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# FIRST FOOT FORWARD:
# TWO-STEP ECONOMETRIC METHOD FOR PARSING AND ESTIMATING THE IMPACTS OF MULTIPLE IDENTITIES

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First Foot Forward: A Two-Step Econometric Method for Parsing and Estimating the Impacts of Multiple Identities
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**ABSTRACT**

Marketing and strategy researchers have often studied how organizations navigate multiple identities in relation to category spanning but extant literature pays less attention to understanding how individuals do so. Moreover, current econometric approaches only scratch the surface with respect to addressing the impact of multiple identities in professional settings. As a model domain to study labor market returns when individuals have more than one identity, we focus on interdisciplinary dissertators in the United States since evidence shows clear uptrends in dissertators engaging multiple professional identities and unclear trends in their outcomes. Our novel estimation method leverages a two-step process to characterize salaries of interdisciplinary dissertators as functions of the identities (academic fields) they acquire as graduate students. We estimate a first-stage regression of log earnings for monodisciplinarians on field dummies and respondent characteristics. After capturing the estimated field coefficients, we then regress log earnings for interdisciplinarians on linear and non-linear functions of these coefficients. Our estimates robustly reject the hypothesis that interdisciplinarians receive a salary premium. We also find evidence that the academic market, but not other employment sectors, particularly compensates researchers based on their primary discipline, an outcome that challenges emphases on interdisciplinarity. While our findings for interdisciplinarians point to the primary identity holding predominant importance for doctoral graduates in the United States, our two-step method provides a framework for parsing and estimating the varied impacts of multiple identities across a wide range of contexts.

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## 1. Introduction

When individuals or organizations need to identify themselves, it is sensible advice to put their best foot forward. Conventionally, most people have had a single foot to put forward but it is increasingly common to have more than one figurative foot (Ramarajan 2014) involving multiple racial and ethnic identities (Tavernise and Gebeloff 2021), non-binary genders (Matsuno and Budge 2017), various kinds of intersectional identities (McCall 2005), or some mix of professional identities (Johnson et al. 2006; Ashforth et al. 2016; Miscenko and Day 2016; Ingram 2022;). Among researchers, for example, there is increasing emphasis on interdisciplinarity – the combination of multiple disciplinary identities – and a recent analysis of more than one million dissertations written in the United States between 1986 and 2015 shows a clear uptrend in the share of doctoral students that are engaging interdisciplinary research, nearly doubling since 2000 (Kniffin, Hanks, Qian, Wang, and Weinberg 2020). Comparable questions related to category spanning (Zuckerman 1999; Nerkar 2003; Pontikes 2012) and organizational ambidexterity (Albert and Whetten 1985; O'Reilly and Tushman 2004; Creary et al. 2015) have also been examined by marketing and management researchers but there has not been comparable attention paid to understanding the outcomes of individuals with multiple identities in professional settings, given that an applicable, efficient, and flexible empirical method to study multiple-identity questions is not yet well-established.

This paper introduces a set of novel methods to parse and estimate the varied impacts of multiple, interacting identities, which we apply to understand the outcomes of interdisciplinary researchers. The key to our method is to treat people with multiple professional identities – determined by expertise in specific academic fields – as potentially complex combinations of their separate identities. In our context, PhD recipients develop their identities by choosing academic fields that signal a specific set of skills, expertise, and knowledge they refined over an average of 5-6 years of training (Nerad 2004). We leverage an important feature of our data, the Survey of Earned Doctorates (SED) overseen by the National Science Foundation (NSF), which asks respondents to list primary and secondary fields if their dissertation research is interdisciplinary. Following conventions (e.g., Millar and Dillman 2010; Kniffin and Hanks 2017), we describe multi-field doctoral graduates as "interdisciplinarians." Then, to reflect interdisciplinarity when estimating near-term outcomes for PhD recipients, we apply a two-step estimation procedure where we first regress (log) salaries for monodisciplinarians on field dummies and respondent characteristics. After capturing the estimated discipline effects, we regress salaries for interdisciplinarians on functions of these estimated discipline effects.

Our empirical work shows that interdisciplinarians' salaries tend to be joint functions of the market salaries of each field in which they specialize and related to both the order of the fields (primary VS secondary) and the relative value of the salaries (higher VS lower). Yet, we find that an interdisciplinarian's salary is considerably more strongly related (more than 2-times) to salaries in the chosen primary field than in the secondary field. Consistent with previous literature, interdisciplinary researchers also experience a small salary penalty relative to monodisciplinary researchers (Kniffin and Hanks 2017; Kniffin et al. 2020), but we observe no difference from choosing a secondary discipline that is more closely or distantly related to the primary discipline. We also find that industry rewards expertise in a highly paid field, whether it is the primary or secondary field, considerably more than academia, hinting that departmental norms driven by primary fields may dominate academic offers while industry values skills and knowledge even if they are from a secondary field. Robustness checks across different sub-samples suggest a commonly existing earning formation pattern among interdisciplinary researchers and show that the identity/order effect dominates any other salary effects, at least in the case of labor market outcomes of interdisciplinary researchers.

While our model domain focuses on the outcomes of interdisciplinary researchers, the broader question of how to understand multiple, complex, and interacting identities has increasing importance as society recognizes the dynamic ways in which people self-identify (Akerlof and Kranton 2000, 2005; Ramarajan 2014; Kranton 2016; Miscenko and Darja 2016). Indeed, there is ample evidence that the ways in which people identify themselves directly influence their behavior in a wide variety of ways (Akerlof and Kranton 2005; Ruebeck et al. 2009; Reed and Forehand 2016; St. Clair and Forehand 2020) and reflect who they are and how they belong in an organization or a society (Akerlof and Kranton 2000; Carvalho 2016). For example, in contrast with classical economic assumptions (Kamenica 2012), Akerlof and Kranton (2005) argue that corporate identity can motivate greater productivity than monetary incentives.

Fortunately, society is increasingly recognizing that identities that have historically been treated using a limited number of discrete and sometimes even binary categories are more complex and frequently interact with each other in important "intersectional" (McCall 2005; Ramarajan 2014) ways. Over time, the U.S. Census Bureau has also modified its classifications to allow for multiple racial and ethnic identities to obtain more accurate snapshots of the population (Tavernise and Gebeloff 2021). Moreover, gender, which has traditionally been measured as a binary characteristic, is no longer conceptualized as one of two options but as fluid and/or lying along a gender identity continuum (Matsuno and Budge 2017).

However, standard analytic methods only scratch the surface when answering basic questions regarding complex and/or multiple identities, such as (*i*) how the underlying identities are rewarded, (*ii*) whether primary identities are rewarded more than secondary identities, and (*iii*) whether people or organizations with multiple categorical memberships experience premia or penalties compared to those without more complex identities. One approach would involve estimating models with a full set of dummies of each field and interactions between all possible identities. With many identities and interactions between them, such an approach would require a massive dataset, would require estimating and then interpreting many interaction terms (potentially over 100,000 in our context!), and risks overfitting. Moreover, this approach also does not directly address the question of whether multiple identities yield a premium or penalty because each pairing of identities is its own category and collinearity would make it impossible to extract empirical regularities. Such an analysis might be constrained using some form of machine learning (e.g., a LASSO estimator) reducing overfitting to some extent, but still not directly address the issue of premia or penalties for multiple identities and, depending on estimation, might still be far from parsimonious. A second approach could be to include dummy variables for just the primary field, without secondary field interactions, and a dummy variable for multiple identities (versus a single identity) in the model. While this simpler approach avoids the need to estimate numerous coefficients for primary and secondary field interactions, it still fails to estimate premia or penalties for interdisciplinarity.

Our empirical approach to multiple identities addresses these gaps in methodology. First, we use a natural single-identity comparison group (e.g., monodiscplinarians) to predict outcomes for single identities. We then use these predicted outcomes to estimate the relative impact of each single identity on outcomes for those claiming multiple identities. Second, our parsimonious method eliminates the need for many interaction terms without sacrificing model validity. In other words, the predicted outcomes we estimate effectively explain the same variation that numerous field interactions capture while at the same time allowing us to estimate premia or penalties for multiple identities. Lastly, our methods can serve as a general econometric tool for instances where individuals or organizations have complex interacting identities, in our case allowing us to estimate the effects of primary and secondary dissertation fields on salary.

Our approach evolved out of work on interdisciplinarity, which is an important and interesting application for three reasons. First, it is socially important to understand the experience of interdisciplinarians given the widespread emphasis placed on interdisciplinary research and the increasing share of researchers conducting interdisciplinary research. As background, universities increasingly encourage collaborative and interdisciplinary research (e.g., Sá 2008; Leahey and Barringer 2020) just as federal funding agencies champion category-spanning work. For example, the National Science Foundation (NSF) declared convergence research as one of its "10 Big Ideas"[1] and has a history of grant programs dedicated solely to fostering interdisciplinary research, such as the Integrative Graduate Education and Research Traineeship (IGERT) and the more recent NSF Research Traineeship (NRT) programs.[2] Despite this emphasis, which might lead some to expect that institutions would pay a premium for such researchers, extant findings are more consistent with the view that interdisciplinary work is more difficult to conduct because it requires integrating methods and concepts from more than one discipline (Fleming 2001; Wagner et al. 2011; Lo and Kennedy 2015; Kaplan et al. 2017). Consistent with our observation that standard analytic methods are not designed to address individuals or organizations with multiple identities, we can observe that research on the returns to graduate education across different fields (e.g., Green and Zhu 2010; Stevenson 2016)

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[1] https://www.nsf.gov/news/special_reports/big_ideas/convergent.jsp
[2] https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=505015

typically fail to recognize that an increasing proportion of PhD holders rely on multiple fields for their dissertation research (Kniffin et al. 2020).

Second, the mixed findings from prior research on interdisciplinarians make the topic a prime candidate for applying a novel analytic approach. Recent research illustrates that those who choose to work on interdisciplinary projects may not publish as much as monodisciplinarians and are less likely to be funded (Bromham et al. 2016), but they do tend to attract more citations to their work (Leahey et al. 2017). In conjunction with publication challenges, evidence also shows a near-term salary penalty that is partially mediated by working as a "postdoc" researcher (Kniffin and Hanks 2017; Kniffin et al. 2020), and together these suggest both salary and employment risk. Similarly, patents that span multiple disciplines are often subject to heightened concerns about their quality (Lo and Kennedy 2015).

Third, among other applications, the study of interdisciplinary researchers offers a topically close model for understanding other aspects of student decision making within education. For instance, a better understanding of the relevance of salaries for decisions to conduct interdisciplinary or monodisciplinary research should shed light on decisions by students to pursue either undergraduate or graduate degrees in fields such as the Humanities that tend to have relatively low salaries (Golde and Dore 2001; Montt 2017). In addition to contributing insights related to the selection of majors, our work provides a pathway for understanding the increasing trend of double majoring among undergraduate students (Hemelt 2010; Zafar 2012; Del Rossi and Hersch 2008, 2016; Stock 2017).

The remainder of this paper is organized as follows. Section 2 describes the data and presents descriptive results. Section 3 builds an innovative theoretical framework and derives our empirical strategy. Section 4 reports empirical estimates from the two-step approach. Section 5 discusses and concludes.

## 2. Data

In this research we rely on data from the SED, an annual survey administered by the NSF that collects a near-census of PhD earners at US institutions (Fiegener 2011). As indicated, this survey contains detailed individual- and university-level data for each respondent. The individual-level data include demographic characteristics, background education information, funding source (if any) as a graduate student, the dissertation subject field(s), and information regarding the first job after graduation such as salary and job sector. University-level data include the university's level of research intensity – from very high research activity to low research activity, whether it is a private or public university, and whether it is a Historically Black College and University (HBCU). In our estimation models, we include university fixed effects that capture all institution-level time-invariant characteristics.

### 2.1 Measuring Interdisciplinarity

The SED also provides information about the interdisciplinary nature of PhD dissertations. For the first time in the 2001 survey wave, the SED included a question that asked respondents to list a secondary dissertation field if they had any. In 2004, the NSF adjusted the question slightly to first ask whether the respondent considers his or her dissertation to be interdisciplinary and if so, follows up by asking the respondent to report the secondary field. In 2010, the NSF preserved the two-part question and added the option to include up to three additional fields. Since the SED began collecting salary data in 2008, the 2010 modification is the only change that affects our sample. Given that very few individuals select three or more fields (especially in the early years) our results are virtually unaffected by this change. When we estimate the same models using a

2010-2016 sample instead of our full (2008-2016) sample, we observe minimal differences in the estimated coefficients.

We follow the initial work of Millar and Dillman (2010) and subsequent applications of their methods (Hanks and Kniffin 2014; Kniffin and Hanks 2017; Kniffin et al. 2020), categorizing a doctoral graduate as interdisciplinarian when reporting a second field. Kniffin et al. (2020) show that the proportion of interdisciplinarians among all US PhD recipients has increased over time and that changes in the SED questionnaire about secondary fields and interdisciplinary dissertations do not seem to correspond to uncharacteristic changes in the trend. The increasing trend, absence of deviations from the trend in years when the questionnaire changed, and robustness of results illustrate our measure's internal consistency over the sample period.

Our approach differs from bibliometric studies of references and citations that are more indirect (e.g., Stirling 2007; Leahey et al. 2017; Leydesdorff and Ivanova 2021), allowing us to identify researchers who self-identify as interdisciplinary and capture their self-reported primary and secondary dissertation fields. The SED also allows us to include detailed individual characteristics and outcome measures. As a result, we are able to estimate the impact of interdisciplinarity on earnings while controlling for individual and institutional characteristics.

We introduce nuance into our measure of interdisciplinarity by categorizing individuals based on the proximity of their topic-combinations. Specifically, the SED taxonomy contains over 300 lower-level academic fields nested within 12 top-level fields and maps to traditional academic disciplines. We label a dissertator as "globally" interdisciplinary if the primary and secondary lower-level fields belong to different top-level fields, or "locally" interdisciplinary if the lower-level secondary field is within the same top-level field as the primary field. To add additional nuance, we group global interdisciplinarians into two categories: broadly or narrowly global. We identify researchers with one field in the natural sciences and one field outside the natural sciences as "broadly global" and researchers whose fields both fall within or outside of the natural sciences as "narrowly global." For example, this approach classifies a researcher who chooses chemical engineering and plant science as narrowly global and someone whose field-pairing spans the natural and social sciences, such as molecular biology and political science, as broadly global. We refer readers to Figure 1C in Kniffin et al. (2020) for a graphical depiction of the mix of interdisciplinary fields based on the upper-level field categories.

In Figure 1, we plot the number of interdisciplinarians for each of the bottom-level field combinations for the full parameter space. Because there are 341 distinct bottom-level fields categorized in the SED, there are 123,552 potential field combinations. Notably, 80% of the combinations are not picked by any interdisciplinarian, 16% are chosen by fewer than 10 people, and only 0.25% of the potential combinations attract more than 100 interdisciplinarians. In Figure 1, we assign different colors to represent different frequency ranges of the field combination sizes, where blue represents fewer than 10 interdisciplinarians, green represents 10 to 50 interdisciplinarians, yellow represents 50 to 100 interdisciplinarians, and red highlights combinations with more than 100 interdisciplinarians. We also add border lines to demarcate top-level fields and, consequently, create boxed areas of both "local" and "global" interdisciplinarity. Notably, the size of each box is determined by the number of bottom-level fields within each top-level field. Therefore, all of the boxes along the 45-degree line are local interdisciplinary combinations since both the primary and secondary bottom-level fields come from the same top-level field. All of the other boxes in Figure 1 that are not along the 45-degree line contain bottom-level field combinations that span different top-level fields and these pairings fall under the categorization of globally interdisciplinary since they span greater topical distance.

*[INSERT FIGURE 1 ABOUT HERE]*

The distribution of bottom-level field combinations in Figure 1 indicates that the largest interdisciplinary combinations are locally interdisciplinary – concentrations of green, yellow, and red areas mostly occur close to the diagonal. The remaining combinations are blue, with some exceptions. We note that globally interdisciplinary combinations are primarily clustered within two larger groupings of fields. Field-grouping 1 (lower left) contains natural science fields, including life sciences, engineering, computer/information sciences, mathematics/statistics, and the physical sciences. Field-grouping 2 (upper right) contains social science fields: psychology, (other) social sciences (e.g., sociology), humanities, education, business, and communication. The concentration of globally-paired fields is highest within these two larger field groupings, our narrowly global interdisciplinary category. Pairs of fields from field-groupings 1 and 2, which we are referring to as broadly global interdisciplinary, are relatively rare. Figure 1 suggests that even when PhD students conduct interdisciplinary research across the category of top-level fields (globally interdisciplinary), they are still more likely to integrate the knowledge from top-level fields that likely share similarities (narrowly global). When we compare the distribution of globally interdisciplinary combinations between field-groupings 1 and 2, researchers from field-grouping 2 seem to conduct global interdisciplinary research more intensively than those in field-grouping 1, and this is especially true in psychology and "other" social sciences (e.g., sociology, anthropology, and linguistics).

To examine the relationship between local and global interdisciplinarity and their relationship to popularity, Figure 2 shows the share of local interdisciplinarity on the x-axis and the share of global interdisciplinarity on the y-axis. The circle for each bottom-level field is sized to reflect the total number of all PhD researchers, including both mono- and inter-disciplinarians, listing that field as their primary field. Colors are used to indicate the top-level field to which each bottom-level field belongs. Most of the circles lie within a triangle with total interdisciplinarity beneath .50, thus there is something of an upper bound to interdisciplinarity. This is sensible since one can imagine that if, say, 95% of individuals in a given field combined the given field with a small number of complementary fields, then it would seem sensible to question whether the given field was still a distinct and independently functioning field. Figure 2 also implicitly shows the correlation between the share of interdisciplinarity and popularity. A 10% increase in the population size of PhD researchers in one field is associated with 0.02% decrease in the share of both local and global interdisciplinarians.

*[INSERT FIGURE 2 ABOUT HERE]*

**2.2 Near-term Job Market Returns**

Outcome measures in the SED that we use for this research are reported salary values for the first year post-PhD and are based on the job that the respondent has already accepted or intends to accept. Beginning with the 2008 wave of the SED, the NSF included two questions that ask respondents about their expected salary. The first provides salary ranges from which the respondent can choose. The second allows the respondent to enter an actual dollar amount. When respondents select a pre-determined salary range, we enter the mid-point of that range as the salary (N=83,163). These ranges are in $10,000 increments except that the lowest range is $30,000 or less – for which we enter $15,000 (N=6,329) – and the top range is capped at $110,001 – for which we enter $110,001 (N=6,377). In our final sample, response rates for actual salary entries are 49.73% (N=158,055) and response rates for entries of salary ranges are 83.44% (N=386,086).

In Figure 3, we provide the first descriptive evidence of an interdisciplinary penalty and potential differences in salaries for local and global interdisciplinarians. In this figure, we map income distributions for monodisciplinarians and interdisciplinarians using a kernel density estimator. Panel A of Figure 3 shows that the distributions for both types of researchers peak at a similar salary; however, greater density appears in the $40,000-$60,000 range for interdisciplinarians whereas the plot for monodisciplinarians has greater density in the $75,000-$125,000 range. In other words, the differences in salary between monodisciplinarians and interdisciplinarians appear to be driven by a set of interdisciplinarians whose salaries are more commonly in the $40,000-$60,000 range instead of the $75,000-$125,000 range that is more common for monodisciplinarians. Since interdisciplinarians tend to accept postdoctoral positions more often (Kniffin and Hanks 2017, Kniffin et al. 2020), these postdoctoral researchers surely explain at least part of the difference in distributions. In Panel B of Figure 3, we map the income distributions for global and local interdisciplinarians. The distribution for global interdisciplinarians appears to be shifted to the right and has a thicker right tail relative to the distribution for local interdisciplinarians. In other words, a higher proportion of global interdisciplinarians receive higher salaries than local interdisciplinarians.

*[INSERT FIGURE 3 ABOUT HERE]*

Table 1 reports starting salaries according to the primary top-level field and disciplinarity. In most cases, the average salary for monodisciplinarians is greater than the average salary for interdisciplinarians except for Mathematics and Humanities. In addition, average salaries for global interdisciplinarians tend to be higher than average salaries for local interdisciplinarians. The exceptions are top-level fields that tend to yield higher starting salaries in general: Engineering, Computer Science, and Business.

*[INSERT TABLE 1 ABOUT HERE]*

To characterize the pairings of salaries across fields for interdisciplinarians, Figure 4 provides a heat map of the average salary for the finer-grained "bottom-level" fields of interdisciplinarians and shows the number of SED respondents for each salary combination. The salary data on each axis represents the average salary for monodisciplinarians from the primary field (X-axis) and secondary field (Y-axis) divided into population-weighted deciles. For example, an interdisciplinarian whose primary and secondary fields both rank in the bottom 10% for average salaries (among monodisciplinarians) will be represented in the 10%-10% box (in the bottom-left corner). The degree of shading for each cell reflects the number of people with that combination of average earnings.

*[INSERT FIGURE 4 ABOUT HERE]*

Figure 4 suggests that the salary rankings of the two fields chosen by the interdisciplinarians are quite symmetric around the 45-degree line. Thus, we do not observe that interdisciplinarians with a relatively low-paying primary field are more likely to select a relatively higher-paying secondary field (or *vice versa*). Figure 4 also shows considerable earning dispersion among interdisciplinarians with the darker colors in both the bottom-left corner and top-right corner areas. However, the number of interdisciplinarians with two lower-paying fields, such as Creative Writing and Humanities, is higher than the number of interdisciplinarians with two high-paying fields (e.g., Marketing Management and Business Administration). These findings are noteworthy because doctoral recipients with a low-paying first field might have a greater incentive to pick a secondary field to add value to themselves in the labor market but they do not appear to do so on a regular basis. Instead, it seems that students who are already studying a very high-paying subject (as a first field) are prone to engage another high-paying field when doing interdisciplinary work to further leverage the returns to human capital since selecting a more distant secondary field may impose a penalty. Alternatively, fields with similar salaries may make more natural pairings.

**2.3 Descriptive Statistics of Main Sample**

Table 2 presents summary statistics of our estimation sample of all SED respondents from 2008 to 2016. Column 1 summarizes the full sample, and the remaining columns summarize respondents in the monodisciplinary group and respondents grouped into the 5 types of interdisciplinarity. Panel A in Table 2 reports the demographic characteristics and panel B shows job sectors. Overall, individual demographic characteristics do not differ dramatically with respect to (inter-)disciplinarity, but there are a few meaningful differences. For example, US citizens are less likely to conduct interdisciplinary doctoral research compared with non-US citizens (66.1% of monodisciplinarians are US citizens while 61.8% interdisciplinarians are US citizens). With respect to race, we find that the percentage of the White population in the monodisciplinary group is about 5 points higher compared with the interdisciplinary group (67.1% versus 62.6%). We also observe differences across gender and race for the broadly global interdisciplinarians and narrowly global interdisciplinarians in columns 6 and 7. For instance, the broadly global interdisciplinary group includes 10 percentage points more women than the narrowly global interdisciplinary group.

While the SED has included questions regarding salaries since 2008, respondents have been answering questions about job placements since the survey began in 1958. Individuals have had the option to indicate whether they have already accepted a position or are still searching. Those who indicate that they have already accepted a position also select the relevant job sector, yielding the following categories: (*i*) education, which includes positions at colleges, universities, and primary and secondary schools; (*ii*) government, which includes local, state, federal, or foreign governments; (*iii*) the private sector, which includes for-profit industry jobs; (*iv*) non-profit entities; and, (*v*) other types of employment, including self-employment. Respondents are also asked to indicate whether they intend to accept a postdoc position.

Panel B of Table 2 shows that 71.4% of interdisciplinarians had accepted a job offer by the time they completed the SED, compared to 73.8% of monodisciplinarians, indicating that interdisciplinarians are slightly less likely to have a job when they complete the SED. In terms of placement sectors, education accounts for nearly 68% of all new doctoral recipients, followed by industry (17.4%), government (8.8%), non-profits (4.8%), and self-employment work (1.0%). Panel B in Table 2 also differentiates education so that postdoctoral research positions are specified as distinct from other positions in the education sector. This is notable since interdisciplinarians are more likely to accept postdoc positions than monodisciplinarians (42.9% versus 36.2%). The flip-side of interdisciplinarians being more likely to accept postdoctoral positions (also see Kniffn and Hanks 2017, Kniffin et al. 2020) is that they are less likely to start with a tenure-track position and they are less likely to accept positions in industry.

*[INSERT TABLE 2 ABOUT HERE]*

## 3. Theoretical Framework and Empirical Strategy

### 3.1 A Multiple Identity Framework

To lay out our empirical framework, we begin with a general model for addressing and estimating premia associated with identities. Let each person, $i$, be characterized by a vector of identities, $\vec{I}_i$. We leave $\vec{I}_i$ flexible but note that special cases of this formulation could be a set of dummy variables that indicate whether a person has a given identity or a continuous measure of the extent to which someone has a certain identity. In our case, we have data on whether people have a given discipline as a primary identity or as a secondary identity or do not have that identity.

Our multiple identity framework is derived from the following model:

$$Y_i = f(\vec{I}_i; \beta) + \boldsymbol{X_i \Gamma} + \varepsilon_i \tag{1}$$

where $Y_i$ is the observed salary of individual $i$; $\boldsymbol{X_i}$ is a set of individual demographic traits; and $\varepsilon_i$ includes unobserved individual features, including preferences and ability. We note that our approach is sufficiently flexible to allow for interactions between $\vec{I}_i$ and $\boldsymbol{X_i}$.

As discussed in our introduction, estimating equation (1) by brute force has a number of disadvantages. These include the risk of overfitting and the informativeness of $\hat{\beta}$ if $f(.)$ is specified very flexibly. In our case, if we allow for a full set of interactions between all observed pairs of identities, $\beta$ in theory could have 116,281 elements if all of the possible ordered pairswere observed (341 monodisciplinary coefficients and 115,940 interdisciplinary coefficients).

Therefore, our response is to first parameterize the identities $\vec{I}_i$ as the market equilibrium earnings of $i$'s primary and secondary identities (fields), $m_{First,i}$ and $m_{Second,i}$, the larger of the market equilibrium salaries for both fields ($m_{Max,i}$) and a dummy variable for whether the person has multiple identities, $M_i$, which is an object of interest.[3] We then model $Y_i$, the individual's observed salary, as a function of these identities:

$$log(Y)_i = \tilde{f}(m_{First,i}, m_{Second,i}, m_{Max,\,i}; \beta) + M_i\delta + \boldsymbol{X_i\Gamma} + \gamma_{j(i)} + \mu_{t(i)} + \varepsilon_i \qquad (2)$$

Because our data cover nine years between 2008-2016 (people appear in our data in the year in which they graduate), we control for time using fixed effects, $\mu_{t(i)}$. To control for differences in training, we also include fixed effects for the institution from which people graduated, $\gamma_{j(i)}$. It is also the case that individuals are nested within year and institutions in our sample.

We assume the multiple identity salary equation is additively separable in all variables and linear in parameters, which is sufficiently flexible for including interaction and quadratic terms. We express this relation in equation (3) below:

$$log(Y_i) = \alpha + \beta_1 m_{First,i} + \beta_2 m_{Second,i} + \beta_3 m_{Max,i} + M_i\delta + \boldsymbol{X_i\Gamma} + \gamma_{j(i)} + \mu_{t(i)} + \varepsilon_i \qquad (3)$$

where $m_{Max,i} = \max\{m_{First,i}, m_{Second,i}\}$. We distinguish the earnings of the primary and secondary fields to see if the order in which people list fields matters, presumably because it reflects the extent to which they are in each field. If, as we expect, $\beta_1 > \beta_2$ ,it would indicate that the primary field has a greater effect on earnings than the secondary field for interdisciplinarians. It is also possible that people who have a higher paying field earn more (or less) conditional on

[3] For people with a single field, we set $m_{First} = m_{Second}$.

the weighted average of their primary and secondary fields implied by $\beta_1$ and $\beta_2$. For instance, companies may see hiring someone who has one foot in a high-paying field and another in a low-paying field as a somewhat less expensive way of hiring someone with expertise in a high-paying field. Alternatively, they may see people who are not "fully" in a high-paying field as having insufficient expertise. If $\beta_3 > 0$, then the higher paying field has a larger effect than the lower paying field while if $\beta_3 > 0$, then the lower paying field has a larger effect than the higher paying field. We note that $\beta_1$ and $\beta_2$ are identified separately from $\beta_3$ because people who have the same pairings of fields may list them in different orders, and the order is allowed to matter. Lastly, if $\delta > (<)0$, then individuals who report multiple identities experience a salary premium (penalty).

**3.2 A Two-Step Strategy**

A challenge with estimating equation (3) empirically is that the market equilibrium earnings of each field are not explicitly available in our data. Therefore, we build a two-step empirical strategy to first predict the market equilibrium earning of each field $k$ using the population salary data of all of the monodisciplinarians in the SED and then utilize the predicted field-level market earnings to estimate the functional form of our multiple-identity earning equation (equation (3)).

***First Stage***: The first stage of our empirical strategy is:

$$log(Y_i) = \sum_{k=1}^{K} \lambda_k D_{k(i)} + \boldsymbol{X_i \Gamma} + \gamma_{j(i)} + \mu_{t(i)} + \varepsilon_i \tag{4}$$

where $Y_i$ is the natural log of individual salary reported by monodisciplinarian $i$ who graduated from institution $j(i)$ in year $t(i)$. $D_{k(i)}$ is a dummy variable that equals 1 if monodisciplinarian $i$ graduated from field $k$. Similar to equation (3), we control for all of the individual traits (age, marital status, parental education, sex, race, US citizenship, and whether the individual received research funding), institution fixed effects, and year fixed effects. Therefore, the estimated $\widehat{\lambda_k}$ is the log of the predicted market equilibrium earning of doctoral recipients who graduated from field $k$: $\widehat{m_k}$, after netting out the control variables' effects.

***Second Stage***: In the second stage, we utilize the log of the predicted market earnings: $\{\widehat{m_k}: k = 1,2, \ldots, K\}$ and estimate the following specification based on equation (3):

$$log(Y_i) = \alpha + \beta_1 \widehat{m_{First,1}} + \beta_2 \widehat{m_{Second,1}} + \beta_3 \widehat{m_{Max,1}} + M_i\delta + \boldsymbol{X_i\Gamma} + \gamma_{j(i)} + \mu_{t(i)} + \varepsilon_i \tag{5}$$

where $\widehat{m_{Max,1}} = \max\{\widehat{m_{First,1}}, \widehat{m_{Second,1}}\}$. We note that for monodisciplinarians, $\widehat{m_{First,1}} = \widehat{m_{Second,1}} = \widehat{m_{Max,1}}$. Thus, if one were to run equation (5) for monodisciplinarians, $\widehat{\beta_1} + \widehat{\beta_2} + \widehat{\beta_3} = 1$, though most software packages would drop two of the variables and estimate the other equal to 1. $\boldsymbol{X_i}$ includes all of the observed demographics included in $\boldsymbol{X_i}$ in our first stage, equation (4). We also add to our baseline regressions by including dummy variables for different job sectors to net out the potential income disparities across different types of jobs.

To allow for a different intercept for interdisciplinarians (i.e., to estimate an interdisciplinarity penalty or premium), we include a variable, $M_i$, that captures whether an individual completed an interdisciplinary dissertation. To further explore whether there is a premium or penalty for interdisciplinarians who combine widely different fields, we also include dummy variables for local versus global interdisciplinarians and/or narrowly global versus broadly global interdisciplinarians in various specifications. In the regression tables, our results reflect these various approaches to characterizing interdisciplinarity. Our other variables, $\gamma_j$ and $\mu_t$, are graduating-institution and graduation-year fixed-effects, respectively.

Because we have estimated regressors in our second stage equation, we need to adjust our standard errors in the second step to account for estimated regressors. In other words, since the market earnings: $\{\widehat{m_k}: k = 1,2, \ldots, K\}$ are predicted from the first stage, the predicted regressors have additional sampling variance that needs accounting. Therefore, we bootstrap the standard errors (Zhang and Smith 2011; Greene 2017) 1,000 times and use a sample size equal to our original sample. Standard errors in equations (4) and (5) are clustered at the institution level.

## 4. Two-Step Model Estimates

We report results from our first-step regressions in Appendix Table A.1. Again, we emphasize that we only use log salaries from monodiscplinarians in the first step.[4] From this first stage, we utilize the coefficient on each separate field dummy to represent the estimated log earning for that field and include these estimates in the second stage. This allows us to capture log salary estimates independent of the variation from individual-specific characteristics, time-invariant institution effects, and year effects.

We report results for our first set of regressions for the second stage in Table 3. Note that columns 1-3 in the table represent regressions from the whole sample with variations in the indicator variables for the types of interdisciplinarity. In column 1, we include general interdisciplinarity. In column 2, we use the global and local interdisciplinarity measures to capture variation in field proximity. In column 3, we further separate global interdisciplinarity into narrowly and broadly global interdisciplinarity. Columns 4-5 represent regressions with only interdisciplinarians and we again vary the controls for the types of interdisciplinarity in these regressions. In column 4, we include global interdisciplinarity and in column 5, we use narrowly global and broadly global.

In all five regressions in Table 3, we observe that the primary field drives salary outcomes. The coefficients indicate that the average log salary of the first field receives a weight of 64-65% in determining the individual's log salary, with the coefficients having *t*-statistics over

[4] For illustration, we only report first-stage regression results based on top-level fields. We do not report first-stage regression results using bottom-level fields to conserve space.

30. Coefficients for the second field earnings indicate that the second field log salary receives a weight of 28-29% in determining the individual's log salary, which is less than half of the contribution of the first field. Put differently, a 10% increase in the market salary of the respondent's primary field corresponds to a 6.4% increase in salary but a similar increase in the market salary of the secondary field only yields a 2.8% increase.

In general, results also (see row 3 in Table 3) indicate that the higher paying field has positive and significant influence on individuals' near-term log earnings regardless of whether the higher paying field is the primary or secondary field (6-8%). For a given level of overall earnings, this effect implies a return to pairing fields with different earnings; however, maximal earnings occur when the primary field is higher-earning.

Strikingly, the coefficients on the three field salaries essentially sum to 1 in all specifications (i.e., $\widehat{\beta_1} + \widehat{\beta_2} + \widehat{\beta_3} \approx 1$). As indicated, this is an identity in a model with only monodisciplinarians, so it is perhaps not completely surprising that it holds in columns 1-3, where a large portion of the sample are monodiscplinarians, but the same relationship persists in columns 4-5 where no such identity holds since we only include interdisciplinarians. In fact, none of our three salary coefficients changes by more than 1 percentage point from any specification to any other specification.

Consistent with previous literature, we also observe a small log salary penalty for general interdisciplinarians. Coefficients in columns 1 and 2 show a small but statistically significant penalty to interdisciplinarity. The similarity between coefficients for local and global interdisciplinarity (in column 2) and local and both narrowly global and broadly global (in column 3) suggests minimal, if any, differences in the penalty based on the relative proximity of the fields. In column 3, we observe that each type of interdisciplinarity yields a small, though statistically significant penalty on log salary, though these coefficients are not statistically different from each other. The results in columns 4-5 for interdisciplinarians validate this outcome and indicate that differences between types of interdisciplinarity are indistinguishable from zero.

*[INSERT TABLE 3 ABOUT HERE]*

In Table 3, our covariates reveal a few interesting patterns, but mainly accord with expectations, providing an additional degree of confidence in our procedure. Earnings are positively related to parental education though the effect sizes are small. PhD recipients who are single have slightly lower earnings than those who are married. Consistent across all our models, women earn about 95% of what men earn. The difference in earnings by race (white versus non-white) are small and statistically insignificant. US citizens tend to earn about 18.5% more than non-US citizens. Lastly, our full model shows that interdisciplinary dissertators who received research funding as their primary source of support earn about 1% less.

Table 4 presents estimates similar to those in Table 3, but these models also include the sector for the respondent's first job after earning the PhD. Most notably, we still observe that the primary field has the largest influence on log salary, comprising anywhere from 66-69% depending on the model. The higher-paying field still has a small influence on log salary among interdisciplinarians. When we control for job sectors, we observe that interdisciplinarians still have lower earnings although the effect is smaller relative to the models that do not control for the job sector.

*[INSERT TABLE 4 ABOUT HERE]*

Our controls for the different job sectors show patterns in Table 4 that we would expect to observe. In these models, we use education excluding postdocs as the baseline sector. Those who accept postdoctoral positions tend to earn nearly 20% less than others in education. Similarly, those in industry tend to earn over 50% more than those working in education. Lastly, compared to educators, those who accept positions in nonprofit organizations or in government tend to earn approximately 14% and 24% more, respectively. These estimates are quite robust across columns and specifications although there is some indication that interdisciplinarians have a larger than average premium (relative to education) from taking a position in industry. Relative to Table 3, most of the coefficients for the covariates in Table 4 are very similar with a notable exception involving research funding. Specifically, the relationship research funding is associated with lower earnings when we do not control for job sector (in Table 3) but positive when we do control for job sector (in Table 4), showing a premium of approximately 2%. This difference highlights the fact that a large majority of those who have research funding accept a position in the relatively lower-paying sectors of education or work as a postdoctoral researcher.

We also conducted additional regressions for a heterogeneity analysis. Results in Tables A.2 and A.3 report results for individuals who accepted a position in education or as a postdoctoral researcher, respectively. In Table A.4, we report results for the subset of our sample who accepted positions in industry. In Tables A5-8, we report results for women and men (without [and with] controls for sector of placement).

When we restrict the sample to those in education (Tables A.2 and A.3), the broad patterns are similar to what we observed with the full sample, but there are differences. The primary field and highest paying field tend to become stronger determinants of earnings while the secondary field becomes a smaller determinant. This finding is consistent with interdisciplinarians obtaining jobs with salaries that are largely determined by their primary field with a slight premium for having one foot in a high paying field. The type of interdisciplinarity again has a minimal influence and we observe no differential impact among types. Also, as expected, postdoctoral research positions are associated with lower log salaries.

In contrast with the roughly two-thirds of our sample who work in education (inclusive of postdoctoral researchers), 17% of our sample work in industry and their log salaries are determined very differently. Namely, the primary and secondary fields become much weaker determinants of earnings, although the ratio of the impact of the secondary field relative to the primary field is approximately the same (Table A.4). In other words, industry still values the primary field over the secondary field though the primary field accounts for only 44.4% of the log salary and the secondary field accounts for 13.2%. At the same time, the higher valued field accounts for 41.7% of log salary, which suggests a market premium for specific fields in industry. From the employer side, this finding suggests that industry, unlike academia, regards people with a foot in a high-paying field as substantially qualified for jobs that rely on that field, even if the higher paying field is secondary. From the student side, it suggests that researchers who have lower-paying primary fields and higher paying secondary fields can boost their income substantially by taking a position in industry. As in the previous regressions, pursuing an interdisciplinary PhD has a negative, though small, influenceon salary and there is no difference in the type of interdisciplinarity. Also similar to previous regressions, we observe a negative influence for women and non-White doctoral graduates and a premium for US citizens, although the citizenship premium is considerably smaller in industry.

In our final test for differences across individual characteristics, we separate the sample by binary, self-reported gender. Our results based on the women-only sample indicate that the primary and secondary fields have slightly higher influences on log salary relative to the full sample (Table A.5). For women, the primary field captures 65% or more and the secondary fields explains 30% or more of the salary, which are both larger than with the whole sample. By contrast, the higher paying field has no statistically significant relationship to the salary for women compared to the moderate (~10%) relationship for the whole sample. Moreover, the interdisciplinary penalty is small and very similar in magnitude to that for the whole sample. The remaining covariates for women are similar to those for the whole sample, except there is a smaller penalty for being single (i.e. less of a premium for being married). When we include the employment sectors (Table A.6), we find that the coefficients on these variables are very similar to those for the whole sample (Table 4).

When we restrict our sample to include only men, the primary and secondary fields have a somewhat lesser influence on overall salary – as low as 60% for the primary field and 25% for the secondary field (Tables A.7 and A.8). Notably, this results in a slightly larger infleunce for the higher-paying field for men relative to the whole sample, and noticeably larger relative to women. For men, the higher-paying field accounts for anywhere from 10-12% of log salary, based on the sample and specification. Thus, it appears that a higher paying field benefits men more, which may contribute to gender gaps in earnings among interdisciplinary researchers. All other covariates have similar coefficients when compared to the original sample (Table 3), but the penalty for being single is larger among men than the entire sample or among women. When we control for job sector, we observe results similar to those from the original sample (Table 4).

### 4.1 Comparison to Alternative Approaches

To assess the value of our two-step method, we compare our methods with two separate specifications referenced in the introduction as possible alternatives. The alternatives we consider are 1) regress the log salary on a set of primary field dummy variables and effectively ignore the secondary field, and 2) regress the log salary on a full set of dummy variables representing combinations of a respondent's primary and secondary field. In the first specification, we still include variables for interdisciplinarity while in the second specification, our interdisciplinarity measures are perfectly collinear with the primary/secondary field combinations so we are unable to estimate these coefficients. Also in the second specification, we only include field combinations that have more than 5 observations to comply with NSF disclosure requirements. In both specifications, we continue to use demographic and institutional controls and cluster standard errors at the institution level.

Table 5 presents general regression statistics from the main model in which we use predicted salary values. Based on $R^2$ values, our main specification (Panel A) outperforms the model with 341 field dummy variables (Panel B) although, not surprisingly, the model with 6,059 interaction variables between the reported primary and secondary fields (Panel C) has higher explanatory power, though overall the $R^2$ values are not dramatically different. More importantly, compared to these other specifications, our parsimonious approach consolidates, with three regressors, information the other specifications generate with 341 or 6,059 variables. In addition, the coefficients for these alternative methods are simply the difference in log salary between the field or filed combination and the baseline case. Our main specification estimates the degree to which the primary and secondary fields directly impact salary. Results in Table 5 also indicate running time for each model and show that the first stage takes just over two minutes but with estimates from this stage, the second step takes 5-6 seconds. This is compared to the nearly three minutes required to estimate models 1, 2, and 3, for the regression with fields only, over 3 hours required to estimate the model with field combinations and interdisciplinarians only, or 23 hours for the whole sample. Table 5 also shows that a large portion of the estimates in the model with 341 field dummies are statistically insignificant while half of the estimates in the fully interacted model are statistically insignificant. The vast majority of the field combinations have relatively small frequencies (5,358 have frequencies < 100) and, as one would expect, there is a strong negative relationship between significance of the dummy variable for a field combination and the number of people in that field combination.

*[INSERT TABLE 5 ABOUT HERE]*

As indicated, our proposed approach summarizes substantial information about secondary fields that is lost when focusing only on primary fields (alternative specification 1) while reducing overfitting inherent in a fully interactive approach (alternative specification 2). Furthermore, with our approach, we are able to estimate the salary penalty for interdisciplinarity while at the same time specifying the salary contribution of individual dissertation fields, which is not possible in the fully interactive approach.

## 5. Discussion and Conclusions

The model domain of doctoral students offers a rich and important environment for improving our understanding of the outcomes associated with individuals who have multiple identities. We contribute to the study of those experiences by joining the literatures on identity economics and earnings estimation to measure the impact of separate identities – primary and secondary PhD fields – on near-term salaries for recent PhD recipients. Our two-step process allows us to isolate the individual influences of the primary and secondary fields while at the same time controlling for interdisciplinarity and a host of other covariates. More basically, this two-step model is scale-independent and can be applied to the study of organizations, for example, where it has been more common to study the varied impacts of category spanning and organizational ambidexterity with respect to, respectively, decisions involving marketing and strategy (e.g., Nerkar 2003, O'Reilly and Tushman 2004).

We find robust evidence that log salaries of PhD recipients who complete an interdisciplinary dissertation are heavily influenced by their primary field. Notably, in nearly all of our specifications, primary field earnings determine somewhere between 60-70% of total earnings. While the secondary field matters, its impact is roughly half as influential. We also observe that among interdisciplinarians, log earnings from the higher paying field significantly contribute to the overall log salary, regardless of whether it is the primary or secondary field although the impact of the higher-paying field is less than one-sixth of the impact of the primary field.

Notably, when we restrict the sample to those who accept positions in industry, we observe a much larger log salary boost from the higher-paying field, regardless of whether the field is primary or secondary. The primary field still matters more than the secondary field, but equally as much as the higher-paying field. In other words, industry seems to care as much about doctoral graduates' most valuable skills, regardless of whether the skills were part of the primary training or obtained through a secondary focus.

Consistent with previous literature, we find that interdisciplinary research tends to entail a small but statistically significant penalty. However, the type of interdisciplinarity, defined by the degree of proximity between primary and secondary fields, does not differentially affect log earnings. Thus, regardless of the similarity between the primary and secondary fields, the penalty is statistically indistinguishable. Our general findings that (*i*) a graduate's primary field tends to be most important and (*ii*) interdisciplinarity has a small but statistically significant impact hold across our different specifications and sub-sample analyses.

While a growing body of evidence suggests that the academic market does not reward, and may even penalize, interdisciplinary researchers, numerous reasons exist to explain why many PhD students work across disciplines. For example, graduate student advisors may have incentives to encourage students to engage in projects that span academic boundaries. Rhoten and Parker (2004) observe that tenured advisors have the professional capital to take risks, such as participate in interdisciplinary research teams. In addition, individuals with a generally lower-paying primary field may seek to develop a more general set of skills that can be transferable to other domains (Gathmann and Schonberg 2010). While this may not be lucrative initially (especially for those entering academia), these researchers may be more adaptable to fluctuations in the labor market and may not experience unemployment or job loss as quickly as others. Lastly, personal preferences may drive graduate students to pursue category-spanning research.

We acknowledge that our earning regressions suffer from endogeneity along multiple dimensions, including self-selection into an interdisciplinary PhD, joint determination of interdisciplinarity and salary, and omitted variables, including ability and preferences. While this clearly biases our regression estimates, we do control for a variety of factors that at least partially affect salaries. Moreover, our goal is to introduce a methodology for estimating the relationship between multiple identities and earnings rather than to estimate the causal relationships between treatment variables and outcomes. Put somewhat differently, the relationships between fields and interdisciplinarity and near-term salaries that underlie our approach also underlie the most natural alternatives. Thus, we have focused on how to provide parsimonious estimates of the strength of relationships rather than address causal inference. While our analysis used the case of multiple identities among dissertators in the United States, the increasing flexibility found within careers across industries shows the importance of these methods. The celebration of "unicorn" companies and founders, for example, who successfully engage multiples areas of expertise (e.g., Mollick 2020) illustrates this trend outside of the academic context of our study.

In the broader context of identity analysis – particularly when more than one identity is potentially relevant, our work illustrates the way in which academic identities contribute to near-term salary outcomes for PhD recipients. When graduate students assume more than one academic identity, the market still focuses on the dominant identity (primary field), regardless of how much influence either field has on the final dissertation. The generalizability of the two-step method that we introduce is clear when one recognizes that people can easily assume more than one identity (Kang and Bodenhausen 2015) in ways that are meaningful for individual-level quality-of-life (Brook et al. 2008). This is important in our work as well as in extensions that examine the impact of various identities (e.g., relating to gender, racial, ethnic, national identification) on individual salaries. Only recently has the US Census allowed someone to identify multiple races. Other recent surveys allow for non-binary and/or fluid gender identities as well. We recognize that each of these can be considered a separate identity and have a separate impact on salary and anticipate that future research will benefit from addressing this phenomenon.

In addition to expanding the array of identity dimensions, we expect that future research can helpfully apply this two-step method for a broader range of outcome variables. For example, earnings at the level of firms could be examined as a function of firm-level identities. More generally, a wide range of performance variables for publications and patents could be considered in light of authors' (multiple) identities (e.g., see Marx and Fuegi 2020 for a discussion of relevant frontiers in patent-focused research).

Returning to the question of "which foot" an individual doctoral graduate should put forward first, we generally find evidence that the "first foot" – in the form of a graduate's primary dissertation field – tends to be most important for those with multiple "feet." The two-step methodology that we introduce to study the experience of doctoral graduates establishes a process that future research can build upon to better differentiate the varied impacts of multiple identities when there are complex intersections among numerous variables. The current study benefits from data where multiple identities were rank-ordered to establish a proof-of-concept for the two-step approach. Future research that further develops this methodology for situations when multiple identities are not rank-ordered would be valuable. Similarly, while the current study focuses on individual identities and experiences, future research can apply this two-step method to better understand how organizations' multiple identities can variably impact outcomes.

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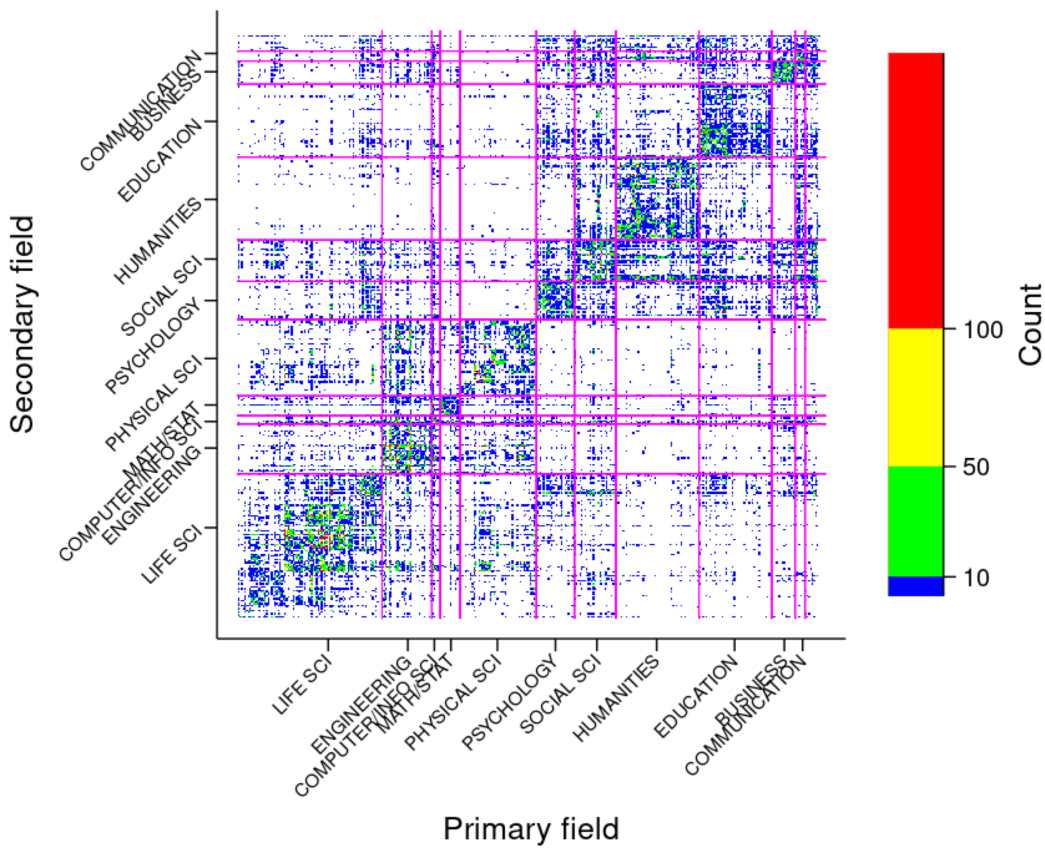
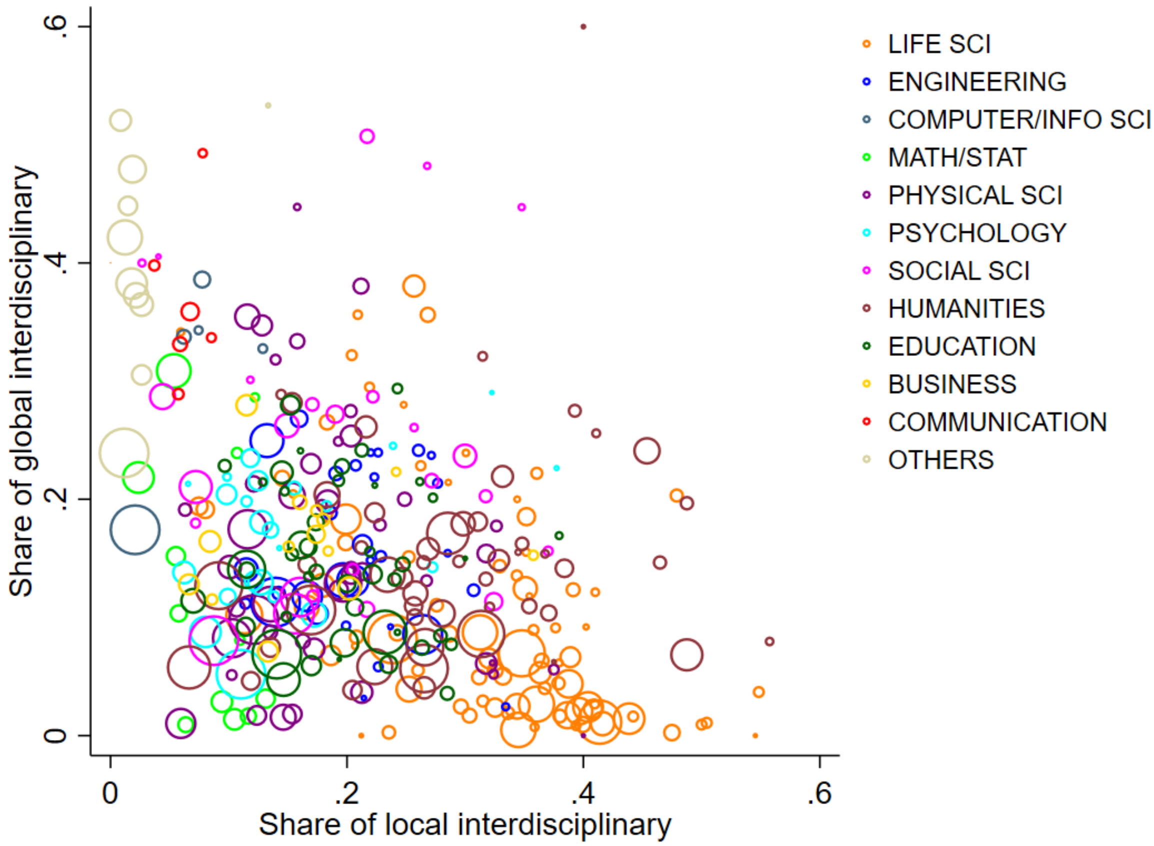
**Figure 1.** Distribution map of bottom-level field combinations among interdisciplinarians




*Notes.* Data source: Survey of Earned Doctorates 2008-2016. The figure plots the number of interdisciplinarians with each combination of bottom-level fields. The border lines demarcate top-level fields and, consequently, create boxed areas of both "local" and "global" interdisciplinarity (i.e., the size of each box is determined by the number of bottom-level fields within each top-level field). All of the boxes along the 45-degree line are local interdisciplinary combinations since both the primary and secondary bottom-level fields come from the same top-level field. All of the off-diagonal boxes contain bottom-level field combinations in different top-level fields (i.e., combinations that we describe as globally interdisciplinary).

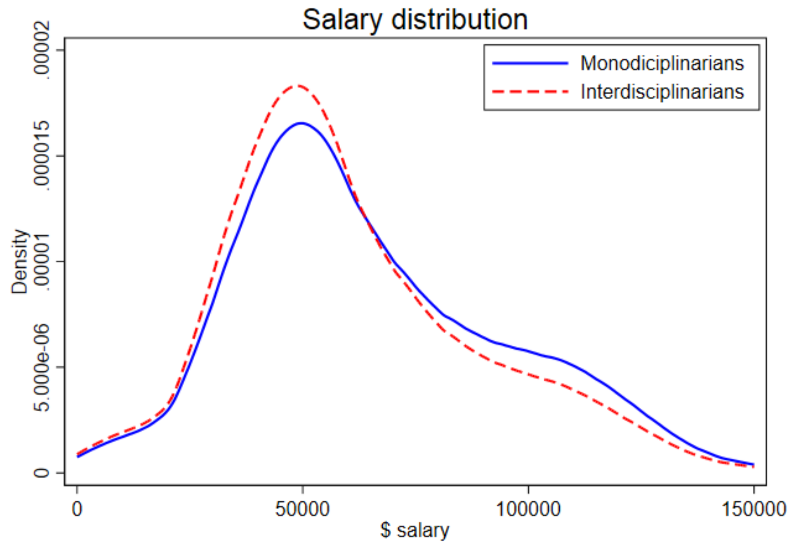
**Figure 2.** Shares of local and global interdisciplinarity and population size of bottom-level fields, grouped by differently colored top-level fields



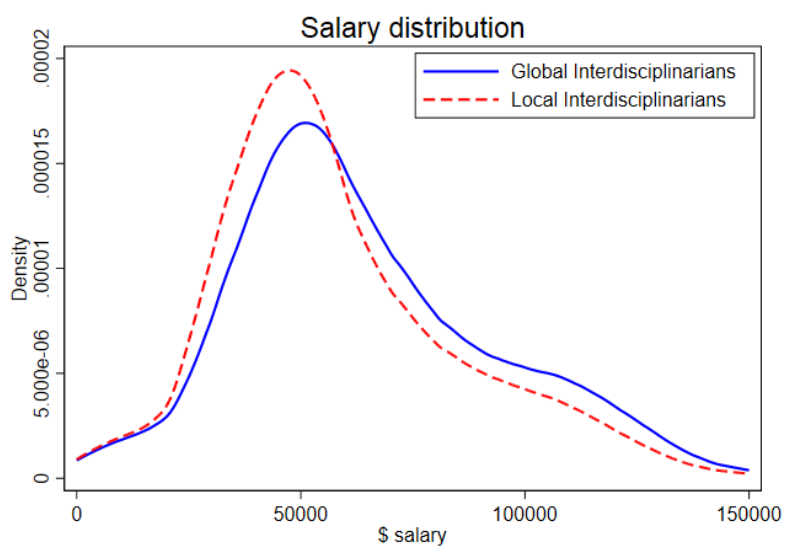

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. The figure plots share of PhD recipients who are globally interdisciplinary (y-axis) against the share who are locally interdisciplinary (x-axis) for each bottom-level field. Markers are sized to reflect the total number of all PhD recipients, including both mono- and inter-disciplinarians, listing that field as their primary field. Colors indicate the top-level field to which each bottom-level field belongs.

**Figure 3.** Salary distribution by interdisciplinarity

Panel A: Mono- and Inter-disciplinarians

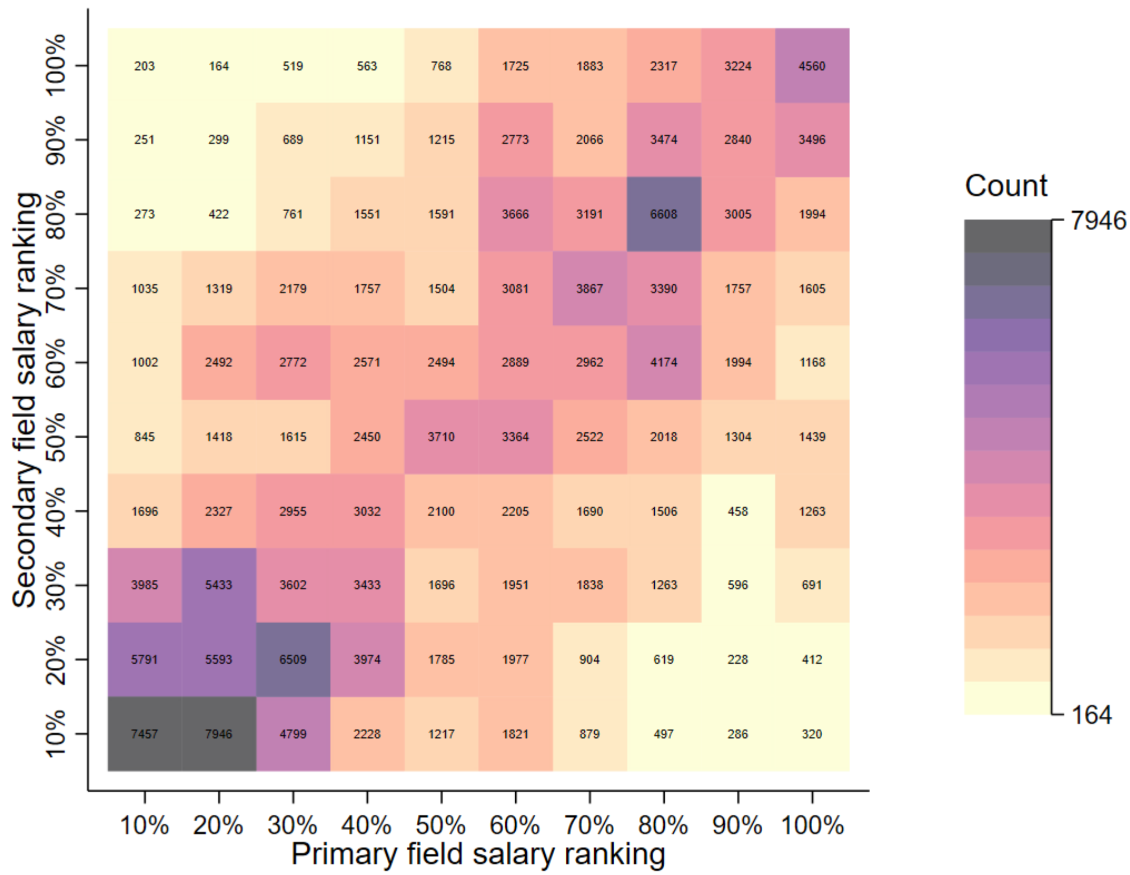



Panel B: Global and Local Interdisciplinarians




*Note.* Data source: Survey of Earned Doctorates 2008-2016. Kernel density of starting salaries.

**Figure 4.** Heat map of salary combinations of primary and secondary fields




*Notes.* Data source: Survey of Earned Doctorates 2008-2016. The salary data on each axis represents the average salary for monodisciplinarians from the primary bottom-level field (X-axis) and secondary bottom-level field (Y-axis) divided into population-weighted deciles. For example, interdisciplinarians whose first and second field average salaries are both ranked at the bottom 10% among monodisciplinarians are placed in the 10%-10% box (in the bottom-left corner). The darker the shading of the cell is, the larger the number of people with that combination of earnings.

**Table 1:** Average Salary by Academic Discipline

| | Sample Population | | | | |
|---|---|---|---|---|---|
| **Salary[a] ($US)** | **Full Sample** | **Mono-Disciplinary** | **General Interdisc** | **Global Interdisc** | **Local Interdisc** |
| Overall | 62392.33 | 63673.04 | 59665.73 | 63546.64 | 56999.67 |
| Life Science | 51984.74 | 52883.42 | 50751.25 | 57676.50 | 49078.87 |
| Engineering | 73021.09 | 75064.79 | 69552.96 | 68915.72 | 70059.07 |
| Computer Science | 88781.62 | 90523.42 | 83842.06 | 82452.59 | 90307.27 |
| Mathematics | 63616.33 | 62556.87 | 66844.47 | 69944.40 | 59178.06 |
| Physical Science | 56996.35 | 57202.92 | 56557.18 | 57614.52 | 55625.22 |
| Psychology | 50203.18 | 49801.30 | 51432.52 | 53994.97 | 48694.59 |
| Social Science | 66337.45 | 67827.24 | 63162.11 | 63134.64 | 63190.31 |
| Humanities | 48398.91 | 48180.33 | 48697.36 | 51520.07 | 47214.42 |
| Education | 68124.88 | 69341.28 | 65101.39 | 64077.36 | 65805.01 |
| Business | 106721.60 | 108798.20 | 101834.19 | 100886.00 | 102758.60 |
| Communication | 56132.76 | 56340.75 | 55866.93 | 56118.24 | 54316.21 |

*Note.* Data source: Survey of Earned Doctorates 2008-2016.

a. The SED collected salary data based on expected salary for the position the respondent had either already accepted or planned to accept

**Table 2:** Sample Summary Statistics

| | Sample Population | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Full Sample** | **Mono-Disciplinary** | **General Interdisc** | **Global Interdisc** | **Local Interdisc** | **Broadly Global** | **Narrowly Global** |
| ***Panel A: Demographic Characteristics (using SED category labels)*** | | | | | | | |
| Age (years) | 34.8 | 34.6 | 34.9 | 35.5 | 34.6 | 36.6 | 35.2 |
| % Female | 46.3 | 46.2 | 46.5 | 45.2 | 47.4 | 53.6 | 43.1 |
| % US citizen | 64.4 | 66.1 | 61.8 | 62.2 | 61.6 | 69.7 | 60.3 |
| % White | 65.4 | 67.1 | 62.6 | 62.8 | 62.4 | 69.2 | 61.1 |
| % Single | 32.0 | 32.0 | 31.0 | 31.0 | 31.0 | | |
| % 1st-gen college grad | 31.5 | 31.4 | 31.6 | 31.3 | 31.9 | 30.9 | 31.4 |
| % R1 school | 78.8 | 79.9 | 79.7 | 80.8 | 78.9 | 79.9 | 81.1 |
| ***Panel B: Near-term Job Market Outcomes*** | | | | | | | |
| %Accepted offer | 73.3 | 73.8 | 71.4 | 72.3 | 70.4 | 75.4 | 72.3 |
| %Education | 67.5 | 66.7 | 69.4 | 67.3 | 70.9 | 68.1 | 67.0 |
| %Postdoc position | 38.2 | 36.2 | 42.9 | 36.9 | 47.0 | 37.3 | 36.8 |
| %Industry | 17.4 | 18.2 | 15.5 | 17.1 | 14.3 | 13.0 | 18.2 |
| %Government | 8.8 | 8.9 | 8.7 | 8.4 | 8.8 | 9.7 | 8.1 |
| %Non-profit | 4.8 | 4.7 | 4.9 | 5.4 | 4.6 | 7.0 | 5.0 |
| %Self-employed | 1.0 | 0.9 | 1.1 | 1.4 | 0.9 | 1.6 | 1.3 |
| Observations | 430,358 | 260,210 | 148,670 | 59,201 | 89,469 | 12,058 | 47,143 |

*Note:* Data source: Survey of Earned Doctorates 2008-2016. Age is measured at the time of graduation. The term "1$^{st}$-gen college grad" stands for PhD students whose parents' education did not go beyond high school. The term "%Accepted-offer" reflects the proportion of SED respondents who had accepted an offer by the time they completed the SED. Education includes both tenure-track positions and postdoc positions.

**Table 3:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries

| | Sample Population | | | | |
|---|---|---|---|---|---|
| VARIABLES | Full Sample<br>(1) | Full Sample<br>(2) | Full Sample<br>(3) | Interdisciplinarians<br>(4) | Interdisciplinarians<br>(5) |
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.643*** | 0.645*** | 0.645*** | 0.638*** | 0.638*** |
| | (0.0172) | (0.0175) | (0.0176) | (0.0191) | (0.0192) |
| Wage of 2nd field | 0.283*** | 0.285*** | 0.285*** | 0.279*** | 0.279*** |
| | (0.0154) | (0.0157) | (0.0157) | (0.0173) | (0.0173) |
| Higher paying field | 0.0731*** | 0.0679*** | 0.0679*** | 0.0742*** | 0.0743*** |
| | (0.0247) | (0.0258) | (0.0259) | (0.0268) | (0.0269) |
| ***Interdisciplinarity Measures*** | | | | | |
| General Interdisciplinarity | -0.0281*** | | | | |
| | (0.00303) | | | | |
| Local Interdisciplinarity | | -0.0286*** | -0.0286*** | | |
| | | (0.00317) | (0.00317) | | |
| Global Interdisciplinarity | | -0.0263*** | | 0.00273 | |
| | | (0.00448) | | (0.00422) | |
| Narrowly Global Interdisciplinarity | | | -0.0263*** | | 0.00292 |
| | | | (0.00465) | | (0.00443) |
| Broadly Global Interdisciplinarity | | | -0.0263*** | | 0.00200 |
| | | | (0.00727) | | (0.00688) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.00655*** | 0.00654*** | 0.00654*** | 0.00465 | 0.00465 |
| | (0.00221) | (0.00221) | (0.00221) | (0.00350) | (0.00350) |
| Mother College Ed | 0.0132*** | 0.0132*** | 0.0132*** | 0.0150*** | 0.0150*** |
| | (0.00193) | (0.00193) | (0.00193) | (0.00341) | (0.00341) |
| Single | -0.0370*** | -0.0370*** | -0.0370*** | -0.0306*** | -0.0306*** |
| | (0.00251) | (0.00251) | (0.00251) | (0.00400) | (0.00401) |
| Age | 0.00367*** | 0.00366*** | 0.00366*** | 0.00276*** | 0.00276*** |
| | (0.000272) | (0.000272) | (0.000271) | (0.000390) | (0.000389) |

| | | | | | |
|---|---|---|---|---|---|
| Female | -0.0550*** | -0.0550*** | -0.0550*** | -0.0542*** | -0.0542*** |
| | (0.00266) | (0.00266) | (0.00267) | (0.00418) | (0.00422) |
| White | -0.00428 | -0.00429 | -0.00429 | -0.00622 | -0.00621 |
| | (0.00376) | (0.00376) | (0.00376) | (0.00483) | (0.00484) |
| US Citizen | 0.170*** | 0.170*** | 0.170*** | 0.176*** | 0.176*** |
| | (0.00669) | (0.00668) | (0.00668) | (0.00767) | (0.00765) |
| Research Funding | -0.00912** | -0.00908** | -0.00908** | -0.0172*** | -0.0172*** |
| | (0.00401) | (0.00400) | (0.00400) | (0.00541) | (0.00542) |
| Constant | 0.0256 | 0.0269 | 0.0269 | 0.104 | 0.107 |
| | (0.0902) | (0.0904) | (0.0907) | (0.124) | (0.125) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 225,109 | 225,109 | 225,109 | 78,671 | 78,671 |
| R-squared | 0.262 | 0.262 | 0.262 | 0.224 | 0.224 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we restrict the sample to include interdisciplinarians only.

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

**Table 4:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries – Job sector controls

| VARIABLES | Full sample<br>(1) | Full sample<br>(2) | Full sample<br>(3) | Interdisciplinarians<br>(4) | Interdisciplinarians<br>(5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.680*** | 0.688*** | 0.688*** | 0.661*** | 0.661*** |
| | (0.0204) | (0.0209) | (0.0212) | (0.0240) | (0.0242) |
| Wage of 2nd field | 0.254*** | 0.262*** | 0.262*** | 0.237*** | 0.237*** |
| | (0.0192) | (0.0201) | (0.0201) | (0.0227) | (0.0227) |
| Higher paying field | 0.0646** | 0.0479 | 0.0475 | 0.0841** | 0.0835** |
| | (0.0306) | (0.0325) | (0.0330) | (0.0349) | (0.0353) |
| ***Interdisciplinarity Variables*** | | | | | |
| General Interdisciplinarity | -0.00987*** | | | | |
| | (0.00273) | | | | |
| Local Interdisciplinarity | | -0.0113*** | -0.0113*** | | |
| | | (0.00283) | (0.00284) | | |
| Global Interdisciplinarity | | -0.00549 | | 0.00591 | |
| | | (0.00408) | | (0.00380) | |
| Narrowly Global Interdisciplinarity | | | -0.00569 | | 0.00547 |
| | | | (0.00417) | | (0.00396) |
| Broadly Global Interdisciplinarity | | | -0.00460 | | 0.00767 |
| | | | (0.00698) | | (0.00657) |
| ***Employment Sector*** | | | | | |
| Postdoctoral Researcher | -0.212*** | -0.212*** | -0.212*** | -0.202*** | -0.202*** |
| | (0.00591) | (0.00591) | (0.00591) | (0.00696) | (0.00695) |
| Industry | 0.419*** | 0.419*** | 0.419*** | 0.437*** | 0.437*** |
| | (0.00573) | (0.00573) | (0.00573) | (0.00685) | (0.00685) |
| Nonprofit | 0.137*** | 0.137*** | 0.137*** | 0.133*** | 0.133*** |
| | (0.00654) | (0.00653) | (0.00653) | (0.00986) | (0.00983) |
| Government | 0.216*** | 0.216*** | 0.216*** | 0.202*** | 0.202*** |
| | (0.00507) | (0.00507) | (0.00507) | (0.00728) | (0.00728) |
| Self-Employed | 0.0492** | 0.0490** | 0.0490** | 0.0295 | 0.0295 |
| | (0.0202) | (0.0202) | (0.0202) | (0.0311) | (0.0311) |

| | | | | | |
|---|---|---|---|---|---|
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.00126 | 0.00125 | 0.00125 | -9.58e-05 | -9.67e-05 |
| | (0.00207) | (0.00207) | (0.00207) | (0.00313) | (0.00313) |
| Mother College Ed | 0.00879*** | 0.00879*** | 0.00879*** | 0.00988*** | 0.00988*** |
| | (0.00183) | (0.00183) | (0.00183) | (0.00296) | (0.00296) |
| Single | -0.0238*** | -0.0238*** | -0.0238*** | -0.0191*** | -0.0190*** |
| | (0.00221) | (0.00221) | (0.00221) | (0.00325) | (0.00326) |
| Age | 0.00277*** | 0.00277*** | 0.00277*** | 0.00190*** | 0.00190*** |
| | (0.000259) | (0.000259) | (0.000259) | (0.000358) | (0.000357) |
| Female | -0.0518*** | -0.0517*** | -0.0517*** | -0.0520*** | -0.0521*** |
| | (0.00254) | (0.00254) | (0.00255) | (0.00385) | (0.00388) |
| White | 0.0138*** | 0.0138*** | 0.0138*** | 0.00648 | 0.00645 |
| | (0.00363) | (0.00363) | (0.00363) | (0.00451) | (0.00451) |
| US Citizen | 0.141*** | 0.141*** | 0.141*** | 0.149*** | 0.149*** |
| | (0.00651) | (0.00651) | (0.00650) | (0.00746) | (0.00745) |
| Research Funding | 0.0202*** | 0.0203*** | 0.0203*** | 0.0159*** | 0.0159*** |
| | (0.00354) | (0.00354) | (0.00354) | (0.00493) | (0.00493) |
| Constant | 0.0321 | 0.0345 | 0.0348 | 0.218 | 0.226 |
| | (0.0940) | (0.0941) | (0.0944) | (0.161) | (0.162) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 223,564 | 223,564 | 223,564 | 78,182 | 78,182 |
| R-squared | 0.393 | 0.393 | 0.393 | 0.361 | 0.361 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we restrict the sample to include interdisciplinarians only.

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

**Table 5:** Comparison of alternative approaches

| | Full Sample[a] (1) | Full Sample (2) | Full Sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| **Panel A: Two-Step Model** | | | | | |
| R-square | 0.2616 | 0.2616 | 0.2616 | 0.2239 | 0.2239 |
| Adjusted R-square | 0.2601 | 0.2601 | 0.2601 | 0.2194 | 0.2194 |
| N | 225,109 | 225,109 | 225,109 | 78,671 | 78,671 |
| First Stage Running Time[b] | 139.5 | | | | |
| Second Stage Running Time[c] | 5.63 | 5.97 | 6.11 | 3.51 | 3.58 |
| **Panel B: Alternative specification 1 -- Regressions with field indicators** | | | | | |
| R-square | 0.2577 | 0.2577 | 0.2577 | 0.2197 | 0.2197 |
| Adjusted R-square | 0.2551 | 0.2551 | 0.2551 | 0.2118 | 0.2118 |
| N | 225,123 | 225,123 | 225,123 | 78,674 | 78,674 |
| Number of Fields[d] | 341 | 341 | 341 | 341 | 341 |
| Number of Insignificant Fields[e] | 98 | 98 | 97 | 140 | 140 |
| Running Time -- Reporting Field Coefficients[f] | 163.08 | 166.02 | 164.94 | 61.73 | 67.51 |
| Running Time – Suppress Field Coefficients[g] | 9.26 | 9.65 | 10.22 | 4.58 | 4.6 |
| **Panel C: Alternative specification 2 -- Regressions with field combinations[h]** | | | | | |
| R-square | 0.2925 | | | 0.3259 | |
| Adjusted R-square | 0.2703 | | | 0.2542 | |
| N | 212,198 | | | 63,541 | |
| Number of Field Combinations[i] | 6,059 | | | 5,669 | |
| Number of Insignificant Field Combinations[j] | 3,496 | | | 2,711 | |
| Running Time[l] | 23.0 hrs | | | 3.4 hrs | |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. a) The models used for these regressions match those used in the previous tables. However, in Panel B and Panel C, we do not use the two-step approach. In Panel B we use field indicators for the primary field; and, in Panel C, we use indicators for all combinations of fields. b) Since we use the same first-stage results in each of the five models, we only report the run-time once for the main specification. c) These times give the number of seconds required to estimate each model. d) This value represents the number of estimable field coefficients in each model. e) These counts represents the number of statistically insignificant ($p < 0.05$) field coefficients. f) These times represent the number of seconds required to estimate each model and generate each field coefficient. g) These times represent the number of seconds required to estimate each model when we suppress each field coefficient. h) The field combination variables are perfectly collinear with the interdisciplinary variables so we only run one regression with the full sample and one regression when the sample only includes interdisciplinarians. i) These values represent the number of field combinations observed in the data with ≥ 5 observations, and not the total number of potential combinations. The number of combinations decreases by 341 in column 4 reflecting the 341 fewer field combinations for mono-disciplinarians. j) These values represent the number of statistically insignificant ($p < 0.05$) field combination coefficients.

## Appendix

**Table A.1:** First-Stage Regression results.

| | (1) | (2) |
|---|---|---|
| Life Science | -0.0434** | -0.130*** |
| | (0.0172) | (0.0185) |
| Engineering | 0.0857*** | 0.228*** |
| | (0.0179) | (0.0197) |
| Computer/Info Science | 0.244*** | 0.420*** |
| | (0.0187) | (0.0209) |
| Mathematics | 0.0971*** | 0.0524*** |
| | (0.0177) | (0.0185) |
| Physical Science | 0.0037 | -0.0397** |
| | (0.0170) | (0.0179) |
| Psychology | -0.105*** | -0.165*** |
| | (0.0161) | (0.0169) |
| Social Science | 0.0623*** | 0.0687*** |
| | (0.0183) | (0.0191) |
| Humanities | -0.263*** | -0.294*** |
| | (0.0178) | (0.0182) |
| Education | 0.112*** | 0.0783*** |
| | (0.0184) | (0.0188) |
| Business | 0.594*** | 0.608*** |
| | (0.0209) | (0.0210) |
| Communication | -0.0241 | -0.0432** |
| | (0.0200) | (0.0205) |
| Placement Sectors | No | Yes |
| Demographics | Yes | Yes |
| Graduation Year Dummies | Yes | Yes |
| Institution Dummies | Yes | Yes |
| Observations | 223,554 | 223,554 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. Model (1) provides coefficients for the first-stage regression results without controls for job sector while Model (2) provides coefficients for the first-stage regression results that include controls for job sector. We note that to conserve space, these first-stage results include coefficients for 11 top-level fields while the actual first-stage coefficients in our second stage models are from the 341 bottom-level fields. We use 2008-2016 waves of the SED. Results in this table reflect the first-stage regression in Equation 4. Standard errors (in parentheses) are clustered at institution level. * $p$<0.1; ** $p$<0.05; *** $p$<0.01.

**Table A.2:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Education sector

| VARIABLES | Full sample (1) | Full sample (2) | Full sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.672*** | 0.670*** | 0.670*** | 0.631*** | 0.631*** |
| | (0.0229) | (0.0230) | (0.0232) | (0.0278) | (0.0279) |
| Wage of 2nd field | 0.219*** | 0.216*** | 0.216*** | 0.176*** | 0.176*** |
| | (0.0221) | (0.0227) | (0.0227) | (0.0256) | (0.0256) |
| Higher paying field | 0.0998*** | 0.105*** | 0.105*** | 0.150*** | 0.150*** |
| | (0.0340) | (0.0351) | (0.0353) | (0.0383) | (0.0384) |
| ***Interdisciplinarity Measures*** | | | | | |
| General Interdisciplinarity | -0.0152*** | | | | |
| | (0.00322) | | | | |
| Local Interdisciplinarity | | -0.0147*** | -0.0148*** | | |
| | | (0.00338) | (0.00338) | | |
| Global Interdisciplinarity | | -0.0167*** | | -0.00118 | |
| | | (0.00461) | | (0.00437) | |
| Narrowly Global Interdisciplinarity | | | -0.0162*** | | -0.000998 |
| | | | (0.00488) | | (0.00465) |
| Broadly Global Interdisciplinarity | | | -0.0186** | | -0.00189 |
| | | | (0.00813) | | (0.00789) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | -0.000938 | -0.000934 | -0.000934 | 0.000296 | 0.000296 |
| | (0.00246) | (0.00246) | (0.00246) | (0.00380) | (0.00380) |
| Mother College Ed | 0.00970*** | 0.00970*** | 0.00970*** | 0.00728* | 0.00728* |
| | (0.00226) | (0.00226) | (0.00226) | (0.00394) | (0.00394) |
| Single | -0.0284*** | -0.0284*** | -0.0284*** | -0.0235*** | -0.0235*** |
| | (0.00264) | (0.00263) | (0.00263) | (0.00421) | (0.00421) |
| Age | 0.00264*** | 0.00264*** | 0.00264*** | 0.00185*** | 0.00185*** |
| | (0.000252) | (0.000252) | (0.000252) | (0.000389) | (0.000389) |
| Female | -0.0458*** | -0.0458*** | -0.0458*** | -0.0460*** | -0.0460*** |
| | (0.00268) | (0.00268) | (0.00269) | (0.00448) | (0.00452) |

| | | | | | |
|---|---|---|---|---|---|
| White | 0.0149*** | 0.0149*** | 0.0149*** | 0.00354 | 0.00355 |
| | (0.00391) | (0.00391) | (0.00390) | (0.00545) | (0.00545) |
| US Citizen | 0.146*** | 0.146*** | 0.146*** | 0.142*** | 0.142*** |
| | (0.00669) | (0.00669) | (0.00668) | (0.00745) | (0.00743) |
| Research Funding | 0.00508 | 0.00506 | 0.00507 | 0.00172 | 0.00173 |
| | (0.00405) | (0.00404) | (0.00404) | (0.00553) | (0.00553) |
| Constant | 0.118 | 0.118 | 0.117 | 0.503*** | 0.501*** |
| | (0.117) | (0.117) | (0.117) | (0.180) | (0.181) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 152,369 | 152,369 | 152,369 | 54,690 | 54,690 |
| R-squared | 0.273 | 0.273 | 0.273 | 0.217 | 0.217 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report accepting a position in education. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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

**Table A.3:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Education sector and controlling for postdoc position

| VARIABLES | Full Sample (1) | Full Sample (2) | Full Sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of $1^{st}$ field | 0.668*** | 0.669*** | 0.669*** | 0.632*** | 0.632*** |
| | (0.0236) | (0.0239) | (0.0240) | (0.0295) | (0.0295) |
| Wage of $2^{nd}$ field | 0.218*** | 0.220*** | 0.220*** | 0.179*** | 0.178*** |
| | (0.0232) | (0.0240) | (0.0240) | (0.0279) | (0.0279) |
| Higher paying field | 0.108*** | 0.105*** | 0.105*** | 0.155*** | 0.155*** |
| | (0.0358) | (0.0373) | (0.0374) | (0.0413) | (0.0414) |
| ***Interdisciplinarity Variables*** | | | | | |
| General Interdisciplinarity | -0.0112*** | | | | |
| | (0.00307) | | | | |
| Local Interdisciplinarity | | -0.0114*** | -0.0114*** | | |
| | | (0.00323) | (0.00323) | | |
| Global Interdisciplinarity | | -0.0104** | | 0.00169 | |
| | | (0.00447) | | (0.00429) | |
| Narrowly Global Interdisciplinarity | | | -0.0105** | | 0.00128 |
| | | | (0.00473) | | (0.00455) |
| Broadly Global Interdisciplinarity | | | -0.00988 | | 0.00324 |
| | | | (0.00786) | | (0.00750) |
| ***Employment Type*** | | | | | |
| Postdoctoral Researcher | -0.176*** | -0.176*** | -0.176*** | -0.170*** | -0.170*** |
| | (0.00696) | (0.00696) | (0.00695) | (0.00802) | (0.00799) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | -0.00184 | -0.00184 | -0.00184 | -0.00204 | -0.00204 |
| | (0.00240) | (0.00240) | (0.00240) | (0.00372) | (0.00372) |
| Mother College Ed | 0.00871*** | 0.00871*** | 0.00871*** | 0.00746* | 0.00747** |
| | (0.00218) | (0.00218) | (0.00218) | (0.00380) | (0.00380) |
| Single | -0.0208*** | -0.0208*** | -0.0208*** | -0.0158*** | -0.0158*** |
| | (0.00263) | (0.00263) | (0.00263) | (0.00405) | (0.00405) |

| | | | | | |
|---|---|---|---|---|---|
| Age | 0.00157*** | 0.00157*** | 0.00157*** | 0.000669 | 0.000666 |
| | (0.000285) | (0.000285) | (0.000285) | (0.000406) | (0.000406) |
| Female | -0.0495*** | -0.0495*** | -0.0495*** | -0.0489*** | -0.0489*** |
| | (0.00266) | (0.00266) | (0.00267) | (0.00457) | (0.00461) |
| White | 0.0122*** | 0.0122*** | 0.0122*** | 0.00130 | 0.00127 |
| | (0.00387) | (0.00387) | (0.00386) | (0.00521) | (0.00521) |
| US Citizen | 0.134*** | 0.134*** | 0.134*** | 0.133*** | 0.133*** |
| | (0.00700) | (0.00700) | (0.00699) | (0.00776) | (0.00775) |
| Research Funding | 0.0236*** | 0.0236*** | 0.0236*** | 0.0200*** | 0.0199*** |
| | (0.00426) | (0.00426) | (0.00426) | (0.00566) | (0.00567) |
| Constant | 0.0848 | 0.0849 | 0.0851 | 0.416** | 0.420** |
| | (0.0994) | (0.0994) | (0.100) | (0.191) | (0.192) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 152,005 | 152,005 | 152,005 | 54,588 | 54,588 |
| R-squared | 0.290 | 0.290 | 0.290 | 0.236 | 0.236 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report accepting a position in education. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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

**Table A.4:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Industry sector

| VARIABLES | Full Sample (1) | Full Sample (2) | Full Sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.444*** | 0.450*** | 0.456*** | 0.428*** | 0.435*** |
| | (0.0495) | (0.0508) | (0.0520) | (0.0534) | (0.0520) |
| Wage of 2nd field | 0.132*** | 0.140*** | 0.147*** | 0.134*** | 0.141*** |
| | (0.0339) | (0.0371) | (0.0367) | (0.0387) | (0.0375) |
| Higher paying field | 0.417*** | 0.401*** | 0.387*** | 0.403*** | 0.383*** |
| | (0.0724) | (0.0772) | (0.0785) | (0.0787) | (0.0772) |
| ***Interdisciplinarity Variables*** | | | | | |
| General Interdisciplinarity | -0.0201*** | | | | |
| | (0.00592) | | | | |
| Local Interdisciplinarity | | -0.0247*** | -0.0240*** | | |
| | | (0.00606) | (0.00574) | | |
| Global Interdisciplinarity | | -0.0127 | | 0.0145** | |
| | | (0.00794) | | (0.00673) | |
| Narrowly Global Interdisciplinarity | | | -0.0148* | | 0.0111 |
| | | | (0.00792) | | (0.00690) |
| Broadly Global Interdisciplinarity | | | 0.00626 | | 0.0370*** |
| | | | (0.0151) | | (0.0135) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.00295 | 0.00288 | 0.00287 | -0.00152 | -0.00162 |
| | (0.00344) | (0.00340) | (0.00334) | (0.00635) | (0.00645) |
| Mother College Ed | 0.00170 | 0.00174 | 0.00176 | 0.00215 | 0.00219 |
| | (0.00339) | (0.00334) | (0.00336) | (0.00697) | (0.00671) |
| Single | -0.0142*** | -0.0143*** | -0.0143*** | -0.0145** | -0.0146** |
| | (0.00346) | (0.00351) | (0.00339) | (0.00671) | (0.00636) |
| Age | 0.00693*** | 0.00694*** | 0.00692*** | 0.00599*** | 0.00594*** |
| | (0.000559) | (0.000522) | (0.000524) | (0.000733) | (0.000731) |
| Female | -0.0398*** | -0.0398*** | -0.0400*** | -0.0441*** | -0.0450*** |
| | (0.00484) | (0.00488) | (0.00469) | (0.00822) | (0.00827) |

| | | | | | |
|---|---|---|---|---|---|
| White | 0.0265*** | 0.0265*** | 0.0265*** | 0.0173* | 0.0172* |
| | (0.00465) | (0.00469) | (0.00451) | (0.00941) | (0.00941) |
| US Citizen | 0.0589*** | 0.0589*** | 0.0588*** | 0.0640*** | 0.0639*** |
| | (0.00604) | (0.00592) | (0.00579) | (0.00957) | (0.00953) |
| Research Funding | 0.0150*** | 0.0152*** | 0.0155*** | 0.0262** | 0.0274** |
| | (0.00531) | (0.00544) | (0.00546) | (0.0105) | (0.0107) |
| Constant | 0.123 | 0.144 | 0.154 | 0.441 | 0.510 |
| | (0.218) | (0.213) | (0.213) | (0.322) | (0.318) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 38,008 | 38,008 | 38,008 | 11,421 | 11,421 |
| R-squared | 0.300 | 0.300 | 0.300 | 0.265 | 0.265 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report accepting a position in industry. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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

**Table A.5:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Women

| VARIABLES | Full Sample (1) | Full Sample (2) | Full Sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.664*** | 0.657*** | 0.657*** | 0.646*** | 0.646*** |
| | (0.0258) | (0.0256) | (0.0256) | (0.0292) | (0.0292) |
| Wage of 2nd field | 0.317*** | 0.309*** | 0.309*** | 0.303*** | 0.302*** |
| | (0.0247) | (0.0252) | (0.0252) | (0.0276) | (0.0277) |
| Higher paying field | 0.0145 | 0.0292 | 0.0300 | 0.0335 | 0.0345 |
| | (0.0380) | (0.0389) | (0.0388) | (0.0409) | (0.0408) |
| ***Interdisciplinarity Measures*** | | | | | |
| General Interdisciplinarity | -0.0228*** | | | | |
| | (0.00392) | | | | |
| Local Interdisciplinarity | | -0.0212*** | -0.0213*** | | |
| | | (0.00426) | (0.00425) | | |
| Global Interdisciplinarity | | -0.0279*** | | -0.00522 | |
| | | (0.00565) | | (0.00589) | |
| Narrowly Global Interdisciplinarity | | | -0.0294*** | | -0.00678 |
| | | | (0.00624) | | (0.00628) |
| Broadly Global Interdisciplinarity | | | -0.0237** | | -0.000900 |
| | | | (0.00928) | | (0.00964) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.00454 | 0.00453 | 0.00453 | 0.00137 | 0.00138 |
| | (0.00326) | (0.00326) | (0.00326) | (0.00505) | (0.00506) |
| Mother College Ed | 0.00851*** | 0.00852*** | 0.00851*** | 0.00793 | 0.00791 |
| | (0.00283) | (0.00283) | (0.00283) | (0.00512) | (0.00512) |
| Single | -0.0135*** | -0.0135*** | -0.0135*** | -0.0151** | -0.0150** |
| | (0.00364) | (0.00364) | (0.00364) | (0.00611) | (0.00612) |
| Age | 0.00371*** | 0.00371*** | 0.00371*** | 0.00290*** | 0.00289*** |
| | (0.000294) | (0.000294) | (0.000294) | (0.000457) | (0.000458) |
| White | -0.00572 | -0.00572 | -0.00576 | 0.00246 | 0.00236 |
| | (0.00454) | (0.00454) | (0.00454) | (0.00655) | (0.00654) |

| | | | | | |
|---|---|---|---|---|---|
| US Citizen | 0.160*** | 0.160*** | 0.160*** | 0.156*** | 0.156*** |
| | (0.00666) | (0.00665) | (0.00665) | (0.00810) | (0.00808) |
| Research Funding | -0.00910* | -0.00924** | -0.00926** | -0.0108 | -0.0109 |
| | (0.00464) | (0.00463) | (0.00464) | (0.00688) | (0.00690) |
| Constant | 0.0655 | 0.0614 | 0.0630 | 0.202 | 0.201 |
| | (0.104) | (0.105) | (0.105) | (0.181) | (0.183) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 101,818 | 101,818 | 101,818 | 35,557 | 35,557 |
| R-squared | 0.233 | 0.233 | 0.233 | 0.194 | 0.194 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report gender as female. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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

**Table A.6:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Women, controlling for job sector

| VARIABLES | Full Sample (1) | Full Sample (2) | Full Sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.671*** | 0.670*** | 0.669*** | 0.632*** | 0.631*** |
| | (0.0289) | (0.0287) | (0.0287) | (0.0328) | (0.0327) |
| Wage of 2nd field | 0.289*** | 0.288*** | 0.287*** | 0.254*** | 0.252*** |
| | (0.0297) | (0.0307) | (0.0307) | (0.0336) | (0.0336) |
| Higher paying field | 0.0305 | 0.0328 | 0.0336 | 0.0679 | 0.0693 |
| | (0.0453) | (0.0470) | (0.0469) | (0.0497) | (0.0497) |
| ***Interdisciplinarity Variables*** | | | | | |
| General Interdisciplinarity | -0.0110*** | | | | |
| | (0.00370) | | | | |
| Local Interdisciplinarity | | -0.0108*** | -0.0108*** | | |
| | | (0.00399) | (0.00399) | | |
| Global Interdisciplinarity | | -0.0117** | | 0.000733 | |
| | | (0.00555) | | (0.00572) | |
| Narrowly Global Interdisciplinarity | | | -0.0146** | | -0.00280 |
| | | | (0.00605) | | (0.00630) |
| Broadly Global Interdisciplinarity | | | -0.00373 | | 0.0107 |
| | | | (0.00887) | | (0.00929) |
| ***Employment Sector*** | | | | | |
| Postdoctoral Researcher | -0.208*** | -0.208*** | -0.208*** | -0.199*** | -0.200*** |
| | (0.00591) | (0.00591) | (0.00592) | (0.00762) | (0.00763) |
| Industry | 0.376*** | 0.376*** | 0.376*** | 0.400*** | 0.400*** |
| | (0.00752) | (0.00752) | (0.00752) | (0.0112) | (0.0112) |
| Nonprofit | 0.108*** | 0.108*** | 0.108*** | 0.102*** | 0.102*** |
| | (0.00785) | (0.00784) | (0.00783) | (0.0128) | (0.0128) |
| Government | 0.200*** | 0.200*** | 0.200*** | 0.188*** | 0.188*** |
| | (0.00640) | (0.00639) | (0.00639) | (0.00974) | (0.00974) |
| Self-Employed | -0.0134 | -0.0134 | -0.0134 | -0.0697 | -0.0698 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.0254) | (0.0254) | (0.0254) | (0.0430) | (0.0429) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.00172 | 0.00172 | 0.00172 | -0.00125 | -0.00124 |
| | (0.00317) | (0.00317) | (0.00318) | (0.00443) | (0.00444) |
| Mother College Ed | 0.00518* | 0.00518* | 0.00517* | 0.00381 | 0.00377 |
| | (0.00265) | (0.00265) | (0.00265) | (0.00476) | (0.00476) |
| Single | -0.00458 | -0.00457 | -0.00455 | -0.00425 | -0.00417 |
| | (0.00334) | (0.00334) | (0.00334) | (0.00561) | (0.00562) |
| Age | 0.00300*** | 0.00300*** | 0.00300*** | 0.00220*** | 0.00218*** |
| | (0.000291) | (0.000291) | (0.000291) | (0.000440) | (0.000441) |
| White | 0.00707 | 0.00706 | 0.00699 | 0.0109* | 0.0106* |
| | (0.00440) | (0.00440) | (0.00440) | (0.00638) | (0.00635) |
| US Citizen | 0.142*** | 0.142*** | 0.141*** | 0.142*** | 0.142*** |
| | (0.00654) | (0.00654) | (0.00654) | (0.00785) | (0.00783) |
| Research Funding | 0.0188*** | 0.0188*** | 0.0188*** | 0.0185*** | 0.0185*** |
| | (0.00456) | (0.00456) | (0.00456) | (0.00675) | (0.00675) |
| Constant | 0.118 | 0.117 | 0.123 | 0.508** | 0.530** |
| | (0.116) | (0.117) | (0.117) | (0.220) | (0.223) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 101,071 | 101,071 | 101,071 | 35,317 | 35,317 |
| R-squared | 0.323 | 0.323 | 0.323 | 0.288 | 0.288 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report gender as female. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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

**Table A.7:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Men

| VARIABLES | Full Sample<br>(1) | Full Sample<br>(2) | Full Sample<br>(3) | Interdisciplinarians<br>(4) | Interdisciplinarians<br>(5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.614*** | 0.623*** | 0.622*** | 0.602*** | 0.601*** |
| | (0.0211) | (0.0221) | (0.0223) | (0.0241) | (0.0243) |
| Wage of 2nd field | 0.259*** | 0.269*** | 0.268*** | 0.251*** | 0.251*** |
| | (0.0184) | (0.0193) | (0.0193) | (0.0209) | (0.0209) |
| Higher paying field | 0.120*** | 0.103*** | 0.104*** | 0.118*** | 0.119*** |
| | (0.0310) | (0.0334) | (0.0337) | (0.0344) | (0.0347) |
| ***Interdisciplinarity Variables*** | | | | | |
| General Interdisciplinarity | -0.0326*** | | | | |
| | (0.00402) | | | | |
| Local Interdisciplinarity | | -0.0347*** | -0.0348*** | | |
| | | (0.00408) | (0.00407) | | |
| Global Interdisciplinarity | | -0.0262*** | | 0.00928* | |
| | | (0.00620) | | (0.00555) | |
| Narrowly Global Interdisciplinarity | | | -0.0254*** | | 0.0103* |
| | | | (0.00640) | | (0.00568) |
| Broadly Global Interdisciplinarity | | | -0.0306*** | | 0.00405 |
| | | | (0.00978) | | (0.00934) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.00780*** | 0.00776*** | 0.00776*** | 0.00750 | 0.00750 |
| | (0.00284) | (0.00284) | (0.00284) | (0.00497) | (0.00498) |
| Mother College Ed | 0.0166*** | 0.0165*** | 0.0165*** | 0.0202*** | 0.0202*** |
| | (0.00290) | (0.00289) | (0.00289) | (0.00469) | (0.00469) |
| Single | -0.0564*** | -0.0564*** | -0.0564*** | -0.0427*** | -0.0427*** |
| | (0.00302) | (0.00302) | (0.00302) | (0.00454) | (0.00454) |
| Age | 0.00370*** | 0.00370*** | 0.00370*** | 0.00264*** | 0.00265*** |
| | (0.000364) | (0.000364) | (0.000363) | (0.000561) | (0.000561) |
| White | -0.00335 | -0.00339 | -0.00336 | -0.0139** | -0.0139** |
| | (0.00552) | (0.00552) | (0.00552) | (0.00700) | (0.00701) |

| | | | | | |
|---|---|---|---|---|---|
| US Citizen | 0.174*** | 0.174*** | 0.174*** | 0.186*** | 0.186*** |
| | (0.00813) | (0.00812) | (0.00812) | (0.0101) | (0.0101) |
| Research Funding | -0.00910** | -0.00898* | -0.00899* | -0.0227*** | -0.0228*** |
| | (0.00460) | (0.00459) | (0.00459) | (0.00664) | (0.00664) |
| Constant | 0.0790 | 0.0845 | 0.0841 | 0.326** | 0.335** |
| | (0.0978) | (0.0977) | (0.0979) | (0.136) | (0.136) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 123,270 | 123,270 | 123,270 | 43,072 | 43,072 |
| R-squared | 0.275 | 0.275 | 0.275 | 0.241 | 0.241 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report gender as male. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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

**Table A.8:** Influence of Primary and Secondary Field Average Market Salaries on Interdisciplinarian Salaries: Men, controlling for job sector

| VARIABLES | Full Sample (1) | Full Sample (2) | Full Sample (3) | Interdisciplinarians (4) | Interdisciplinarians (5) |
|---|---|---|---|---|---|
| ***Wage Variables*** | | | | | |
| Wage of 1st field | 0.659*** | 0.671*** | 0.668*** | 0.628*** | 0.625*** |
| | (0.0255) | (0.0267) | (0.0274) | (0.0301) | (0.0308) |
| Wage of 2nd field | 0.231*** | 0.244*** | 0.243*** | 0.206*** | 0.205*** |
| | (0.0224) | (0.0237) | (0.0239) | (0.0267) | (0.0268) |
| Higher paying field | 0.102*** | 0.0774* | 0.0820** | 0.126*** | 0.130*** |
| | (0.0372) | (0.0400) | (0.0413) | (0.0427) | (0.0440) |
| ***Interdisciplinarity Variables*** | | | | | |
| General Interdisciplinarity | -0.00943*** | | | | |
| | (0.00339) | | | | |
| Local Interdisciplinarity | | -0.0120*** | -0.0122*** | | |
| | | (0.00348) | (0.00348) | | |
| Global Interdisciplinarity | | -0.00255 | | 0.00982** | |
| | | (0.00509) | | (0.00473) | |
| Narrowly Global Interdisciplinarity | | | -0.00142 | | 0.0109** |
| | | | (0.00522) | | (0.00496) |
| Broadly Global Interdisciplinarity | | | -0.0100 | | 0.00358 |
| | | | (0.00935) | | (0.00890) |
| ***Employment Sector*** | | | | | |
| Postdoctoral Researcher | -0.212*** | -0.212*** | -0.212*** | -0.206*** | -0.206*** |
| | (0.00721) | (0.00722) | (0.00721) | (0.00929) | (0.00928) |
| Industry | 0.445*** | 0.445*** | 0.445*** | 0.457*** | 0.457*** |
| | (0.00623) | (0.00624) | (0.00624) | (0.00743) | (0.00742) |
| Nonprofit | 0.168*** | 0.167*** | 0.167*** | 0.163*** | 0.163*** |
| | (0.00876) | (0.00876) | (0.00875) | (0.0123) | (0.0123) |
| Government | 0.228*** | 0.228*** | 0.228*** | 0.212*** | 0.212*** |
| | (0.00588) | (0.00588) | (0.00588) | (0.00917) | (0.00916) |
| Self-Employed | 0.141*** | 0.141*** | 0.141*** | 0.169*** | 0.169*** |

| | | | | | |
|---|---|---|---|---|---|
| | (0.0294) | (0.0294) | (0.0294) | (0.0476) | (0.0476) |
| ***Demographic Characteristics*** | | | | | |
| Father College Ed | 0.000477 | 0.000435 | 0.000441 | 0.000693 | 0.000707 |
| | (0.00248) | (0.00248) | (0.00248) | (0.00445) | (0.00446) |
| Mother College Ed | 0.0116*** | 0.0115*** | 0.0115*** | 0.0147*** | 0.0147*** |
| | (0.00262) | (0.00262) | (0.00262) | (0.00388) | (0.00388) |
| Single | -0.0399*** | -0.0400*** | -0.0400*** | -0.0313*** | -0.0313*** |
| | (0.00259) | (0.00259) | (0.00259) | (0.00372) | (0.00373) |
| Age | 0.00254*** | 0.00254*** | 0.00254*** | 0.00153*** | 0.00154*** |
| | (0.000341) | (0.000341) | (0.000340) | (0.000489) | (0.000488) |
| White | 0.0197*** | 0.0197*** | 0.0197*** | 0.00261 | 0.00268 |
| | (0.00480) | (0.00480) | (0.00481) | (0.00628) | (0.00628) |
| US Citizen | 0.138*** | 0.138*** | 0.138*** | 0.149*** | 0.149*** |
| | (0.00763) | (0.00763) | (0.00762) | (0.00985) | (0.00984) |
| Research Funding | 0.0211*** | 0.0212*** | 0.0212*** | 0.0145** | 0.0145** |
| | (0.00392) | (0.00392) | (0.00392) | (0.00600) | (0.00601) |
| Constant | 0.0934 | 0.0991 | 0.0975 | 0.467** | 0.473** |
| | (0.108) | (0.107) | (0.107) | (0.185) | (0.185) |
| Institution FE | Y | Y | Y | Y | Y |
| Graduation Year FE | Y | Y | Y | Y | Y |
| Observations | 122,471 | 122,471 | 122,471 | 42,823 | 42,823 |
| R-squared | 0.442 | 0.442 | 0.442 | 0.415 | 0.415 |

*Notes.* Data source: Survey of Earned Doctorates 2008-2016. We restrict the sample to respondents who report gender as male. Results in this table reflect the second stage regression in equation (5). We bootstrap standard errors (in parentheses) and cluster them by institution. In columns 4 and 5, we also restrict the sample to include interdisciplinarians only.

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