multiple location variable than the alternative measure.

data are pooled across fields. While Figure 1 shows that the mean time to begin Nobel work is fairly tightly clustered across fields and cohorts, Figure 2 shows that the distributions are right-skewed with considerable individual-level dispersion. While between 5 and 10% of the sample (depending on the period) begin their Nobel work in the first year of their career (i.e., three years before receiving their highest degree),[13] Many people take 10 or 20 years to begin their Nobel work, and some take 30 or even 40 years. Appendix Figure A1 presents results broken down by field and period. These are, as expected, noisy but consistent with considerable dispersion and the right skewness in time to begin Nobel work.

Figure 3 presents a breakdown of the pooled data in terms of the share of time (i) in neither a new location nor in multiple locations (in blue), (ii) in a new location but not in multiple locations (grey), (iii) in both a new location and in multiple locations (pink) and (iv) in multiple locations but not in a new location (dark brown) broken down by period of high degree. The scientists are overwhelmingly (between 87% to 88%) in a single, non-new location. The next most common configuration is to be in both a new location and multiple locations, ranging from 6% to 7%. Fewer people are in a new location but not multiple locations and even fewer are in multiple locations but not a new location. In Figure A2, we break down Figure 3 by field. The only real difference with Figure 3 is the larger fraction of scientists in multiple locations but not a new location in Physics in the most recent period.

Figure 4 shows the share of laureates in new and/or multiple locations in the years before they begin their Nobel work, in the year they start their Nobel work, and in the years after beginning their Nobel work. (We report breakdowns by field in Appendix Figure A.3 and the differences

[13] This may also be something of an artifact in that we begin the career in the year in which someone begins their Nobel work in the small number of cases that the person begins their Nobel work more than 3 years before receiving their highest degree.

across fields are relatively small.) Consistent with Figure 3, most Nobel laureates are neither in a new location nor multiple locations for most of their careers. Moreover, few Nobel laureates are in multiple locations but not in a new location (3-4%) in each phase. By contrast, 10% of Nobel laureates are in a new location but not in multiple locations in the years before beginning their Nobel work and in the year that they begin, but this fraction is much smaller in the years after they begin (1%) their Nobel work). At the same time, the share of time that Nobel laureates spend in both new and multiple locations is 13% before beginning their work and 21% in the year they begin, dropping to 4% after beginning.

Since we need to estimate the effects of being in multiple locations, Figure 4 suggests that there may not be enough variation in this variable over the life cycle for us to do this. However, given our relatively standard parameterization, we can estimate the new location and multiple locations coefficients from the variation in being in a new location but not in multiple locations and the variation in being in a new location and in multiple locations across the life cycle.

Figure 5 plots the country of residence for the Nobel laureates for each year of their careers by year of highest degree and field. The figure shows the remarkable increase in the share of laureates in the U.S., which rises from between 10% (for Chemistry) and 21% (for Medicine) for those receiving highest degrees before 1918 to between 46% (for Chemistry) and 54% (for Medicine) for those receiving highest degrees between 1919 and 1945 (inclusive). The shares continue to increase but at a lower rate for those receiving highest degrees after 1945 to between 57% (for Chemistry) and 65% (for Medicine). There are also some differences across fields, with more Medicine laureates in the U.S. than Physics laureates and more Physics laureates in the U.S. than Chemistry laureates in all periods. Moreover, because there is considerably more variation in the first period than in the two later periods, Chemistry, which starts with the lowest share in the

U.S., experiences the largest increase between the first two periods.

Figure 6 plots the country in which Nobel laureates received their highest degrees by year of highest degree and field. For all fields, it shows a large increase in the share of laureates receiving their highest degrees in the U.S. over time and a sharp decline in the fraction receiving their degrees in Europe. The fraction receiving their degrees in other countries is always small, and the trend depends on the specific field.

4 Estimating the Hazard Function Parameters and Counterfactual Effects

To estimate the parameters of the hazard function, we must first define what is a new location. For example, should it be a location that the scientist had not been for five, ten or twenty years? Second how many years does the effect of moving to a new location last, one, three or five years? We let the data guide us on these questions through our use of the Akaike Information Criteria (AIC).[14] Conditional on defining a new location as one that the scientist had not been in for five years, the AIC leads us to define the new location benefits as lasting only for the current period. Then, assuming the length of the benefits is one year, we let the AIC guide us in terms of whether it is best to define a new location as one that the scientist has not been in for five, ten or twenty years. We find that the AIC is extremely insensitive to defining a new location as one that the scientist has not been in for five, ten, or twenty years and set it equal to five years. There is no point in iterating on this as the AIC will return that the period of the benefits is one year.

Table 1 reports our main results on the determinants of the probability of commencing Nobel prize-winning work in each year. Throughout our analysis, we control for the quality of each scientist's colleagues (number of ENLs) in a given year, as well as those in her first job, since we

[14] Since the number of parameters and number of observations are both equal across these specifications, using the Bayesian Information Criterion (BIC) is equivalent to using the AIC criterion. For one of many descriptions in the literature of the AIC and BIC, see Konishi and Kitagawa (2008).

believe that this specification produces the cleanest "ability-free" impacts of a new location and being in multiple locations. That is, the effects we estimate net out any effects of being in new locations or in multiple locations that operate through being exposed to more high-quality colleagues.[15]

Panel A provides estimates of the coefficients of the hazard functions, where we include discipline dummies. Panel B shows the estimated effects of changes in our independent variables of interest on the expected interval before the commencement of Nobel prize-winning work. Because there is generally no difference in the statistical significance of the hazard function coefficients and the respective expected duration effects, we focus on the latter since they are easier to interpret. Our hazard functions depend on the variables discussed above to control for peer quality and ability and duration dummies. All specifications include calendar year and calendar year squared, as well as field dummy variables; the coefficients are not shown for these variables.

We could not find evidence of unobserved heterogeneity in any of the models we estimated for commencing prize-winning work. One potential explanation for this is that the differences in unobserved productivity between scientists in our sample are relatively small, especially once we condition on the current number of ENLs in a scientist's location. This result is reassuring as it implies that our estimates are unlikely to be confounded by unobserved productivity differences.

Consider the parameter estimates for the hazard function in Panel A of Table 1. All the results in this table control for colleague quality. In column (1), we show the results when we include the new location variable in the hazard function, but not the multiple locations variable; the new location variable is statistically significant. From the expected duration calculations in column (1)

[15] If we do not include this number of eventual laureates as a conditioning variable in the beginning hazard function, the expected duration effects of new locations and multiple locations become somewhat larger, as one would expect. See Appendix Table A1.

of Panel B, we estimate that being in a new location every 2, 3, and 5 years[16] significantly decreases the expected interval before commencing Nobel prize-winning work by 2.63, 1.90, and 0.97 years, respectively.[17] In terms of differences across disciplines, the expected durations are shortest in Chemistry, somewhat longer in Medicine, and a bit longer still in Physics, but none of these differences are statistically significant. Column (2) includes in the hazard function the multiple locations variable, but not the new location variable, and the multiple locations variable is also strongly significant. Further, the parameter estimates indicate that always being in multiple locations, as opposed to never being in multiple locations, reduces the expected interval before commencing Nobel prize-winning work by a statistically significant 3.493 years. All of the above effects are relative to an expected average duration of 10.57 years before commencing Nobel prize-winning work. Thus, these effects are substantial.

In column (3), when we control for both the new location and multiple location variables simultaneously, both variables are individually significant and jointly significant using a likelihood ratio test. We estimate that moving to a new location every 2, 3, and 5 years significantly decreases the expected interval before commencing Nobel prize-winning work by 2.00, 1.39, and 0.69 years, respectively.[18] Further, always being in multiple locations, as opposed to never being in multiple locations, now significantly reduces the expected interval before commencing Nobel prize-winning work by a statistically significant 2.50 years. Thus, the impacts of the new location variable and the multiple locations variable are diminished somewhat when we simultaneously

[16] Note that here we are simply doing different simulations, not definitions for estimation.

[17] We do not report counterfactuals for changes in the number of laureates since we are essentially using this variable as a control variable. These counterfactuals are available on request. As one would expect from Table 1, these effects are substantial.

[18] Note that the impacts of changes in the variables on expected duration tend to be significant at lower confidence levels than the coefficients (e.g., 0.01 vs. 0.05), reflecting the fact that the expected duration impacts depend on all of the parameters of the hazard function, and their standard errors reflect the variance-covariance matrix for all of the estimated parameters.

account for both variables. Still, both variables continue to be very significant.

Appendix Table A1 reports estimates from similar specifications that do not include the colleague quality variable, i.e., the number of laureates to which each ENL is exposed in each year is not used as a control variable. These estimates are slightly larger than those in Table 1, as one would expect if the colleague quality picks up unobserved differences across scientists. However, the relatively modest increase in estimates when we drop colleague quality is reassuring as it suggests that there is indeed little variation in unobserved productivity differences across the ENLs.[19]

Our estimates show how being in a new location or multiple locations in a given year affects the probability of starting novel and important work for people who do very high-quality work. We argue that it is best to consider the effects as local, in the sense that we would not want to extrapolate these effects to much less able scientists.

5 Conclusion

We extend existing data sets on eventual Nobel Laureates to include data on their locations in each year of their careers. We use these data to give a picture of top scientists over time. The most dramatic phenomena in the data are (i) the increase over time in the fraction of top scientists in chemistry, medicine, and physics living in the U.S. and (ii) the fraction of top scientists in chemistry, medicine, and physics who received their highest degree in the U.S. Another important result from our analysis: how similar scientists are across these fields at a given moment in time.

Drawing on recombinant innovation logic, we provide the first evidence for our novel knowledge spillover mechanisms. Being in a new location, as a measure of exposure to new ideas, and being in multiple locations, as a measure of exposure to a wide-ranging set of ideas than most

[19] This would also be consistent with our not being able to estimate an unobserved heterogeneity distribution.

others are exposed to, are associated with a substantially and significantly higher probability of commencing Nobel prize-winning work in a given period. We analyze an extremely highly selected sample — Nobel laureates — for whom we have data that is rich enough to leverage their career histories and measure our variables of interest each year.

At a practical level, our estimates suggest the value of intense cross-pollination in stimulating important innovative work for those at the highest end of the ability distribution. These results stand in contrast to previous conceptualizations of knowledge spillovers, which emphasize concentrating innovators in clusters over the research life cycle.

References

Azoulay, Pierre, Ina Ganguli, and Joshua Graff Zivin. 2017. "The mobility of elite life scientists: Professional and personal determinants." *Research Policy,* 46: 573–590.

Azoulay, Pierre, Joshua S. Graff-Zivin, and Jialan Wang. 2010. "Superstar Extinction." *Quarterly Journal of Economics,* 125: 549–590.

Ba, Bocar, John C. Ham, Robert LaLonde, and Xianghong Li. 2017. "Estimating (Easily Interpreted) Dynamic Training Effects from Experimental Data." *Journal of Labor Economics,* 35: S149–S200.

Michael Baker and Angelo Melino. 2000. "Duration Dependence and Nonparametric Heterogeneity: A Monte Carlo Study." *Journal of Econometrics*, 96: 357–393.

Michael Baker and Samuel Rea. 1998. "Employment Spells and Unemployment Insurance Eligibility Requirements." *Review of Economics and Statistics* 80: 80–94.

Borjas, George and Kirk Doran. 2015. "Which Peers Matter? The Relative Impacts of Collaborators, Colleagues, and Competitors." *Review of Economics and Statistics,* 97: 1104–1117.

________________. 2012. "The Collapse of the Soviet Union and the Productivity of American Mathematicians." *Quarterly Journal of Economics,* 127:1143–1203.

Eberwein, Curtis, Ham, John C., and Robert LaLonde. 1997. "The Impact of Being Offered and Receiving Classroom Training on the Employment Histories of Disadvantaged Women: Evidence from Experimental Data." *The Review of Economic Studies,* 64: 655–682.

Elbers, Chris and Geert Ridder. 1982."True and Spurious Duration Dependence: The Identifiability of the Proportional Hazard Model." *The Review of Economic Studies*, 49: 403-409.

Fitzenberger, Bernd, Aderonke Osikominu, and Marie Paul. 2022. "The Effects of Training Incidence and Planned Training Duration on Labor Market Transitions." *Journal of Econometrics*, in press. Available at https://www.sciencedirect.com/science/article/pii/S0304407622000690.

Flinn, C., & J. Heckman. 1982. "Models for the Analysis of Labor Force Dynamics." In Basmann, & Rhodes (Eds.), *Advances in Econometrics 1* JAI Press.

Friedman, Robert Marc. 2001. *The Politics of Excellence: Behind the Nobel Prize in Science*. New York: Times Books / Harry Holt.

Glaeser, Edward L., Hedi D. Kallal, Jose A. Scheinkman, and Andrei Shleifer. 1992. "Growth in Cities." *Journal of Political Economy,* 100: 1126–1152.

Glaeser, Edward L. and Glenn Ellison. 1997. "Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach." *Journal of Political Economy,* 105: 889–927.

Goldstein, Joseph L. and Michael S. Brown. 2012. "A Golden Era for Nobel Laureates." *Science,* 338: 1033–1034. DOI: 10.1126/science.1231699

Ham, John C. and Robert LaLonde. 1996. "The Effect of Sample Selection and Initial Conditions in Duration Model: Evidence from Experimental Data on Training." *Econometrica,* 64: 175–205.

Ham, John C., X. Li and L. Shore-Sheppard. 2016. "The Employment Dynamics of Disadvantaged Women: Evidence from the SIPP." *Journal of Labor Economics* 34: 899–944.

Ham, John C. and Samuel Rea. 1987. "Unemployment Insurance and Male Unemployment Duration in Canada." *Journal of Labor Economics,* 5: 325–353.

Heckman, James J. and Burton Singer. 1984a. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica,* 52: 271–320.

Heckman, James J. and Petra E. Todd. 2009. "A Note on Adapting Propensity Score Matching and Selection Models to Choice-Based Samples." *Econometrics Journal*, 12: S230–S234.

Iacus, Stefano M., Gary King, and Giuseppe Porro. 2012. "Causal Inference without Balance Checking: Coarsened Exact Matching." *Political Analysis*, 20: 1–24.

Konishi, Sadanori and Genshiro Kitagawa. (2008). *Information Criteria and Statistical Modeling.* New York: Springer Science & Business Media.

Jacobs, Jane. 1961. *The Death and Life of Great American Cities*. New York: Vantage Books.

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics,* 108: 577–598.

Jones, Benjamin F. 2010. "Age and Great Invention." *Review of Economics and Statistics,* 42: 1–14.

Jones, Benjamin F. and Bruce A. Weinberg. 2011. "Age Dynamics in Scientific Creativity." *Proceedings of the National Academy of the Sciences* 108(47): 18910–18914.

Kaiser, David. 2005. *Drawing Theories Apart: The Dispersion of Feynman Diagrams in Postwar Physics*. Chicago: University of Chicago Press.

Kaplan, Greg, Giovanni L. Violante, and Justin Weidner. 2014. "The Wealthy Hand-to-Mouth," *Brookings Papers on Economic Activity,* 2014: 77-138.

Kim, E. Han, Adair Morse, and Luigi Zingales. 2009. "Are Elite Universities Losing their Competitive Edge?" *Journal of Financial Economics,* 93: 353–381.

Konishi, Sadanori, and Genshiro Kitagawa, 2008. *Information Criteria and Statistical Modeling.* Springer.

Krugman, Paul, 1991. "Increasing Returns and Economic Geography." *Journal of Political Economy,* 99: 483–499.

Larsson, Ulf. 2002. *Cultures of Creativity: The Centennial Exhibition of the Nobel Prize*. Canton, MA: Science History Publications.

McCall, Brian P. 1996. "Unemployment Insurance Rules, Joblessness, and Part-time Work." *Econometrica,* 64: 647–682.

Nobel Foundation. 2014a. "The Nobel Prize in Chemistry 2012 – Press Release." Nobelprize.org. Nobel Media AB 2014. Accessed: Web. 28 Mar 2016. http://www.nobelprize.org/nobel_prizes/chemistry/laureates/2012/press.html .

Nobel Foundation. 2014b. "The Nobel Prize in Chemistry 2012 – Popular Information." Nobelprize.org. Nobel Media AB 2014. Web. 28 Mar 2016. http://www.nobelprize.org/nobel_prizes/chemistry/laureates/2012/popular.html .

Osikominu, Aderonke. 2013. "Quick Job Entry or Long-Term Human Capital Development? The Dynamic Effects of Alternative Training Schemes." *Review of Economic Studies*, 80: 313–342.

Romer, Paul M. "Increasing Returns and Long-Run Growth." 1986. *Journal of Political Economy*, 94: 1002–1037.

Stephan, Paula G. and Sharon E. Levin. 1993. "Age and the Nobel Prize Revisited." *Scientometrics,* 28: 387–399.

Thompson, Peter and Melanie Fox-Kean. 2005. "Patent Citations and the Geography of Knowledge Spillovers: A Reassessment." *American Economic Review,* 95: 450–460.

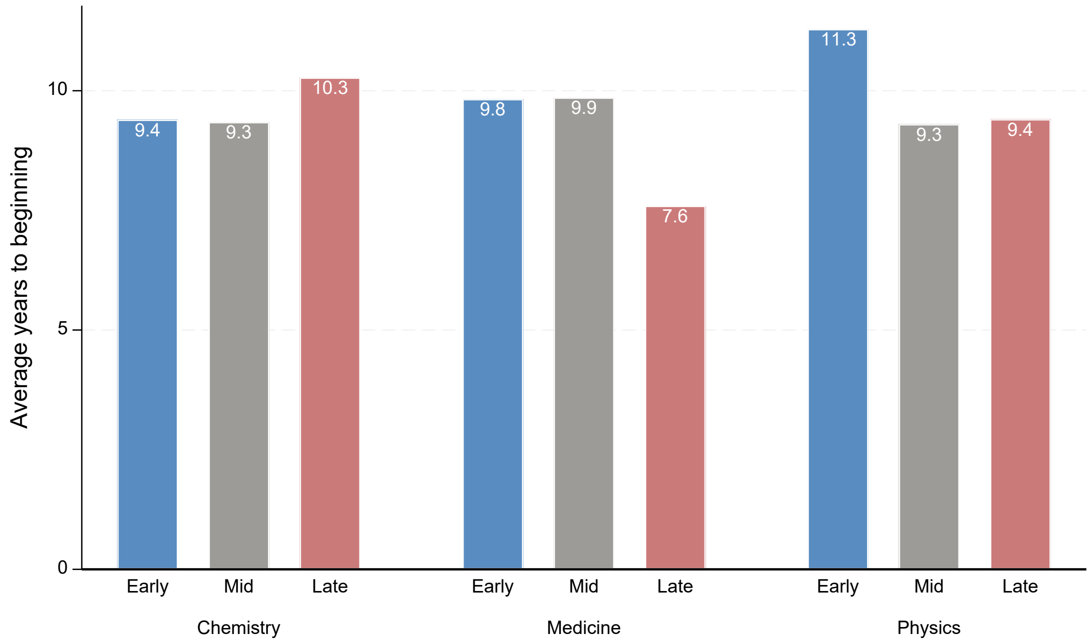
Waldinger, Fabian. 2012. "Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany." *The Review of Economic Studies,* 79: 838–861.

________________. 2010. "Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany." *Journal of Political Economy,* 118: 787–831.

Zucker, Lynne G., Michael R. Darby, and Marilynn B. Brewer. 1998. "Intellectual Human Capital and the Birth of U.S. Biotechnology Enterprises." *American Economic Review,* 88: 209–306.

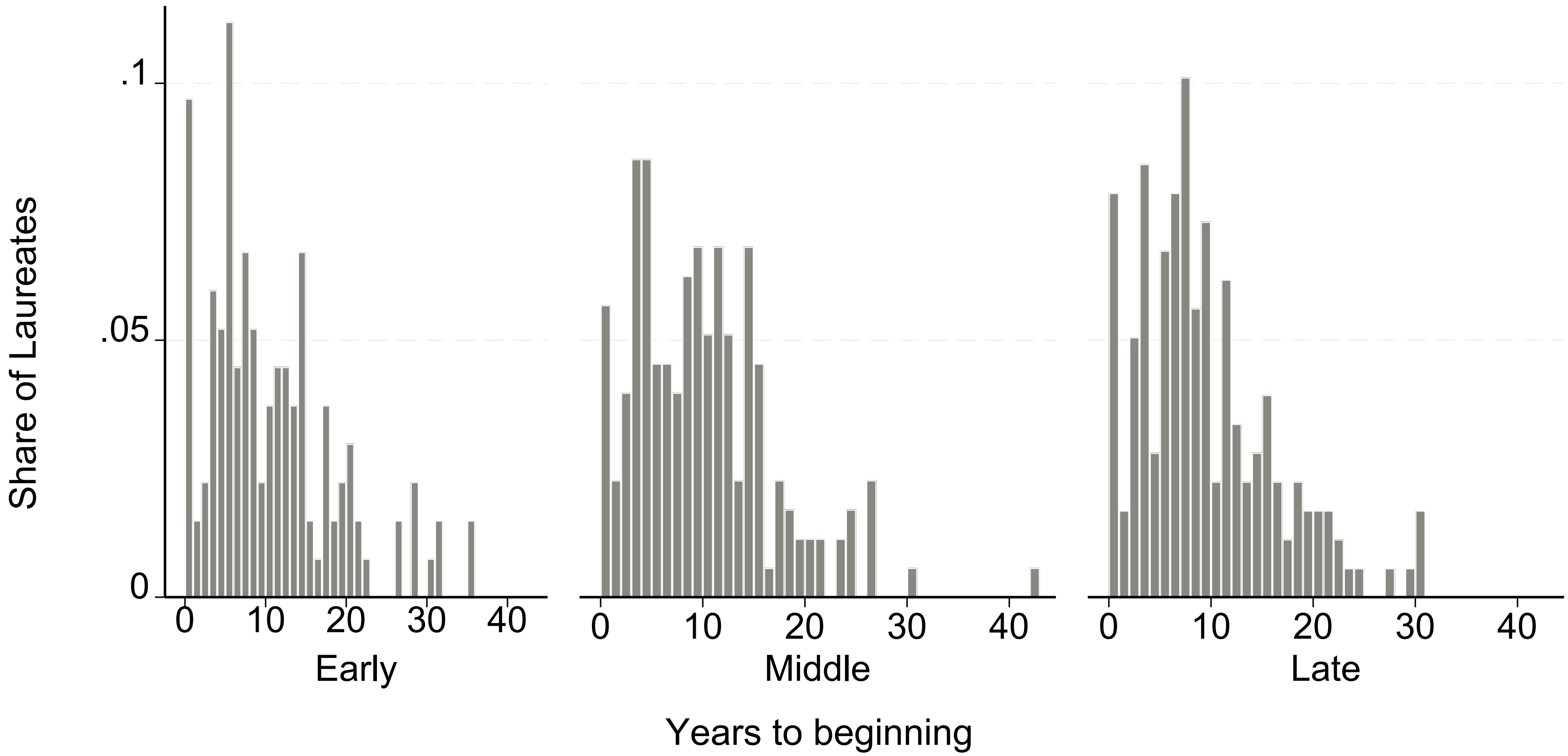
Zuckerman, Harriett. 1977. *Scientific Elite*. New York: Free Press.

Figure 1. Mean time to beginning Nobel work, by time of high degree and field.



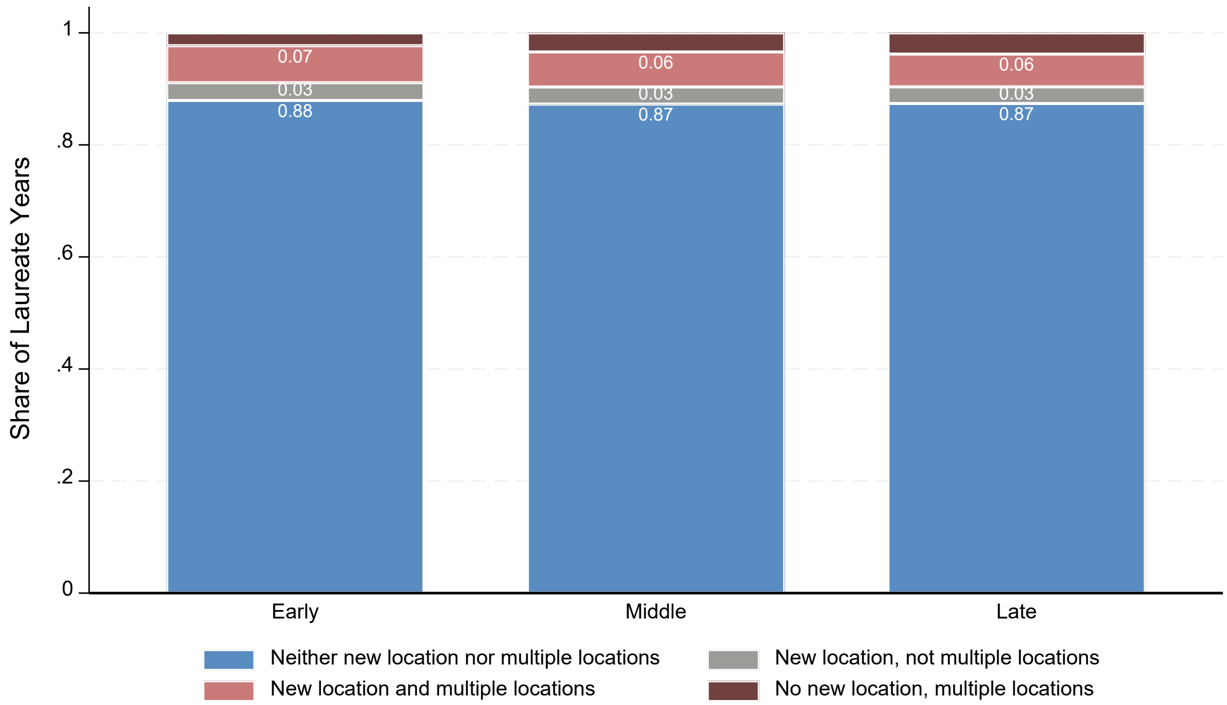
Notes: The figure plots the mean number of years to begin prize-winning work relative to the beginning of the career (three years before receiving the highest degree) by field for people receiving their high degree in the three indicated periods. Early indicates graduation before 1918, middle indicates graduation between 1918 and 1945 (inclusive), and late indicates graduation after 1945. Observations are at the individual level. The sample includes 142 Chemistry laureates, 179 Medicine laureates, and 167 Physics laureates.

Figure 2. Distribution of time to beginning Nobel work, by time of high degree



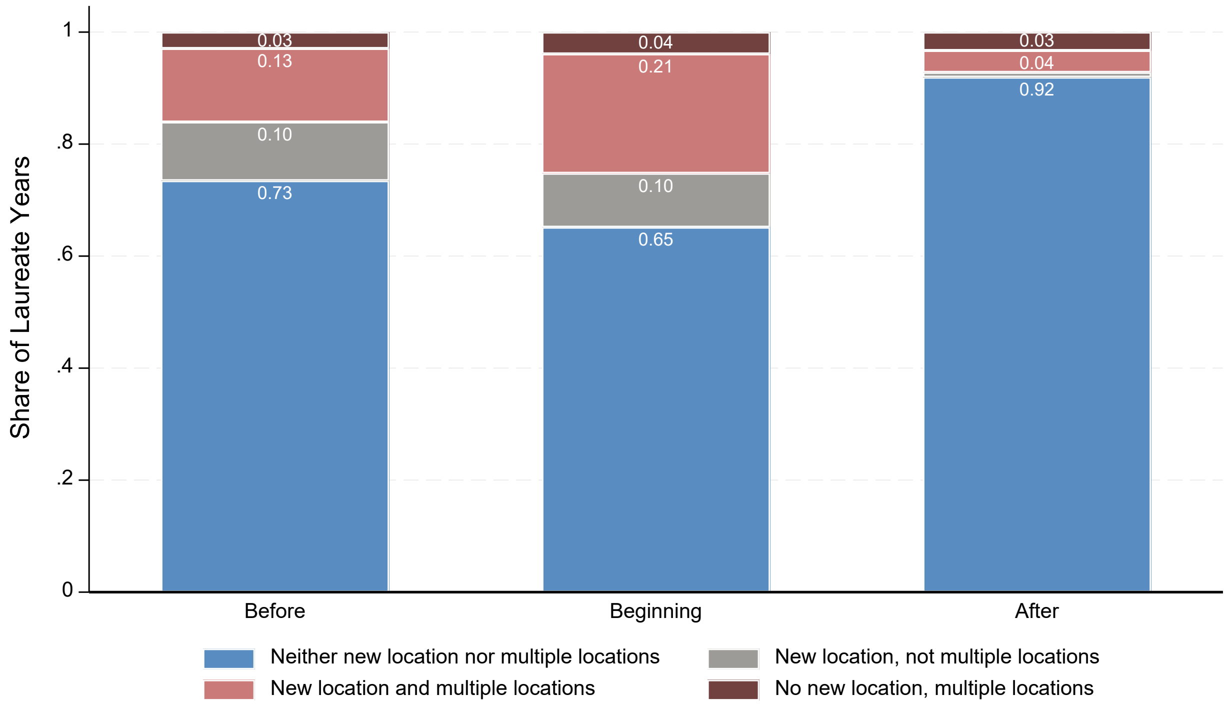
Note. The histogram shows the distribution of years to begin prize-winning work relative to the beginning of the career (three years before receiving the highest degree) for people receiving their high degree in each of the three periods indicated. See notes in Figure 1.

Figure 3. Time in multiple locations and new locations by time of high degree



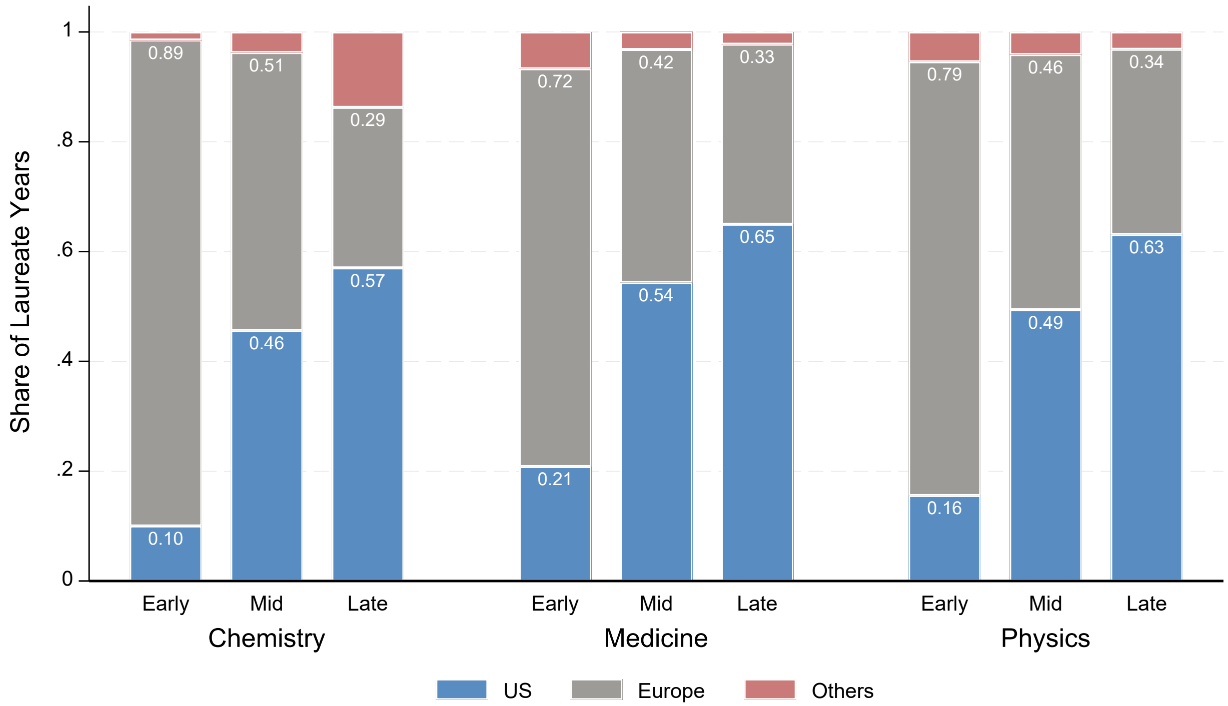
Note. The figure shows the share of time (i) in neither a new location nor in multiple locations (in blue), (ii) in a new location but not in multiple locations (grey), (iii) in both a new location and in multiple locations (pink) and (iv) in multiple locations but not in a new location (dark brown) by field and time of high degree. This figure is based on all years of data on all laureates.

Figure 4. Time in multiple locations and new locations relative to before, beginning and after Nobel work



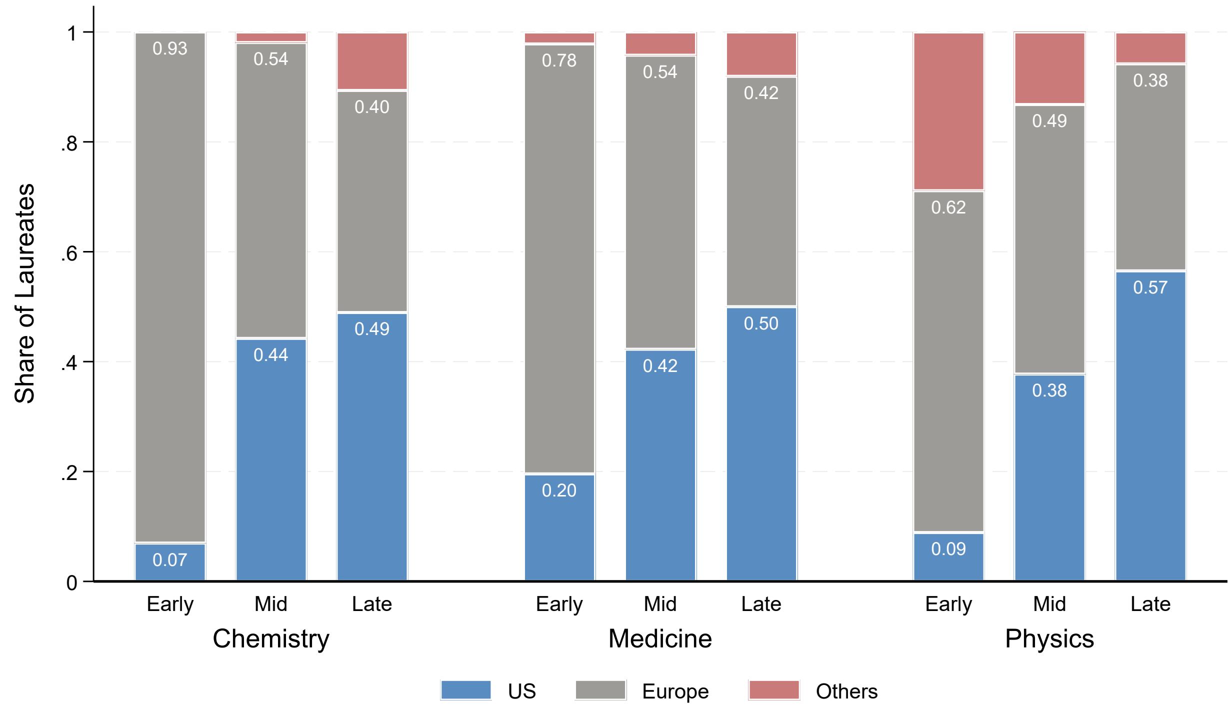
Notes: The figure shows the share of time in new and/or multiple locations relative to beginning Nobel work. Before indicates all years before the laureates begin their Nobel work, beginning indicates the year they began Nobel work, and after indicates all years after the laureates began their Nobel work.

Figure 5. Country of residence over career by field and time of the highest degree



Note. The figure shows the share of time spent in different countries (US, Europe, others) by field and year of highest degree. Observations for laureates located in multiple regions are prorated across these regions. See notes in Figure 1. Observations are at the individual-year level. This figure is generated using all years of data on each laureate.

Figure 6. Country of highest degree by field and time of the highest degree



Note. The figure shows where (US, Europe, others) the laureates received their highest degree by the period they received it. See notes in Figure 1 and Figure 5.

Table 1

Parameter Estimates for the Hazard Function of *Commencing* Prize-winning Work in a Given Year

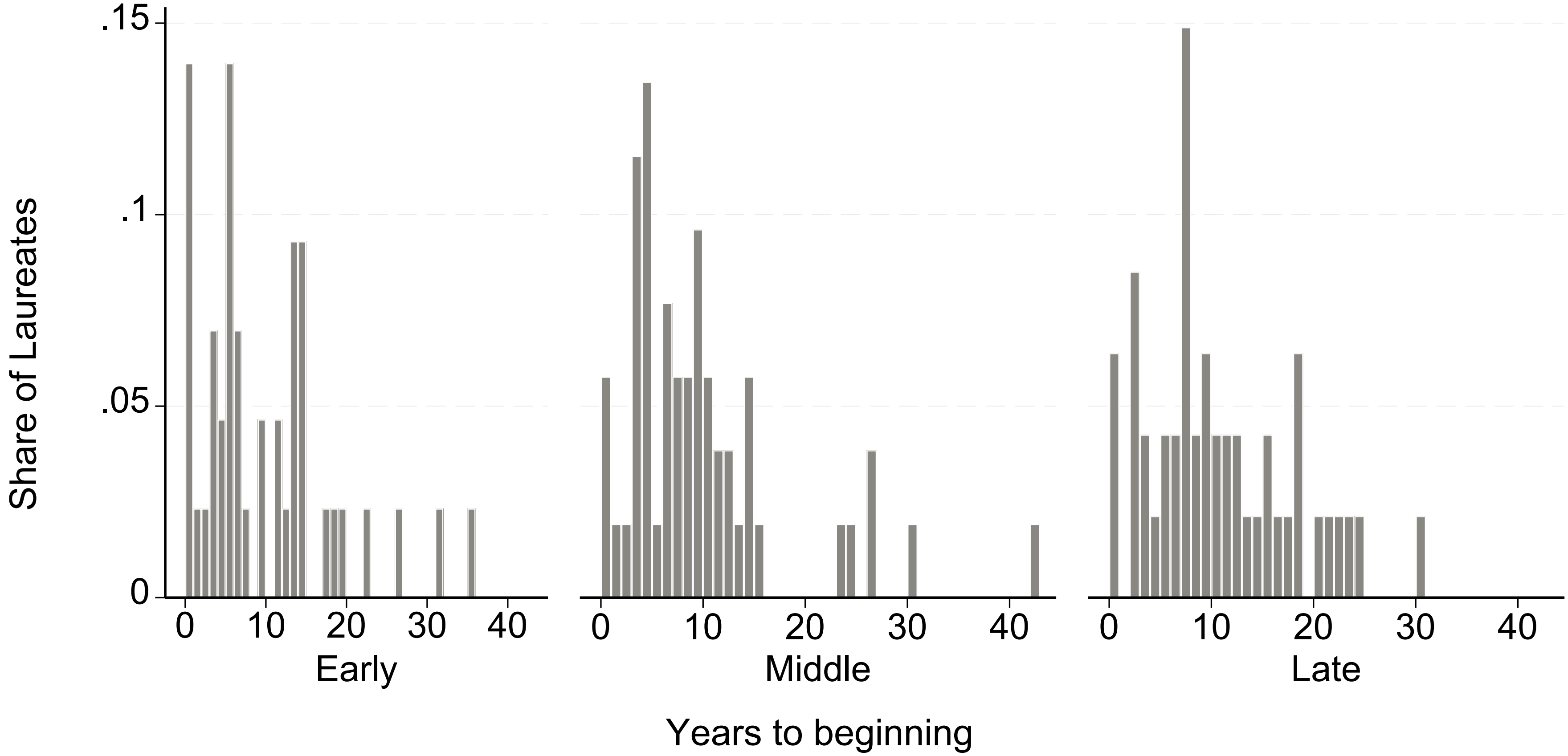
	(1)	(2)	(3)
A. Coefficients			
New Location (5 Year Definition)	0.780***		0.591***
	(0.166)		(0.175)
Multiple Locations		0.617***	0.426***
		(0.130)	(0.138)
Number of Laureates	0.432***	0.272**	0.277**
	(0.127)	(0.137)	(0.141)
Num. of Laur. at Start	0.061	0.135	0.130
	(0.185)	(0.186)	(0.186)
First 5 Years of Career	-1.159***	-0.988***	-1.144***
	(0.143)	(0.132)	(0.144)
Second 5 Years of Career	-0.366***	-0.386***	-0.399***
	(0.127)	(0.128)	(0.128)
Medicine	0.035	0.101	0.084
	(0.136)	(0.134)	(0.136)
Physics	-0.131	-0.080	-0.086
	(0.137)	(0.134)	(0.135)
B. Expected Duration Calculations			
Expected Duration (Years) to Commence	10.560***	10.572***	10.561***
	(0.358)	(0.348)	(0.354)
Effect on Expected Duration of:			
A New Location Every 2 Years	-2.638***		-1.991***
	(0.588)		(0.618)

A New Location Every 3 Years	-1.907***		-1.385***
	(0.468)		(0.467)
A New Location Every 5 Years	-0.968***		-0.688***
	(0.259)		(0.246)
Always Multiple Location vs. Never Multiple Location		-3.576***	-2.589***
		(0.692)	(0.785)
All Chemistry to All Medicine	-0.223	-0.635	-0.533
	(0.867)	(0.847)	(0.864)
All Medicine to All Physics	1.089	1.162	1.102
	(0.909)	(0.879)	(0.898)
All Physics to All Chemistry	-0.866	-0.527	-0.569
	(0.909)	(0.886)	(0.897)
Log L	-1547.7	-1548.6	-1543.0

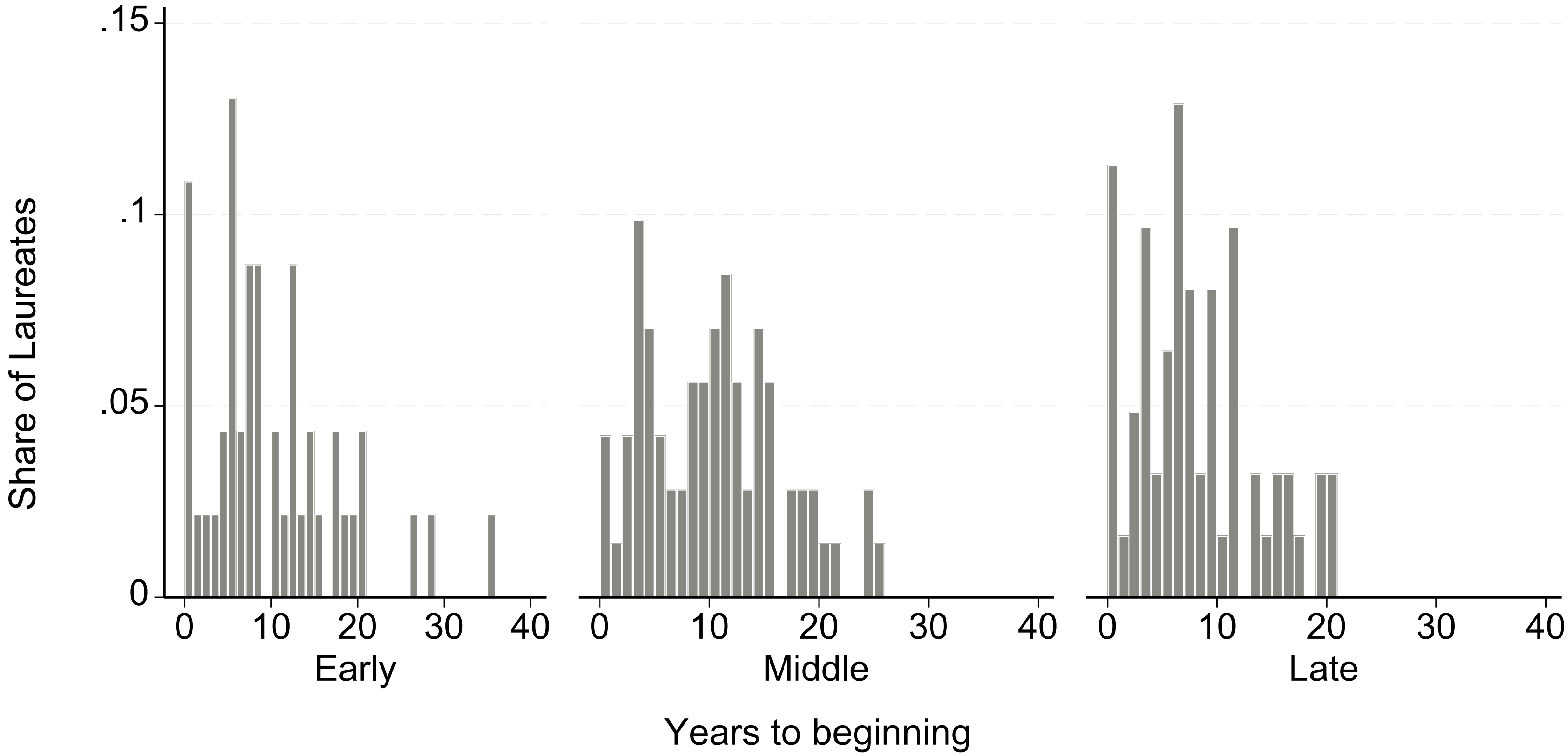
Notes: Based on 485 Nobel laureates; Standard errors in parentheses; Significance: ***; **; and * denote significance at the 1%, 5%, and 10% level, respectively. All specifications also include calendar year and calendar year squared (coefficients not shown).

Appendix Figure A1. Distribution of time to beginning Nobel work, by field and time of highest degree

A. Chemistry

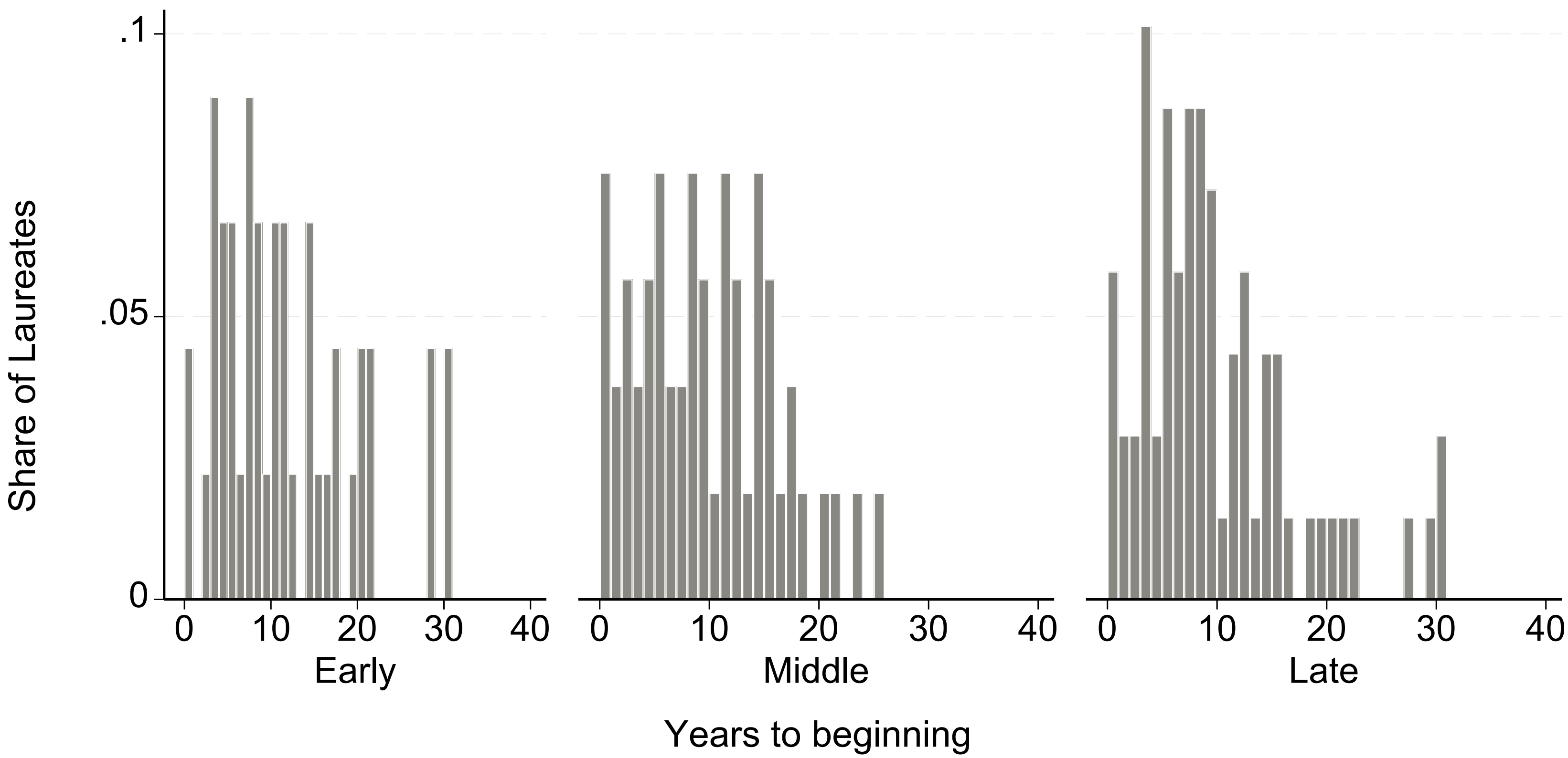


B. Medicine



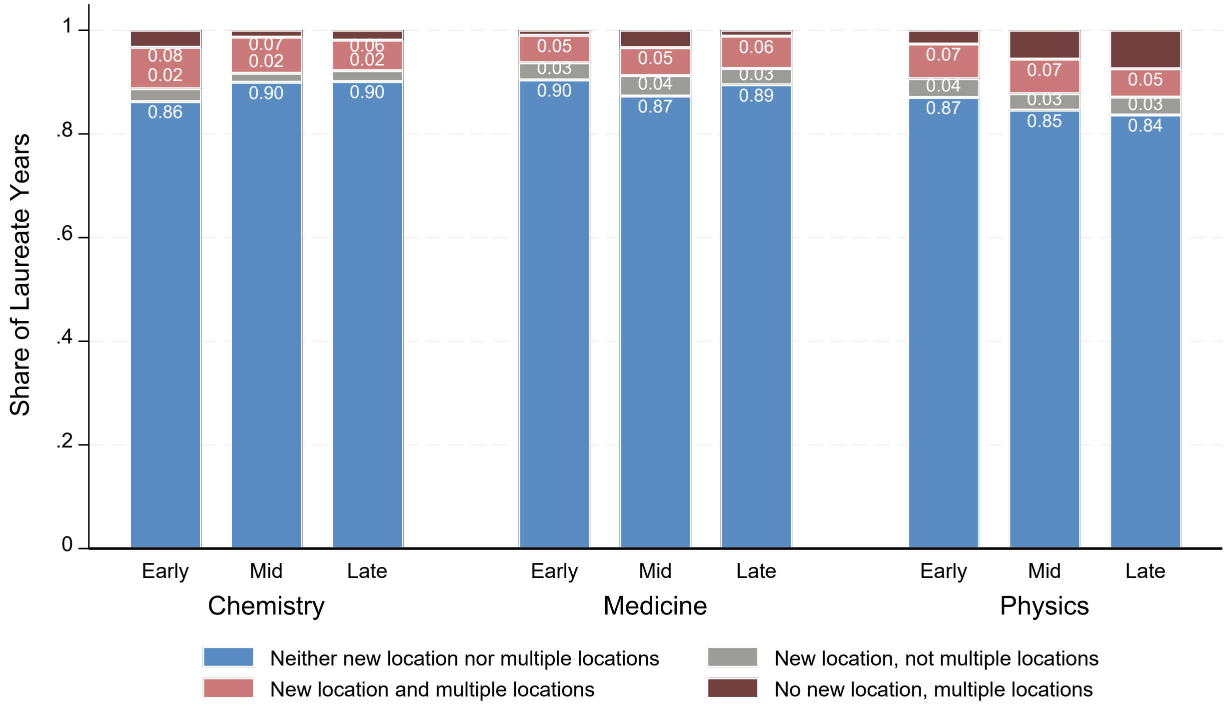
.15
.1
.05
0
Share of Laureates
0
10
20
30
40
Early
Middle
Late
Years to beginning

C. Physics



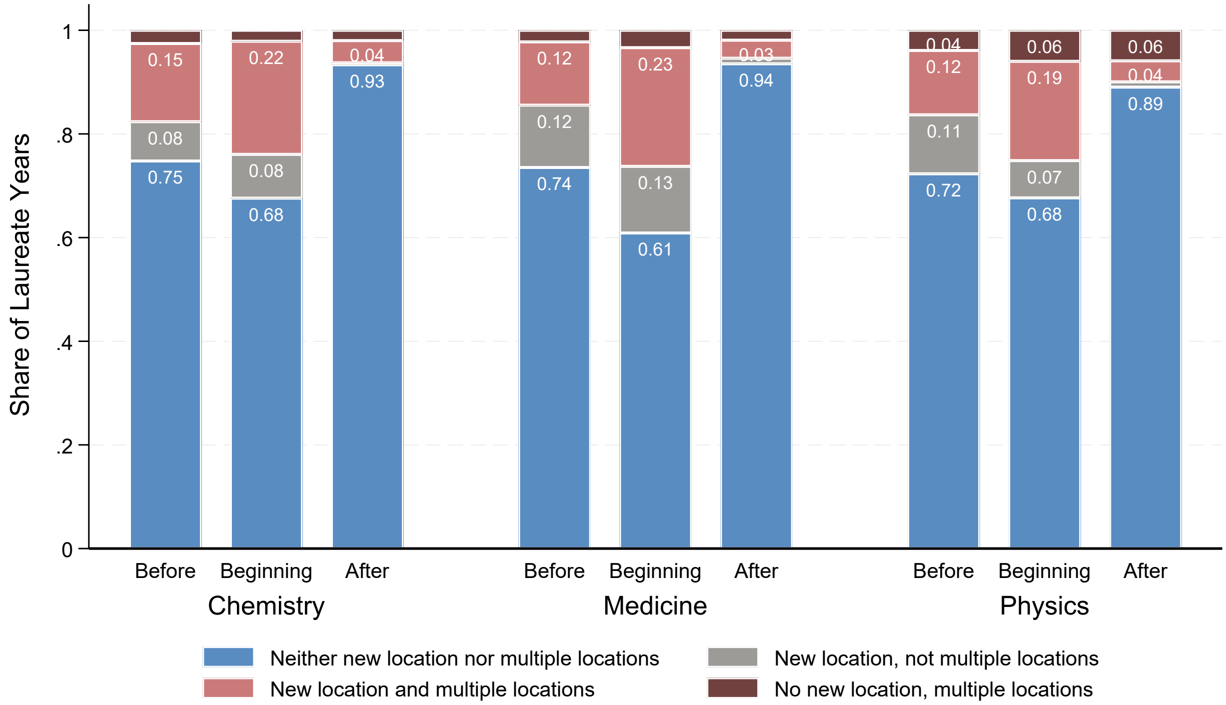
Note. The histograms show the distribution of years to beginning prize-winning work relative to the beginning of the career (three years before receiving the highest degree) for people graduating in each period. See notes in Figure 1

Figure A2. Time in multiple locations and new locations by time of highest degree and field



Note. The figure shows the share of time (i) in neither a new location nor in multiple locations (in blue), (ii) in a new location but not in multiple locations (grey), (iii) in both a new location and in multiple locations (pink) and (iv) in multiple locations but not in a new location (dark brown) by field and time of high degree. This figure is based on all years of data on all laureates.

Figure A3. Time in multiple locations and new locations relative to beginning Nobel work by field



Notes: The figure shows the share of time in new and/or multiple locations relative to beginning Nobel work by field. See Figure 3 for color coding and the sample. Before indicates all years before the laureates begin their Nobel work, beginning indicates the year they began Nobel work, and after indicates all years after the laureates began their Nobel work.

Table A1

Parameter Estimates for the Hazard Function of *Commencing* Prize-Winning Work in A Given Year When the Current Number of ENLs is *Not* Included

	(1)	(2)	(3)
A. Coefficients			
New Location (5 Year Definition)	0.855*** (0.162)		0.586*** (0.175)
Multiple Locations		0.730*** (0.117)	0.544*** (0.127)
First 5 Years of Career	-1.149*** (0.142)	-0.964*** (0.130)	-1.120*** (0.143)
Second 5 Years of Career	-0.333*** (0.124)	-0.370*** (0.126)	-0.383*** (0.126)
Medicine	0.118 (0.133)	0.161 (0.131)	0.145 (0.133)
Physics	-0.023 (0.130)	-0.003 (0.132)	-0.008 (0.131)
B. Expected Duration Calculations			
Expected Duration (Years) to Commence	10.471*** (0.353)	10.546*** (0.345)	10.534*** (0.351)
Effect on Expected Duration of:			
A New Location Every 2 Years	-2.884*** (0.571)		-1.979*** (0.616)
A New Location Every 3 Years	-2.119*** (0.464)		-1.376*** (0.465)
A New Location Every 5 Years	-1.090*** (0.263)		-0.686*** (0.246)
Always Multiple Location vs. Never Multiple Location		-4.141*** (0.608)	-3.240*** (0.692)
All Chemistry to All Medicine	-0.771 (0.860)	-1.029 (0.833)	-0.939 (0.851)
All Medicine to All Physics	0.924 (0.900)	1.047 (0.874)	0.991 (0.885)
All Physics to All Chemistry	-0.153 (0.877)	-0.017 (0.879)	-0.052 (0.875)
Log L	-1555.7	-1552.4	-1546.9

Notes: See notes in Table 1.