Faculty Entrepreneurship and the Gender Earnings Gap*

Joseph Staudt†

June 2022
PRELIMINARY: PLEASE DO NOT CITE OR CIRCULATE.

Abstract

This paper analyzes the contribution of entrepreneurial activities to gender earnings gaps among university faculty. Administrative data from universities (UMETRICS) linked to the universe of confidential W2 and 1099 tax records allow me to precisely classify earnings sources and measure faculty commercial engagement. I find substantial faculty gender gaps. Female faculty are 20 percentage points less likely to engage in entrepreneurial activities, with the entire participation gap driven by the gap in self-employment. The raw total male-female faculty earnings gap is $63k (on a base of $162k), with the gap in non-university earnings accounting for $18k (29%). Thus, though university earnings account for most of the total gap, commercial engagement opportunities substantially expand the gap. Earnings gaps also exist for all components of non-university earnings, including earnings from self-employment as well as from incumbent, young/startup, high-tech, and low-tech firms. Quantile regressions show that, as faculty move up the earnings distribution, gender earnings gaps grow and entrepreneurial activity becomes a more important contributor to the total gap, which is suggestive of a "glass ceiling" effect for female faculty. I also find that earnings gaps are small at career outset and then grow over time, but that the contribution of entrepreneurial activities to the total gap is relatively constant over the lifecycle.

JEL Classification Numbers: O30, J16, J31

Keywords: entrepreneurship, academic commercial engagement, economics of gender, gender wage gap, university faculty

*This paper uses data from the U.S. Census Bureau. Any views expressed are those of the author and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Avoidance Officers have reviewed this data product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. DRB Approval Numbers: CBDRB-FY22-CES007-001 and CBDRB-FY22-CES007-006. Thanks to Emek Basker, Elisabeth Perlman, Jean Moore, and Donna Ginther for useful comments. Also thanks to participants at the SEA 2021 Entrepreneurship Session and the 2022 International Conference on the Science of Science & Innovation (ICSSI). All errors are mine.

†Center for Economic Studies (CES), U.S. Census Bureau, joseph.staudt@census.gov.

1 Introduction

University faculty frequently receive earnings from entrepreneurial endeavors such as founding startups or consulting. This faculty engagement with the private sector has been heavily studied – often with a focus on tech transfer – typically revealing large gender gaps in most entrepreneurial activities (Perkmann et al., 2013; Miller et al., 2018; Staudt, Forthcoming). These findings suggest a startling possibility: one of the primary pathways through which university research is brought to market – the commercial engagement of faculty (Bozeman, 2000; Bozeman et al., 2015) – may also have a deleterious effect on equity by exacerbating the gender earnings gap among faculty. Indeed, since universities often encourage and facilitate faculty engagement with industry – for instance, through institutions like technology transfer offices (TTOs) – a fuller accounting of its possibly disparate impacts is of direct interest to both policymakers and university administrators.

Though the gender earnings gap has been intensively studied in economics and other disciplines, both generally (Blau and Kahn, 2017; Goldin, 2021) and in academia specifically (Li and Koedel, 2017; Ceci et al., 2014; Renzulli et al., 2013; Kelly and Grant, 2012), there has been very little work on how academic commercial engagement might affect the faculty earnings gap. In principle, the relationship is unclear. If male faculty are the primary beneficiaries of commercial opportunities, then entrepreneurship is likely to widen the total earnings gap (i.e. university plus non-university earnings). In contrast, entrepreneurial activities may provide a source of earnings for female faculty that help close the total earnings gap – though, in this case, the need for female faculty to top up their university salaries to reach parity with male peers may indicate other barriers faced by women in the academy.

In this paper, I examine the interaction between entrepreneurship and gender earnings gaps among U.S. faculty using detailed administrative data on university employees linked to detailed earnings histories derived from tax records. These linked data allow me to precisely classify sources of faculty earnings, and thus examine whether faculty entrepreneurial activities exacerbate or dampen the faculty gender earnings gap as well as identify which activities are the most important contributors to the gap. Specifically, I use data from UMETRICS to obtain a sample of about 60k faculty across 25 large U.S. research universities and link these faculty to their W2 and 1099 tax records as well as their unemployment insurance (UI) earnings records. Tax data on the universe of U.S. businesses – including information on firm age and industry – are then used to categorize different sources of earnings, such as earnings from universities as well as earnings from entrepreneurial activities like self-employment and work at high-tech or startup firms.[1]

[1]UMETRICS is maintained by the Institute for Research on Innovation and Science (IRIS) at the Uni-

My first main set of results confirm, as found in a variety of other work (see Section 2), that there exist large gender gaps in entrepreneurial engagement (i.e. the extensive, or participation margin) for the faculty in my linked administrative data. In a typical year, nearly 50% of male faculty receive positive non-university earnings compared to just 30% of female faculty. Thus, while it is common for both male and female faculty to receive earnings from outside the academy, the 20 percentage point participation gap makes it clear that men are much more likely to engage in commercial endeavors.

Breaking these participation results out by type of commercial engagement, I show that the overall participation gap in levels is driven entirely by self-employment. Indeed, female faculty are slightly more likely to receive positive earnings from an employer firm. The level gaps in male-female participation are also small for various subsets of employer firm, such as incumbent, young/startup, high-tech, and low-tech firms.

Though the female-male participation gaps at employer firms are small in *levels*, the baseline rates of faculty engagement are quite different across firm types. Scaling participation gaps relative to baseline reveals that female faculty are 17% less likely than male faculty to receive positive earnings from a high-tech firm and 22% more likely to receive positive earnings from a low-tech firm. This suggests that male and female faculty commercially engage for different reasons – perhaps men have opportunities to collaborate with high-tech firms on research endeavors, while women attempt to supplement lower pay by taking on work at low-tech firms.

The high overall rate of faculty participation in entrepreneurial endeavors is suggestive of the important role these activities play in the process of commercializing research outputs. At the same time, the large gender gaps on the participation margin suggest that the very process bringing research to market may also expand earnings gaps between male and female faculty. Indeed, my second main set of results – and the heart of the paper – explore just this phenomenon: the contribution of faculty entrepreneurial engagement to gender gaps in faculty earnings.

I find that the raw total faculty earnings gap is large, both in levels and percentages, and that commercial engagement clearly expands this raw gap (accounting for nearly a third of the total). Using ordinary least squares (OLS) regressions with wage levels as

versity of Michigan (Lane et al., 2015). The W2 and 1099 tax records are available to qualified researchers through agreements between the IRS and the U.S. Census Bureau. The 1099 tax records are maintained through the Integrated Longitudinal Business Database (ILBD) program at Census (Goetz et al., 2021; Jarmin, 2007). The UI earnings records are available from the Longitudinal Employer-Household Dynamics (LEHD) program at Census (Vilhuber et al., 2014). Information on firms is available from the Business Register (DeSalvo et al., 2016) and the Longitudinal Business Database (LBD) (Jarmin and Miranda, 2002), both maintained by Census. See Section 3 for additional details on the data sources and how they are combined.

outcomes and excluding covariates (except year fixed effects), I estimate that the raw *total* earnings (university plus non-university earnings) gap between male and female faculty is about $63k. How does the existence of commercial engagement opportunities affect this total earnings gap? In other words, what is the contribution of non-university earnings? OLS regressions show that non-university earnings (i.e. earnings derived from commercial engagement) account for about $18k (29%) of the raw total gender earnings gap among faculty. Earnings from universities account for the remaining $45k (71%). Thus, in dollar terms, university earnings account for the bulk of the raw total earnings gap, but non-university earnings substantially widen the gap, accounting for nearly a third.

Since total faculty earnings has a mean of $162k (real 2018 dollars), these wage regressions suggest that, on average, female faculty earn about 40% less than male faculty.[2] Though the gap in *levels* is much larger for university than for non-university earnings, the baseline mean is also much higher – $138k for university versus $24k for non-university earnings. This implies that the *percentage* effect is larger for non-university earnings – women earn about 33% less than men from university sources and 75% less from non-university sources.[3] In any case, whether measured in dollar or percentage terms, the existence of commercial engagement opportunities substantially widens the total male-female faculty earnings gap relative to what would exist if universities were the only source of faculty income.

Turning to the components of non-university earnings, I find that the self-employment gap is $10,300 and the gap in earnings from employer firms is $7,900. Relative to baseline means, these gaps are 119% and 51%.[4] Thus, the gap in earnings from self-employment is larger in both dollar and percentage terms. In dollar terms, the earnings gap from employer firms is dominated by the earnings gaps from incumbent ($7,100) and high-tech ($6,600) firms rather than young/startup ($800) and low-tech ($1,400) firms. However, relative to baseline, variation across employer firm type is less dramatic with gaps of 50.6%, 66.4%, 55.9%, and 24.1% for incumbent, high-tech, young/startup, and low-tech firms.[5]

After documenting the existence of large *raw* gender gaps in faculty earnings and quantifying the contribution of entrepreneurial activities to these gaps, I next examine how covariates – including controls for field, university, access to scientific resources, age, race, ethnicity, and place of birth – alter these results. I find that conditioning on covariates attenuates the total earnings gap by about $13k to $51k. Thus, a large gap remains. Conditioning

[2]Log and Poisson Pseudo Maximum Liklihood (PPML) estimates of -0.4096 and -0.4164 suggest very similar percent differences.

[3]PPML estimates are -0.3444 and -0.8811 for university and non-university earnings.

[4]PPML estimates are -1.727 and -0.5560 for earnings from self-employment and employer firms.

[5]PPML estimates are -0.5498, -0.6201, -0.7525, and -0.2485 for incumbent, young/startup, high-tech, and low-tech firms.

on covariates also attenuates the university earnings gap by about $12k to $33k, but does not meaningfully attenuate the non-university earnings gap. The large attenuation of the university earnings gap combined with the small attenuation of the non-university earnings gap implies that, conditional on covariates, commercial engagement plays a relatively more important role in explaining the (now smaller) gender gap in total earnings. Indeed, the fraction of the total gap accounted for by university earnings declines from 71% to 65% and the fraction accounted for by non-university earnings increases from 29% to 35%.

Decompositions show that the full set of covariates explain about 22% of the raw gap in total earnings and 31% of the raw gap in university earnings. In contrast, the covariates explain very little of the raw male-female gap in non-university earnings – specifically, they explain about 1.1%, with the remaining 98.9% left unexplained. These decompositions suggest that the determinants of earnings within the academy are different than the determinants of earnings received through faculty commercial engagement.

As with most earnings distributions, the faculty earnings distribution is highly right-skewed. Thus, I next move away from OLS regressions, which focus on differences at the mean, and use recentered influence functions (RIFs) to examine gender gaps at other points of the faculty earnings distribution (Firpo et al., 2018; Rios-Avila, 2020). At the median (50th quantile), these regressions suggest that the raw gaps in total, university, and non-university earnings are $41k, $32k, and $0.[6] For faculty higher in the earnings distribution, these gaps increase. At the 75th quantile, the the gaps in total, university, and non-university earnings increase to $73k, $54k, and $12k. At the 90th quantile, the gaps increase further to $122k, $82k, and $47k. These patterns are consistent with a 'glass-ceiling" effect, where female faculty do not have access to the most lucrative opportunities both within and outside of academia (Blau and Kahn, 2017).

I construct a variety of measures to provide a sense of the relative contribution of faculty commercial engagement to the total gender gap at a each earnings quantile.[7] All of these measures suggest that commercial engagement plays a more important role as faculty move up the earnings distribution. That is, the gap in non-university earnings accounts for a higher fraction of the total earnings gap at higher quantiles.

Adding covariates to the quantile regressions has a similar effect as adding covariates to the OLS regressions. The total and and university earnings gaps are attenuated, but remain large. In contrast, the non-university earnings gaps are not attenuated at all. This implies

[6] No gap in non-university earnings at the median is unsurprising since only 40% of faculty receive positive non-university earnings in a given year.

[7] Unfortunately, when using quantile regression, gender gaps in total earnings do not nicely partition into contributions from component parts (as is the case for OLS). For instance, the gender gaps in university and non-university earnings do not sum to the gap in total earnings.

that, conditional on covariates, commercial engagement becomes a relatively more important contributor to the (smaller) total earnings gap at each quantile.

In a final set of results, I estimate gender earnings gaps across the faculty age distribution, shedding light on how these gaps evolve over the course of the career. Consistent with other work on gender earnings gaps over the lifecycle (Juhn and McCue, 2017), I find that gaps begin small at career outset and then expand as the career progresses. These trends are present for total, university, and non-university earnings. Moreover, they are present in models with and without faculty fixed effects. Perhaps surprisingly, with the exception of changes very early in the career, the importance of commercial activity in accounting for the total earnings gap is relatively constant over the lifecycle.

Much remains to be done. Future versions of this paper will incorporate information on which faculty are principal investigators (PIs). This will allow me to estimate how much of their university earnings are derived from grants and how much are from base salaries paid by the university. As it currently stands, "university" earnings is a combination of these two sources and partly reflects differences across faculty in grant funding.[8] Future versions will also incorporate publication histories to control for faculty research productivity. Finally, when available, I will incorporate data from the 2020 Decennial Census to explicitly examine the role childbearing plays in career dynamics.

The rest of the paper is organized as follows. Section 2 situates my work within the large literature on faculty commercial engagement and the equally large literature on gender earnings gaps. Section 3 discusses the various sources of administrative data and the linkages between them. Section 4 presents the results. Section 5 provides some discussion, direction for future work, and concludes.

2 Previous Literature

This paper contributes to two main strands of literature. First, it contributes to work measuring the extent and determinants of faculty entrepreneurship or faculty commercial engagement. Second, it contributes to work on the gender earnings gap, especially for highly educated subsets of the population such as university faculty.

Though both strands of literature are heavily studied, this paper is novel in examining the interaction of faculty entrepreneurship with the faculty earnings gap. That is, I examine how faculty engagement in various entrepreneurial activities contributes to the earnings gap between male and female faculty. To my knowledge, this is the first work to explicitly examine this relationship using high quality administrative data.

[8] Thanks to Donna Ginther for pointing this out.

2.1 Faculty Entrepreneurship

University faculty are widely thought to be important vectors for the technology transfer process – moving knowledge from lab to market (Bozeman, 2000; Bozeman et al., 2015). Thus, the engagement of faculty in entrepreneurial endeavors has been heavily studied. Perkmann et al. (2013) and Miller et al. (2018) provide overviews of this work.

Traditionally, studies measuring the extent of faculty commercial engagement have relied on cross-sectional survey data. Though survey data have important strengths, particularly the granularity of commercial activities that can be assessed, they also have the significant drawback of quite low response rates. These studies (with response rates in brackets) include: Bird and Allen (1989) [27%], Blumenthal et al. (1996) [65%], Boardman (2008) [38%], Boardman and Corley (2008) [38%], Boardman and Ponomariov (2009) [38%], Boardman (2009) [38%], Bozeman and Gaughan (2007) [38%], Campbell and Slaughter (1999) [34%], Lee (1996) [43%], Lee (1998) [43%], Lee (2000) [64%], Lin and Bozeman (2006) [44%], Link et al. (2017) [38%], Louis et al. (2001) [64%], Ponomariov (2008) [38%], Ponomariov and Boardman (2008) [37%], and Renault (2006) [14%].

More recently, there have been attempts to bring administrative data to bear on the question of faculty commercial engagement. Though administrative data typically include less detail than surveys, their comprehensiveness makes them an attractive alternative way to study faculty commercial engagement. Perkmann et al. (2015) studies faculty engagement using administrative data from Imperial College London. More recently, using the same faculty sample as this paper, Staudt (Forthcoming) examines the rates at which UMETRICS faculty engage in a variety of commercial activities.

Much of the work on faculty commercial engagement include breakdowns by gender. Nearly all of this work finds that male faculty are more likely to commercially engage than women (see Perkmann et al. (2013) for an overview).

2.2 Gender Earnings Gap

Earnings gaps between men and women have been studied for many years across a wide range of disciples. For broad overviews, see Blau and Kahn (2017) and Goldin (2021).

In addition to examining gender gaps for broad swathes of the population, many researchers have examined gaps for highly trained subsets of the population, including law school graduates (Noonan et al., 2005; Wood et al., 1993), MBA graduates (Bertrand et al., 2010), STEM Ph.D. recipients (Buffington et al., 2016), and other highly-trained individuals (Wilde et al., 2010). Typically, these studies find large raw earnings gaps that are attenuated (to varying degrees, depending on the specific study) by including covariates controlling for school performance, occupation, marital status, and the presence of children. Another consistent finding is that the gender earnings gap varies dramatically over the career. In particular, men and women typically start at similar levels of pay and a gap emerges as careers progress, often coinciding with the arrival of children (Juhn and McCue, 2017).

There has also been a variety of work focusing specifically on gender earnings gaps among university faculty. This includes Brower and James (2020), Li and Koedel (2017), Ceci et al. (2014), Renzulli et al. (2013), Kelly and Grant (2012), and Porter et al. (2008). As with work using other highly-trained populations, these studies typically find large raw gender earnings gaps that are attenuated (sometimes disappearing altogether) when covariates are taken into account. The most relevant covariates in the context of university faculty tend to be field, academic rank (e.g. assistant, associate, full professor), institution type (e.g. research-intensive, liberal arts university), and family structure, including marital status and presence of children.

The subset of these studies based on U.S. faculty have primarily used data from the Survey of Earned Doctorates (SDR), the National Study of Postsecondary Faculty (NSOPF), and state websites that report salaries of public employees. As with surveys geared toward measuring academic entrepreneurship, the the SDR and NSOPF offer important benefits, especially the detailed information that can be gathered. However, administrative data – again, given their comprehensiveness – offer a very attractive alternative. As detailed in Section 3, this paper obtains earnings information from the universe of W2 and 1099 tax records as well as unemployment insurance (UI) earnings records.

3 Data

3.1 UMETRICS

UMETRICS is transaction-level data on all payments made by university grants to employees and vendors, and is directly captured through university payroll and human resources records (Lane et al., 2015).[9] The data include information on the occupation of each individual paid by a grant (e.g. "faculty", "graduate student", "post-doc", "undergraduate", "staff"), which is used to identify faculty. The vintage of UMETRICS data used for this paper includes approximately 59,500 faculty (which comprise about 20% of all individuals in UMETRICS) across 25 universities.

[9]The UMETRICS data are stored in a data enclave at the Institute for Research on Innovation and Science (IRIS) at the University of Michigan. Annually, a snapshot of the data is added to the Federal Statistical Research Data Centers (FSRDCs).

The data also include precise dates on which payments are made to each individual, which is important because some individuals transition, over time, from graduate students or post-docs into faculty. However, I am only interested in the commercial engagement of these individuals *while they are faculty*, not before or after. Thus, the payment dates combined with the occupation information allows me to infer the years that an individual is actually a faculty member.

I also use UMETRICS to construct a variety of individual-level covariates for each faculty member. These include covariates characterizing their UMETRICS university, field, and access to scientific resources. I construct a covariate for each faculty member's university by identifying their "dominant" university. This is done by using payment dates to determine the number of days that each faculty member spent at each university. I then create a set of UMETRICS university fixed effects using these dominant universities.[10]

I characterize a faculty member's field in three ways. First, I identify their dominant funding source (e.g. NIH, NSF, etc.) in terms of the number of days they were paid by a grant from that funding source. Second, I identify their dominant CFDA code in terms of the number of days they were paid by a grant with that code.[11] Finally, I identify each faculty member's dominant sub-organization unit, which closely corresponds to university department (e.g. Arts & Sciences, Health Sciences, etc.), again, in terms of the number of days the faculty member spent in that unit. For each faculty member, I characterize their field using three separate sets of fixed effects for dominant funding agency, CFDA code, and sub-organization unit.

I use two measures to characterize a faculty member's access to scientific resources. First, I compute the total expenditures of all grants on which they were paid. Second, I compute the total number of other employees (i.e. coworkers) paid by grants that also paid the faculty member. These funding amount and coworker count variables proxy for a variety of underlying characteristics, including quality, networks, and prestige, which I group under the banner of "scientific resources".

[10]I cannot easily construct a time-varying measure of UMETRICS university because I track faculty in earnings data after they may have left their UMETRICS university.

[11]CFDA stands for Catalog of Federal Domestic Assistance, and is maintained by the federal government to track federal assistance programs. Each CFDA program is related to a particular field of research, and thus the codes are well-suited to characterize a faculty member's field. The first two digits of a CFDA code identify the major funding agency, such as Department of Defense, Department of Justice, etc. See here. For additional general information, see here.

3.2 Individual Characteristics

The gender of each UMETRICS faculty member is available from the Individual Characteristics File (ICF), which is part of the data infrastructure of the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau (Vilhuber et al., 2014). The ICF is constructed from information contained in the Social Security Administration (SSA) Numident and the Decennial Census.

In addition to information on the gender of each individual, the ICF provides information on race, ethnicity, place of birth, and date of birth. These are used to create covariates and are included in some regressions. I use date of birth to construct an age variable for each faculty-year, which is used as a control and to examine faculty gender earnings gaps throughout the career.

3.3 Employment and Earnings History

UMETRICS faculty are linked to three key sources of administrative earnings data: 1) IRS W2 tax records, 2) LEHD UI earnings records, and 3) IRS 1099 tax records through the Integrated Longitudinal Business Database (ILBD). Taken together, these provide a complete picture of the domestic earnings history of every UMETRICS faculty member between 2005 and 2018. This includes earnings from universities, private firms, government, and self-employment.

The W2 tax records provide annual information on individual earnings along with a federal tax identification number (EIN). The universe of state unemployment insurance (UI) earnings records are available from the Person History File (PHF), a key component of the LEHD infrastructure (Vilhuber et al., 2014). The LEHD PHF contains quarterly information on earnings for most U.S. workers as well as firm identifiers (including EIN). The 1099 tax records are available through the Integrated Longitudinal Business Database (ILBD) which is the universe of non-employer firms in the United States and can be used to measure earnings from self-employment (Goetz et al., 2021). It is the complement of the Longitudinal Business Database (LBD), which is the universe of employer firms in the United States (Jarmin and Miranda, 2002). The ILBD is derived from 1040 tax forms with attached schedule C(s). Overall, non-employer businesses account for about 75% of businesses in the United States (Jarmin, 2007), so incorporating income derived from self-employment is crucial to properly measuring faculty commercial engagement.

I distinguish between university and non-university earnings by linking a list of public-use EINs for all universities, technical schools, and vocational schools in the U.S. to the W2 and LEHD PHF records. This EIN list is available from the Integrated Postsecondary Education

Data System (IPEDS), which is maintained by the National Center for Education Statistics (NCES). It is important to emphasize that university earnings in this paper is defined as earnings from *any* IPEDS university, not only earnings from a faculty member's UMETRICS university. It is also important to emphasize that "university" earnings is a combination of earnings derived from grants and base salaries paid directly from the university. As noted, future versions of this paper will incorporate information on which faculty are principal investigators (PIs), which will allow me to better distinguish between these two sources.

I categorize the sources of non-university earnings by linking W2 records to firm-level information in the LBD and linking LEHD PHF records to firm-level information in the LEHD Employer Characteristics File (ECF). Firm age is used to determine whether a faculty member's W2/LEHD earnings come from an "incumbent" firm or a "young/startup" firm. An incumbent firm is defined as a firm that is over five years old and a young/startup firm is defined as a firm that is five years old or younger. Firm industry (NAICS code) is used to determine whether a faculty member's W2/LEHD earnings come from a "high-tech" or "low-tech" firm, with definitions of high- and low-tech industries derived from Goldschlag and Miranda (2020).

Using this richly categorized earnings data, I define the following nine variables:

- `Total`: Earnings from all sources (W2/LEHD plus 1099)
- `University`: W2/LEHD earnings from an EIN contained in IPEDS
- `Non-University`: 1099 earnings plus W2/LEHD earnings from a non-IPEDS EIN
- `Self-Employment`: 1099 earnings
- `Employer`: W2/LEHD earnings from a non-IPEDS EIN
- `Incumbent`: W2/LEHD earnings from a non-IPEDS EIN older than five years
- `Young/Startup`: W2/LEHD earnings from a non-IPEDS EIN five years or younger
- `High-Tech`: W2/LEHD earnings from a non-IPEDS EIN with a high-tech NAICS code
- `Low-Tech`: W2/LEHD earnings from a non-IPEDS EIN with a low-tech NAICS code

The following relationships exist among these earnings variables:

$$\texttt{Total} = \texttt{University} + \texttt{Non-University}$$

$$\texttt{Non-University} = \texttt{Self-Employment} + \texttt{Employer}$$

$$\texttt{Employer} = \texttt{Incumbent} + \texttt{Young/Startup}$$

$$\texttt{Employer} = \texttt{High Tech} + \texttt{Low-Tech}$$

None of these earnings measures are mutually exclusive. For instance, it is perfectly possible for a UMETRICS faculty member to receive earnings from a university and a low-tech firm in the same year. Indeed, this sort simultaneous commercial engagement of faculty is the focus of the paper. Figure A.1 provides a graphical representation of how these earnings variables are hierarchically related.

3.4 Final Sample

For every year between 2005 and 2018, my final sample includes the set of UMETRICS faculty with positive university earnings (from *any* IPEDS university, not necessarily their UMETRICS university) and non-missing gender information from the ICF. Therefore, by construction, the fraction of faculty with positive university earnings (and thus positive total earnings) is 1.

Moreover, because I am interested in the commercial engagement of faculty *while they are faculty*, I only keep the years after the individual has been identified as a faculty member at their UMETRICS university. For instance, if an individual is classified in UMETRICS as a post-doc in 2005-2007 and as a faculty member in 2008-2018, I only keep the 2008-2018 period for this individual.

In all, there are approximately 59,500 faculty in my sample. Note that my panel is unbalanced in the sense that not all faculty appear in every year. Also, note that all of my analyses take place at the faculty-year level, not the faculty level.

3.5 Earnings Summary Statistics

Table 1 displays summary statistics for each earnings source. Specifically, it shows the means and standard deviations of both positive earnings indicators and earnings levels, by source. The earnings levels are measured in real 2018 dollars.

As noted, all faculty in my sample receive positive university earnings (and thus positive total earnings). Each year, about 43% of faculty receive positive earnings from some non-university source. Thus, a sizable minority of faculty engage in some form of entrepreneurial activity each year. Self-employment is about twice as common as working at an employer firm – 32% versus 16%. Faculty are much more likely to receive positive earnings from an incumbent firm than from a young/startup firm – 14% versus 2.6%. This is unsurprising since incumbents tend to be much larger. Finally, faculty are about equally likely to work at high-tech and low-tech firms – 8.4% versus 9.3%.

Turning to earnings, the typical faculty member earns about \$161,600, of which about \$137,500 (85.1%) comes from universities and \$24,100 (14.9%) comes from non-university sources. Thus, the typical faculty member receives the bulk of their income from universities, but still receives a non-trivial portion through the pursuit of entrepreneurial endeavors. Of non-university earnings, \$8,624 (35.8%) comes from self-employment and \$15,480 (64.2%) comes from employer firms. Breaking down earnings from employer firms by age, \$14,090 (91.0%) comes from incumbent firms and \$1,391 (9.0%) comes from young/startup firms. Breaking down by industry, \$9,865 (63.7%) comes from high-tech and \$5,613 (36.3%) comes from low-tech firms.

4 Results

4.1 Gender Gaps in Participation

Figure 1 displays raw participation rates for both female and male faculty. Specifically, the plot shows the fraction of faculty that receive positive earnings from non-university sources. Though the fraction of both male and female faculty with positive university earnings is 1 by construction, the fraction with positive non-university earnings differs dramatically by gender. Indeed, the fraction of male faculty receiving positive non-university earnings fluctuates between 50% and 52% while the fraction of female faculty fluctuates between 26% and 29%. These fractions have been quite stable over time, implying a 20 percentage point male-female gap in commercial engagement that has persisted for at least a decade.

Figure 2 breaks out the fraction of faculty that commercially engage by source – specifically, whether the non-university earnings come from self-employment (left plot) or an employer firm (right plot). The results are stark: the entire 20 percentage point male-female gap in commercial engagement is driven by the gap in self-employment. Around 42-44% of male faculty receive positive earnings from self-employment in a given year, compared to just 12-15% of female faculty. In contrast, in all time periods, female faculty are slightly *more* likely to receive positive earnings from employer firms (15-19%) than are male faculty (14-17%).

In Table 2, I present extensive (participation) margin OLS regressions that summarize the information presented in Figures 1 and 2 while allowing me to condition on faculty age.[12] Indicators for positive earnings from a given source are the outcomes and are regressed on an indicator for female faculty. The coefficient on the female faculty indicator represents the female-male participation gap (in percentage points) for that commercial activity.

Column (1) of Table 2 confirms that female faculty are about 21.3 percentage points less likely to commercially engage – i.e., receive positive earnings from a non-university

[12]Controlling for faculty age is potentially important because the men and woman in my sample may be at different points in their careers and thus at different points on their earnings-age profile. I flexibly control for faculty age by including, in all regressions, a full set of age fixed effects interacted with year fixed effects.

source. Moreover, columns (2) and (3) verify that this male-female faculty participation gap is entirely driven by the gap in self-employment – women are 25.8 percentage points less likely to receive positive earnings from self-employment and are 0.5 percentage points more likely to receive earnings from an employer firm (though this latter gap is essentially a precise zero).

Of course, the baseline rates of faculty participation in each of these activities are quite different. To give a sense of the participation gaps' sizes relative to baseline, Table 2 also displays the estimated coefficients scaled by the unconditional means from Table 1 (see row labeled "Percent of Mean"). These scaled coefficients translate into effects that are about -49.9%, -80.8%, and 2.95% of the baseline fractions of faculty with positive non-university, self-employment, and employer firm earnings. Thus, even relative to baseline, male-female participation gaps are much larger for self-employment than they are for employer firms.

Table 2 also shows participation gaps for different types of employer firms, grouped by firm age and industry. Columns (4) and (7) suggest that women are 0.7 and 2.0 percentage points more likely to receive positive earnings from an incumbent and low-tech firm. In contrast, columns (5) and (6) suggest that women are 0.07 and 1.5 percentage points less likely to receive earnings from a young/startup and high-tech firm. Thus, the level differences in employment rates at firms are relatively trivial compared to the very large level difference in the rate of self-employment.

Though the scaled gaps remain relatively small for both firm age groups (4.7 percent for incumbents and -2.5 percent for young/startup firms), the scaled gaps for the two industry groups reveal important gender differences. Indeed, as a percent of the baseline fractions, female faculty are 17.4% less likely than male faculty to receive positive earnings from a high-tech firm and 21.9% more likely to receive earnings from a low-tech firm. This gender divergence in participation at high/low-tech firms may be driven by male and female faculty commercially engaging for different reasons: for instance, men may have opportunities to work at high-tech firms to advance their research, while women need to supplement lower pay from their university by working at low-tech firms.

4.2 Gender Earnings Gap at the Mean

4.2.1 Raw Gaps

Table 3 exhibits regressions of total, university, and non-university earnings outcomes on an indicator for female faculty. The coefficient on the female faculty indicator represents the female-male earnings gap, either in level or percentage terms (depending on the model used). Each cell of the table displays a separate coefficient from a separate regression. Panels A, B, and C display coefficients from level wage regressions, PPML regressions, and log wage regressions, respectively. The coefficients from the PPML and log wage regressions have a semi-elasticity interpretation – the percent difference in earnings between male and female faculty.[13]

I first focus on the raw earnings gaps – the specifications without covariates (except year fixed effects) – in the odd numbered columns of Table 3. Column (1) shows that the raw total earnings gap in levels is about $63,240. Columns (3) and (5) show that $45,060 (71.3%) of the total gap is due to the gap in university earnings and the remaining $18,180 (28.7%) is due to the gap in non-university earnings. Thus, the raw gender earnings gaps (in levels) are quite large. Moreover, while university earnings account for the bulk of the raw total gap, non-university earnings substantially expand this gap – in other words, commercial engagement clearly widens the earnings advantage of male faculty over female faculty.

As with baseline participation probabilities, Table 1 shows that baseline earnings vary considerably across source. Relative to baseline, the raw regression coefficients in columns (1), (3), and (5) of Table 3 suggest that female faculty earn 39.1%, 32.8%, and 75.4% less than male faculty in total, university, and non-university earnings. The PPML estimates similarly suggest that women earn $|100 * [exp(-0.4164) - 1]| = 34.1\%$ less in total earnings, 29.1% less in university earnings, and 58.6% less in non-university earnings. Similarly, log regressions for total and university earnings suggest that female faculty earn 33.6% and 31.1% less than male faculty. Thus, though non-university earnings account for a minority share of the level gap in earnings, the much lower baseline mean for non-university earnings implies a much larger gap in percentage terms.

Table 4 breaks out the raw non-university earnings gap into its constituent parts. In levels, the gap in earnings from self-employment is about $10,280, which accounts for 56.5% of the non-university earnings gap, and the gap in earnings from an employer firm is about $7,902, accounting for the remaining 43.5%. These estimated coefficients are 119% and 51.0% of the baseline means. The PPML estimates of -1.727 and -0.556 imply that female faculty earn 82.2% less than male faculty from self-employment and 42.7% less from an employer firm. Thus, the earnings gap from self-employment is larger in both level and percentage terms. However, given the much lower baseline mean for self-employment earnings ($8,624 vs $15,480), the self-employment earnings gap between male and female faculty is about twice the employer firm earnings gap in percentage terms.

The remaining columns of Table 4 separate out the raw employer earnings gap along age

[13] Recall that, by construction, total and university earnings are always positive, allowing me to run log regressions for these outcomes. In contrast, since many faculty have zero non-university earnings, log regressions cannot be run for this outcome.

(incumbent vs. young/startup firm) and industry (high-tech vs. low-tech firm) dimensions. Along the age dimension, the $7,124 incumbent gap accounts for 90.2% of the gap in employer earnings and the $778 young/startup gap accounts for the remaining 9.8%. Along the industry dimension, the $6,550 high-tech gap accounts for 82.9% of the employer earnings gap and and the $1,352 low-tech gap accounts for the remaining 17.1%. Thus, in levels, the male-female gap in faculty earnings from an employer firm is dominated by gaps in earnings from incumbent and high-tech firms. Relative to baseline means, the level gaps from incumbent, young/startup, high-tech, and low-tech firms are 50.6%, 55.9%, 66.4%, and 24.1%. Similarly, the PPML estimates of -0.5498, -0.6201, -0.7525, and -0.2485 imply that women earn 42.3%, 46.2%, 52.9%, and 22.0% less than men. Therefore, female faculty earn less than male faculty across all subcategories of employer firms. In percentage terms, the gaps are fairly similar for incumbent, young/startup, and high-tech firms. The gap in earnings from low-tech firms (where, recall, female faculty are more likely to work) is about half the size of the other three subcategories.

4.2.2 Gaps with Covariates

I next examine how adding covariates to the regressions affects the the male-female earnings gaps as well as how it affects the relative contribution of faculty commercial engagement to the total earnings gap. The covariates include age fixed effects, field fixed effects, and university fixed effects as well as controls for race, ethnicity, place of birth, and scientific resources. The coefficients on the female faculty indicator, from specifications that include these covariates, are displayed in the even numbered columns of Table 3.

Column (2) shows that the total earnings gap in levels is attenuated by about $12,630 to $50,610, which is 100*($12,630/$63,240)% = 20.0% of the original raw gap. Columns (4) and (6) show that the gaps in university and non-university earnings are attenuated by $12,330 and $290 to $32,730 and $17,890, which are 27.4% and 1.6% of the original raw gaps. Thus, while adding covariates certainly closes the total male-female earnings gap, a substantial gap remains. Moreover, nearly all of the covariate-induced total earnings gap attenuation is due to an attenuation of the university earnings gap. This implies that, conditional on covariates, non-university earnings account for a larger fraction of the the total gap – indeed, the fraction of the (now smaller) total gap accounted for by university earnings declines to 64.7% and the fraction accounted for by non-university earnings increases to 35.3% (without covariates these were 71.3% and 28.7%).

Relative to baseline, these regressions suggest that female faculty earn 31.3%, 23.8%, and 74.2% less than male faculty in total, university, and non-university earnings. The PPML regression estimates of -0.3284, -0.2466, and -0.8537 tell a consistent story, implying that women earn 28.0% less in total earnings, 21.9% less in university earnings, and 57.4% less in non-university earnings. The log regressions for total and university earnings suggest that women earn 25.0% and 19.7% less than men. As with the raw gaps, university earnings account for the majority of the total level gap, but the lower baseline mean for non-university earnings implies that the gap in non-university earnings is much larger in percentage terms.

4.2.3 Decompositions

As shown, adding the *full set* of covariates to the earnings regressions attenuates the gaps between female and male faculty. In this section, I explore the role that *specific groups* of covariates play in closing (or expanding) the raw female-male faculty earnings gaps. Specifically, I use Oaxaca-Blinder decompositions (Oaxaca, 1973; Blinder, 1973) to examine which sets of covariates are most important in explaining (in an accounting sense) the raw male-female gaps in total, university, and non-university faculty earnings.[14]

Columns (1) and (2) of Table 5 suggest that, overall, the full set of covariates explain about 22.17% of the raw gap in total earnings and 30.7% of the raw gap in university earnings. Put another way, 77.8% and 69.3% of these raw gaps *cannot* be explained by the observable covariates included in the regressions. This unexplained, or "residual", is often thought of as discrimination, but it can also be due to other factors such as unobserved productivity differences between male and female faculty.[15] Thus, though the covariates explain important portions of the raw total and university earnings gaps, most of the gaps remain unexplained.

Column (3) shows that, in contrast, the full set of covariates explain almost none of the raw male-female gap in non-university earnings. More precisely, they explain about 1.1%, with the remaining 98.9% left unexplained by the covariates. This is consistent with covariates having a negligible effect on the raw non-university earnings gap at the mean (see Table 3) and at other points in the faculty earnings distribution (see Table 6 in the next

[14]It is important to note that controlling for covariates such as field, while common, is not appropriate for all types of analyses. The problem arises because the choice of field may itself be the result of barriers that women face (including discrimination) earlier in life. For instance, if high school girls are steered away – either explicitly or implicitly – from college majors that more often lead to faculty positions in higher paying fields, then the field in which a faculty member ends up working is a *mechanism* through which female faculty earn less than male faculty. Controlling for this mechanism will misleadingly attenuate the relevant male-female earnings gaps. In other words, controlling for field is tantamount to controlling for a covariate that is itself impacted by treatment, where the treatment in this context can be thought of as sex assignment at birth. Nevertheless, adding controls to regressions is useful for examining how much of the raw earnings gap can be explained by observable characteristics, and which of these characteristics are most important.

[15]Future versions of UMETRICS data will have publications linked to faculty, allowing me to probe for productivity differences between men and women, and include publications (and quality of publications) as covariates in regressions.

section).[16]

Turning to specific groups of covariates, it is clear that the age fixed effects are by far the most important factor accounting for all three raw earnings gaps, explaining 17.01% of the total earnings gap, 19.73% of the university earnings gap, and 10.27% of the non-university earnings gap. For total and university earnings, field also accounts for a significant portion of the raw gaps, explaining 7.9% and 11.6%. However, field explains a negligible portion (-1.3%) of the non-university earnings gap. Finally, the faculty member's place of birth plays a relatively important role in *expanding* the faculty gender earnings gaps: it accounts for -4.1% of the total raw gap, -3.6% of the university raw gap, and -5.3% of the non-university raw gap (the negative percentages indicate that, on net, these variables *expanded* the male-female earnings gap). This suggests that female faculty tend to be born in countries whose citizens earn relatively high salaries as faculty at U.S. universities.

The remaining covariates – race/ethnicity, scientific resources, university fixed effects and year fixed effects – explain a relatively small portion of the faculty gender earnings gaps. Together, these variables account for 1.3% of the raw total earnings gap, 2.9% of the raw university earnings gap, and -2.6% of the raw non-university earnings gap.

4.3 Gender Earnings Gaps at the 50th, 75th and 90th Quantiles

4.3.1 Raw Gaps

As with most earnings distributions, the faculty earnings distribution is highly right-skewed, with a small number of faculty receiving a disproportionate fraction of earnings. Therefore, in this section, I move away from examining male-female gaps in faculty earnings at the mean, and toward examining gaps at other points in the earnings distribution. Specifically, I use recentered influence functions (RIFs) to examine earnings gaps at various quantiles of the earnings distribution (Firpo et al., 2018; Rios-Avila, 2020). These quantile regressions are displayed in Table 6, with panels A, B, and C containing RIF regression coefficients for the 50th, 75th, and 90th quantiles, respectively. Analogous to Table 3, each cell contains a separate coefficient from a separate regression, the odd-numbered columns show the raw earnings gaps without covariates (except year fixed effects), and the even-numbered columns

[16]To put these results in context, Blau and Kahn (2017), using a much more heterogeneous sample of workers from the Panel Study of Income Dynamics (PSID) and a rich set of covariates, are able to reduce their unexplained gender wage gap to about 38%. Given my very homogeneous sample – which implicitly conditions on occupation (faculty) and education level (graduate degree) – perhaps it is unsurprising that remaining earnings gaps are more difficult to explain by adding additional covariates. It is also important to note that I am using *annual* earnings variables as outcomes, and cannot observe hours worked, which is an important source of unobserved heterogeneity with previous work showing substantial wage penalties for working shorter hours (e.g. Bertrand et al. (2010)).

show the gaps after controlling for covariates.

Column (1) of panel A shows that, at the 50th quantile of the faculty earnings distribution, the total raw male-female earnings gap in levels is about \$40,750, which is substantially less than the \$63,240 gap at the mean. Columns (3) and (5) of panel A show that the raw gaps in university and non-university earnings at the 50th quantile are about \$32,100 and a negligible \$39.23. Thus, at the median, the gap in university earnings remains large, but the gap in non-university earnings disappears. Since only 40% of faculty receive positive non-university earnings each year (see Table 1) – implying the median faculty member receives zero non-university earnings – it is unsurprising that the gap in non-university earnings disappears at the 50th quantile.

Panels B and C show that, as faculty move up the earnings distribution, male-female gaps grow larger for all three outcome variables. The raw total earnings gap increases to \$72,880 at the 75th quantile and to \$121,700 at the 90th quantile. The raw university earnings gap increases to \$54,450 and \$81,520 at the 75th and 90th quantiles. The raw non-university earnings gap increases to \$12,170 and \$47,110 at the 75th and 90th quantiles. The existence of much larger gaps at higher points in the faculty earnings distribution is a common phenomena in the wage gap literature, and is consistent with a "glass-ceiling" effect, where female faculty do not have access to the most lucrative opportunities both within and outside of academia (Blau and Kahn, 2017).

Unfortunately, quantile regressions do not allow a neat partition of gender earnings gaps into contributions from constituent parts. This is in contrast to the OLS regressions from Table 3, where, for instance, the raw gaps of \$45,060 and \$18,180 for university and non-university earnings sum to the raw total earnings gap of \$63,240. To shed light on the contribution, at a given quantile, of the university earnings gap to the total earnings gap, I compute two ratios: 1) divide the university earnings gap by the total earnings gap and 2) divide the university earnings gap by the sum of the university and non-university earnings gaps. For instance, using the regression coefficients on the female faculty indicator from columns (1), (3), and (5) of Table 6 Panel A, these ratios of raw gaps for the 50th quantile are: 100*(-\$32,100/-\$40,750) = 78.8% and 100*(-\$32,100/(-\$32,100 - \$39.23)) = 99.9%. Thus, at the 50th quantile, the university earnings gap is 78.8% of the total earnings gap and is 99.9% of the sum of the university and non-university earnings gaps. I compute analogous ratios for the 75th and 90th quantiles. I also compute these ratios for non-university earnings.

These ratios of gaps are organized and presented in Figure 3. The left plot displays the first ratio type and the right plot displays the second ratio type. Both plots clearly show that the importance of faculty entrepreneurial activity, as a contributor to the total earnings gap, increases as faculty move up the faculty earnings distribution. At the 50th quantile, non-university earnings account for almost none of the gap in total earnings (left plot) or the sum of the gaps in university and non-university earnings. At the 75th quantile, both ratios increase to around 20%. At the 90th quantile, they both increase to around 40%. On the flip side, the relative importance of university earnings, as a contributor to the total earnings gap, decreases as faculty move up the faculty earnings distribution.

4.3.2 Gaps with Covariates

I now turn to the even-numbered columns of Table 6, which show earnings gaps, at different quantiles, conditional on the same set of covariates discussed in Section 4.2.2. As with gaps at the mean, adding covariates attenuates the gaps for total and university earnings. Column (2) of panel A shows that, for total earnings, the gap at the 50th quantile is attenuated by \$12,610 to \$28,140, which is a decrease of 100*(\$12,610/\$40,750) = 30.9% of the original raw gap. Panels B and C show that, at the 75th and 90th quantiles, the gaps in total earnings are attenuated by \$14,520 and \$13,100 to \$58,360 and \$108,600, which are 19.9% and 10.8% of the original raw total gaps. Column (4) shows that, for university earnings, the gaps at the 50th, 75th, and 90th quantiles are attenuated by \$12,860, \$15,500, and \$14,040 to \$19,240, \$38,950, and \$67,480, which are 40.1%, 28.5%, and 17.2% of the original raw gaps in university earnings.

Thus, for both total and university earnings, covariates certainly attenuate the male-female faculty gap. However, large gaps remain for both variables at all three quantiles. Moreover, the covariate-induced attenuation becomes less extreme for faculty higher up the earnings distribution – that is, the dollar amount of the attenuation becomes a smaller fraction of the original raw gap. This suggests that observables explain less of the gap at the top of the faculty earnings distribution than near the middle of the distribution.

In contrast to total earnings and university earnings, adding covariates has a negligible impact on the non-university faculty gender earnings gap. At the 50th quantile, the gap is attenuated by \$11.79 to \$27.44. At the 75th and the 90th quantiles, the gaps actually *expand* slightly by \$330 and \$2,620 to \$12,500 and \$49,730. As with the gaps at the mean, this implies that covariates increase the relative importance of non-university earnings to the (now smaller) total gaps at the 50th, 75th, and 90th quantiles. Indeed, the ratios of gaps presented in Figure 3 confirm that non-university earnings becomes a more important contributor to the total earnings gap – that is the commercial engagement of faculty plays a bigger role conditional on covariates.

4.4 Gender Earnings Gaps by Age

In this section, I present a final set of results examining how the gaps in total, university, and non-university earnings vary across the age distribution. This analysis is motivated by findings in a variety of work, including Juhn and McCue (2017), showing small gender earnings gaps at the outset of the career, which then grow as the career progresses. These expansions are often associated with family formation – in particular, having children, which tends to more negatively affect the career outcomes of women than men.

The left plot in Figure 4 presents estimated male-female gaps for all three earnings outcomes, separately for ten different 5-year age bins.[17] These are obtained from OLS regressions of each earnings outcome on the indicator for female faculty interacted with indicators for each of the ten age bins.[18] These regressions shed light on how gender earnings gaps vary across the age distribution. The green series of triangles represent the gender gaps in total earnings. This series shows that, for faculty 25 and younger, there is essentially no gender gap in total earnings. For faculty aged 26-30, there is a $4,800 gap. For mid-career faculty (aged 41-50), the gap is larger still at $45-60k. The gap continues to get larger for older faculty, reaching a nadir of $85k for faculty aged 56-65. These patterns are consistent with small gaps at the outset of faculty careers that then grow as time goes on.

The blue series of circles and the red series of squares represent gender gaps in university and non-university earnings. The overall patterns are similar to the gaps in total earnings. Both gaps are negligible for young faculty (aged 25 and under). For faculty aged 26-30, there is a $5,340 gap in university earnings, but the gap remains zero for non-university earnings. For faculty aged 31-35, the gap is yet larger at $11,830 for university earnings and a $3,501 gap opens up for non-university earnings. As with total earnings, these gaps grow larger for each older age group until around age 56-65, where the gap in university earnings is $57-58k and the gap in non-university earnings is $26-28k. Again, this evidence is consistent with small earnings gaps at career outset, which then grow over time, partly due to growth in the university earnings gap and partly due to growth in the gap in earnings from commercial engagement.

The estimates in the right plot of Figure 4 add faculty fixed effects to the regressions. Unfortunately, this requires one of the estimated female faculty by age group interactions to be omitted from the regression. In this case, the gender gap for the 25 or younger group is omitted. This prevents us from pinning down the initial gap (which, without faculty fixed effects, is essentially zero), only allowing us to observe gap sizes relative to the gap size for

[17] The ten bins are: 25 and under, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, and 66 and older.

[18] Regressions include year fixed effects and the full set of age fixed effects (not only fixed effects for the 5-year bins).

the omitted group. However, only using within-faculty variation gives a clearer picture of how the gender gaps evolve over the lifecycle for a given faculty member.[19] The right plot confirms the basic patterns in the left plot, showing that the gender faculty earnings gaps, for all three outcomes, grow over the course of the career. However, the expansion of the gaps, relative to the gaps at the outset of the career, are less dramatic when faculty fixed effects are included. This is especially true for the profile of university earnings gaps, which now has a gradient similar to the profile of non-university earnings gaps.

For total earnings, again represented by the green triangles, the gender gap for faculty aged 26-30 is \$4,731 larger than the gap at career outset. By mid-career (aged 41-50), the gap has expanded to \$33-39k larger than the initial gap. The gap reaches its lowest point for faculty aged 61-65, where it stands at \$53k lower than the initial gap. These lifecycle patterns also hold for university earnings (blue circles) and non-university earnings (red triangles). The gaps for faculty aged 31-35 are around \$2,000 less than the initial gaps for both earnings outcomes. The gaps increase through mid-career, where they stand at \$15-19k less for university earnings and \$18-20k less for non-university earnings (relative to the gaps at career outset). As with total earnings, the gender gaps in university and non-university earnings bottom out near the end of the career (ages 61-65) at \$24k for university earnings and \$29k for non-university earnings (again, relative to the gaps career outset).

Figure 5 gives a sense of how the importance of faculty entrepreneurial activity, as a contributor to the total gender earnings gap, changes over the course of the career. Overall, the importance is fairly stable. In models without faculty fixed effects, the gap in non-university earnings accounts for around 30% of gap in total earnings over the lifecycle (with the exception of the first two age groups). In models with fixed effects, the gap in non-university earnings accounts for about 50-60% of the gap in total earnings.

In sum, the evidence presented in this section is very consistent with the idea that gender gaps in faculty earnings largely play out over the course of a career. Male and female faculty begin their careers at similar levels of both university and non-university earnings. However, as time goes on, the gaps in both types of earnings grow. Thus, without opportunities for commercial engagement, the gender earnings gap for faculty would be dramatically reduced (though it would still remain large) at all points of the career.

[19] Regressions without faculty fixed effects use variation across faculty and are best thought of as gender earnings gaps *across the age distribution* rather than a set of estimates showing how the gender earnings gap *evolves over the lifecycle.* Without the faculty fixed effects, these estimates confound the effects of age with the effects of cohort – faculty in the older age groups must come from earlier cohorts, which may have had larger wage gaps than later cohorts at all points during their career. Since cohort is constant over time, including faculty fixed effects accounts for its impact on the gender gap estimates (as well as any other fixed unobservable characteristic of faculty).

5 Discussion and Conclusion

The results presented in this paper clearly show that the existence of faculty entrepreneurial opportunities exacerbate the faculty gender earnings gap. Indeed, these activities (as measured by non-university earnings) account for 29% of the $63k raw total gender earnings gap and 35% of the $51k gap conditional on covariates. Therefore, while the lion's share of the total gender earnings gap (raw or conditional) is due to the gap in university earnings, entrepreneurial endeavors account for about a third of the total. These patterns are not limited to differences at the mean. Indeed, quantile regressions show that, as faculty move up the distribution of faculty earnings, non-university earnings become a larger fraction of the total earnings gap. Moreover, female faculty earn less than male faculty, at both the mean and upper quantiles of the faculty earnings distribution, for every constituent part of non-university earnings – earnings from self-employment and from incumbent, young/startup, high-tech, and low-tech firms.

The earnings patterns uncovered in this paper raise the obvious question of why male faculty have greater access than their female peers to commercial opportunities outside the academy. There are several possibilities that I will explore in future versions of this paper. First, unobserved productivity differences may exist between female and male faculty, which could account for both the higher university and non-university earnings that male faculty enjoy. Future versions of UMETRICS data will include linkages of faculty to publications (and citations), which will allow me to assess whether controlling for traditional measures of academic productivity decrease gender earnings gaps.

Second, even women as highly-trained as university faculty may bear a disproportionate share of childcare responsibilities, which may decrease university earnings as well as opportunities to earn from entrepreneurial activities. As the 2020 Decennial Census becomes available for research, I can link UMETRICS faculty to their Census records and explore this possibility by explicitly controlling for family structure – marital status and the presence of children.

Recall that the decompositions in this paper show that existing covariates – e.g. field, scientific resources, and demographic characteristics – explain about a quarter and one-third of the gender gaps in total and university earnings and almost none of the gender gap in non-university earnings. Thus, it will be quite interesting to learn whether a substantial portion of these gaps can be explained by a faculty member's publication record and family structure.

Finally, discrimination is always a lurking possibility, though testing for it explicitly is difficult in my setting. However, it is important to emphasize that "accounting" for gender participation or earnings gaps using decompositions does not necessarily imply a diminished role for discrimination. Indeed, even if barriers faced by women are reduced by the time they reach a faculty position, they may have traveled a long road filled with barriers in order to reach opportunities equal to those enjoyed by their male peers. Moreover, the covariates that "account" for gender gaps – including publication histories and child-rearing responsibilities – may themselves be the result of such barriers.

In the end, whatever the ultimate sources of the disparities, the existence of faculty entrepreneurship unambiguously increases the earnings gap between male and female faculty. Given universities' central role in promoting faculty collaboration with industry, these results should prove useful to policymakers and administrators seeking to provide equal opportunities for faculty to commercialize their research and benefit from their expertise.

References

Bertrand, Marianne, Claudia Goldin, and Lawrence F Katz (2010), "Dynamics of the gender gap for young professionals in the financial and corporate sectors." *American Economic Journal: Applied Economics*, 2, 228–55. 7, 18

Bird, Barbara J and David N Allen (1989), "Faculty entrepreneur/ship in research university environments." *The Journal of Higher Education*, 60, 583–596. 7

Blau, Francine D and Lawrence M Kahn (2017), "The gender wage gap: Extent, trends, and explanations." *Journal of Economic Literature*, 55, 789–865. 2, 5, 7, 18, 19

Blinder, Alan S (1973), "Wage discrimination: reduced form and structural estimates." *Journal of Human Resources*, 436–455. 17

Blumenthal, David, Nancyanne Causino, Eric Campbell, and Karen Seashore Louis (1996), "Relationships between academic institutions and industry in the life sciences—an industry survey." *New England Journal of Medicine*, 334, 368–374. 7

Boardman, P Craig (2008), "Beyond the stars: The impact of affiliation with university biotechnology centers on the industrial involvement of university scientists." *Technovation*, 28, 291–297. 7

Boardman, P Craig (2009), "Government centrality to university–industry interactions: University research centers and the industry involvement of academic researchers." *Research Policy*, 38, 1505–1516. 7

Boardman, P Craig and Elizabeth A Corley (2008), "University research centers and the composition of research collaborations." *Research Policy*, 37, 900–913. 7

Boardman, P Craig and Branco L Ponomariov (2009), "University researchers working with private companies." *Technovation*, 29, 142–153. 7

Bozeman, Barry (2000), "Technology transfer and public policy: a review of research and theory." *Research Policy*, 29, 627–655. 2, 7

Bozeman, Barry and Monica Gaughan (2007), "Impacts of grants and contracts on academic researchers' interactions with industry." *Research Policy*, 36, 694–707. 7

Bozeman, Barry, Heather Rimes, and Jan Youtie (2015), "The evolving state-of-the-art in technology transfer research: Revisiting the contingent effectiveness model." *Research Policy*, 44, 34–49. 2, 7

Brower, Ann and Alex James (2020), "Research performance and age explain less than half of the gender pay gap in new zealand universities." *PLoS One*, 15, e0226392. 8

Buffington, Catherine, Benjamin Cerf, Christina Jones, and Bruce A Weinberg (2016), "Stem training and early career outcomes of female and male graduate students: Evidence from umetrics data linked to the 2010 census." *American Economic Review*, 106, 333–38. 7

Campbell, Teresa Isabelle Daza and Sheila Slaughter (1999), "Faculty and administrators' attitudes toward potential conflicts of interest, commitment, and equity in university-industry relationships." *The Journal of Higher Education*, 70, 309–352. 7

Ceci, Stephen J, Donna K Ginther, Shulamit Kahn, and Wendy M Williams (2014), "Women in academic science: A changing landscape." *Psychological Science in the Public Interest*, 15, 75–141. 2, 8

DeSalvo, Bethany, Frank Limehouse, and Shawn D Klimek (2016), "Documenting the business register and related economic business data." *US Census Bureau Center for Economic Studies Paper No. CES-WP-16-17*. 3

Firpo, Sergio P, Nicole M Fortin, and Thomas Lemieux (2018), "Decomposing wage distributions using recentered influence function regressions." *Econometrics*, 6, 28. 5, 18

Goetz, Christopher, Zachary Kroff, et al. (2021), "Recent improvements to the integrated longitudinal business database (ilbd)." Technical report, Center for Economic Studies, US Census Bureau. 3, 10

Goldin, C. (2021), *Career and Family: Women's Century-Long Journey Toward Equity*. Princeton University Press, URL `https://books.google.com/books?id=BAoOEAAAQBAJ`. 2, 7

Goldschlag, Nathan and Javier Miranda (2020), "Business dynamics statistics of high tech industries." *Journal of Economics & Management Strategy*, 29, 3–30. 11, 36, 38, 41

Jarmin, Ron S (2007), "Integrated longitudinal business database: Presentation." In *2007 Kauffman Symposium on Entrepreneurship and Innovation Data*. 3, 10

Jarmin, Ron S and Javier Miranda (2002), "The longitudinal business database." *Available at SSRN 2128793*. 3, 10

Juhn, Chinhui and Kristin McCue (2017), "Specialization then and now: Marriage, children, and the gender earnings gap across cohorts." *Journal of Economic Perspectives*, 31, 183–204. 6, 8, 21

Kelly, Kimberly and Linda Grant (2012), "Penalties and premiums: The impact of gender, marriage, and parenthood on faculty salaries in science, engineering and mathematics (sem) and non-sem fields." *Social Studies of Science*, 42, 869–896. 2, 8

Lane, Julia I, Jason Owen-Smith, Rebecca F Rosen, and Bruce A Weinberg (2015), "New linked data on research investments: Scientific workforce, productivity, and public value." *Research Policy*, 44, 1659–1671. 3, 8

Lee, Yong S (1996), "'technology transfer'and the research university: a search for the boundaries of university-industry collaboration." *Research Policy*, 25, 843–863. 7

Lee, Yong S (1998), "University-industry collaboration on technology transfer: Views from the ivory tower." *Policy Studies Journal*, 26, 69–84. 7

Lee, Yong S (2000), "The sustainability of university-industry research collaboration: An empirical assessment." *The Journal of Technology Transfer*, 25, 111–133. 7

Li, Diyi and Cory Koedel (2017), "Representation and salary gaps by race-ethnicity and gender at selective public universities." *Educational Researcher*, 46, 343–354. 2, 8

Lin, Min-Wei and Barry Bozeman (2006), "Researchers' industry experience and productivity in university–industry research centers: A "scientific and technical human capital" explanation." *The Journal of Technology Transfer*, 31, 269–290. 7

Link, Albert N, Donald S Siegel, and Barry Bozeman (2017), "An empirical analysis of the propensity of academics to engage in formal university technology transfer." In *Universities and the Entrepreneurial Ecosystem*, Edward Elgar Publishing. 7

Louis, Karen Seashore, Lisa M Jones, Melissa S Anderson, David Blumenthal, and Eric G Campbell (2001), "Entrepreneurship, secrecy, and productivity: a comparison of clinical and non-clinical life sciences faculty." *The Journal of Technology Transfer*, 26, 233–245. 7

Miller, Kristel, Rodney McAdam, and Maura McAdam (2018), "A systematic literature review of university technology transfer from a quadruple helix perspective: toward a research agenda." *R&D Management*, 48, 7–24. 2, 7

Noonan, Mary C, Mary E Corcoran, and Paul N Courant (2005), "Pay differences among the highly trained: Cohort differences in the sex gap in lawyers' earnings." *Social forces*, 84, 853–872. 7

Oaxaca, Ronald (1973), "Male-female wage differentials in urban labor markets." *International Economic Review*, 693–709. 17

Perkmann, Markus, Riccardo Fini, Jan-Michael Ross, Ammon Salter, Cleo Silvestri, and Valentina Tartari (2015), "Accounting for universities' impact: Using augmented data to measure academic engagement and commercialization by academic scientists." *Research Evaluation*, 24, 380–391. 7

Perkmann, Markus, Valentina Tartari, Maureen McKelvey, Erkko Autio, Anders Broström, Pablo D'Este, Riccardo Fini, Aldo Geuna, Rosa Grimaldi, Alan Hughes, et al. (2013), "Academic engagement and commercialisation: A review of the literature on university–industry relations." *Research Policy*, 42, 423–442. 2, 7

Ponomariov, Branco and P Craig Boardman (2008), "The effect of informal industry contacts on the time university scientists allocate to collaborative research with industry." *The Journal of Technology Transfer*, 33, 301–313. 7

Ponomariov, Branco L (2008), "Effects of university characteristics on scientists' interactions with the private sector: An exploratory assessment." *The Journal of Technology Transfer*, 33, 485–503. 7

Porter, Stephen R, Robert K Toutkoushian, and John V Moore III (2008), "Pay inequities for recently hired faculty, 1988-2004." *The Review of Higher Education*, 31, 465–487. 8

Renault, Catherine Searle (2006), "Academic capitalism and university incentives for faculty entrepreneurship." *The Journal of Technology Transfer*, 31, 227–239. 7

Renzulli, Linda A, Jeremy Reynolds, Kimberly Kelly, and Linda Grant (2013), "Pathways to gender inequality in faculty pay: The impact of institution, academic division, and rank." *Research in Social Stratification and Mobility*, 34, 58–72. 2, 8

Rios-Avila, Fernando (2020), "Recentered influence functions (rifs) in stata: Rif regression and rif decomposition." *The Stata Journal*, 20, 51–94. 5, 18

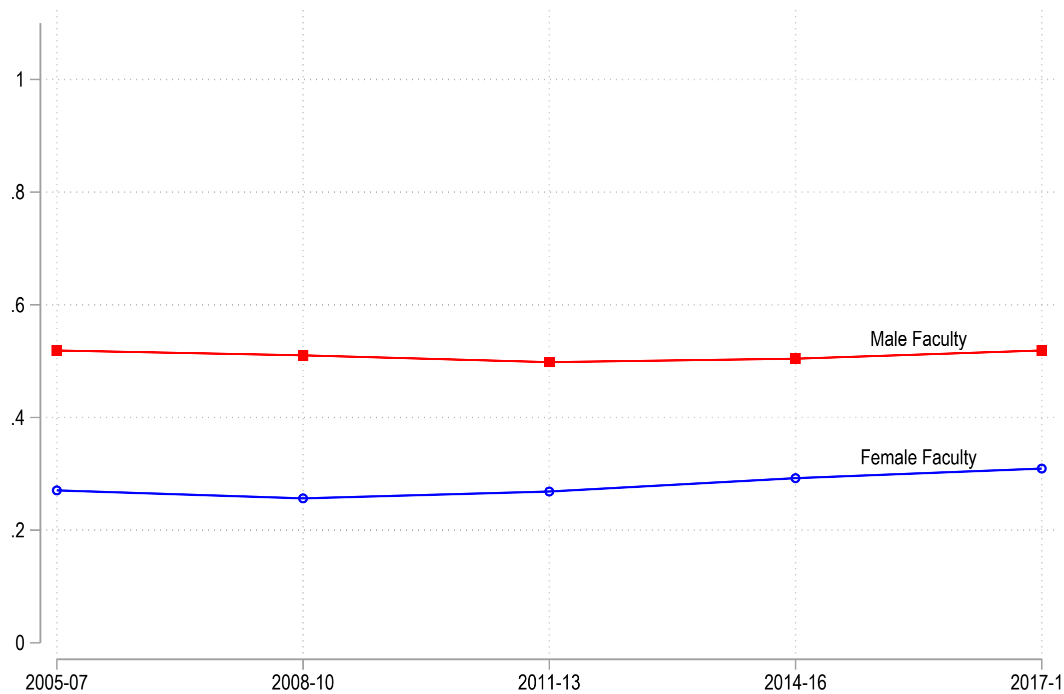
Staudt, Joseph S (Forthcoming), "Academic entrepreneurship and inequality: Evidence from administrative data." *ECIE 2022 - Proceedings of the 17th European Conference on Innovation and Entrepreneurship*. 2, 7

Vilhuber, Lars, Kevin McKinney, et al. (2014), "Lehd infrastructure files in the census rdc-overview." *Center for Economic Studies, US Census Bureau Working Papers*. 3, 10

Wilde, Elizabeth Ty, Lily Batchelder, and David T Ellwood (2010), "The mommy track divides: The impact of childbearing on wages of women of differing skill levels." Technical report, National Bureau of Economic Research. 7

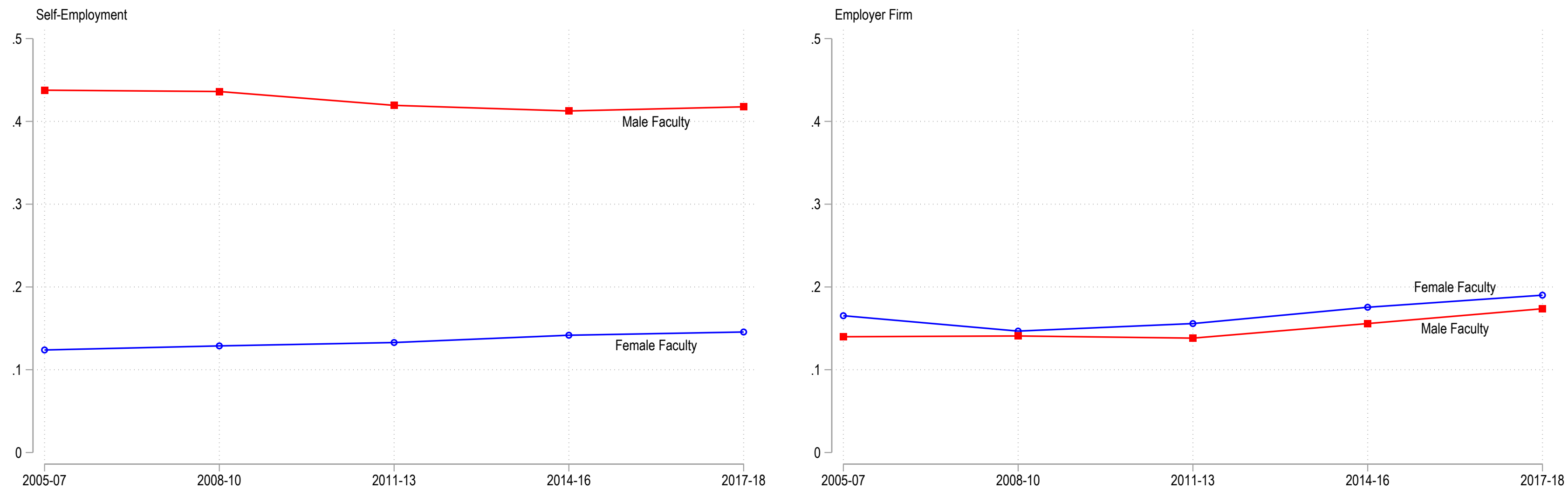
Wood, Robert G, Mary E Corcoran, and Paul N Courant (1993), "Pay differences among the highly paid: The male-female earnings gap in lawyers' salaries." *Journal of Labor Economics*, 11, 417–441. 7

Figure 1: Fraction of Female/Male Faculty With Positive Non-University Earnings



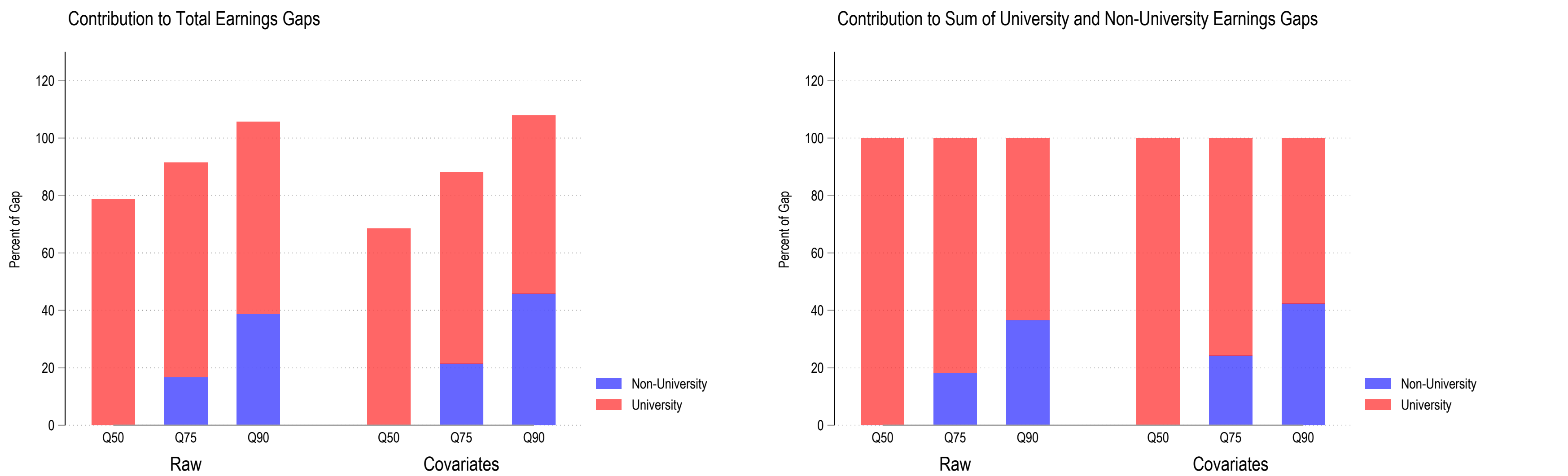
Notes – This figure shows the faction of female and male UMETRICS faculty that receive positive non-university earnings. University earnings are W2 or LEHD earnings from an EIN contained in IPEDS. Non-university earnings are W2/LEHD earnings from a non-IPEDS EIN plus 1099/ILBD earnings. The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university earnings is 1 for all time periods.

Figure 2: Fraction of Female/Male Faculty With Positive Earnings from Self-Employment and an Employer Firms



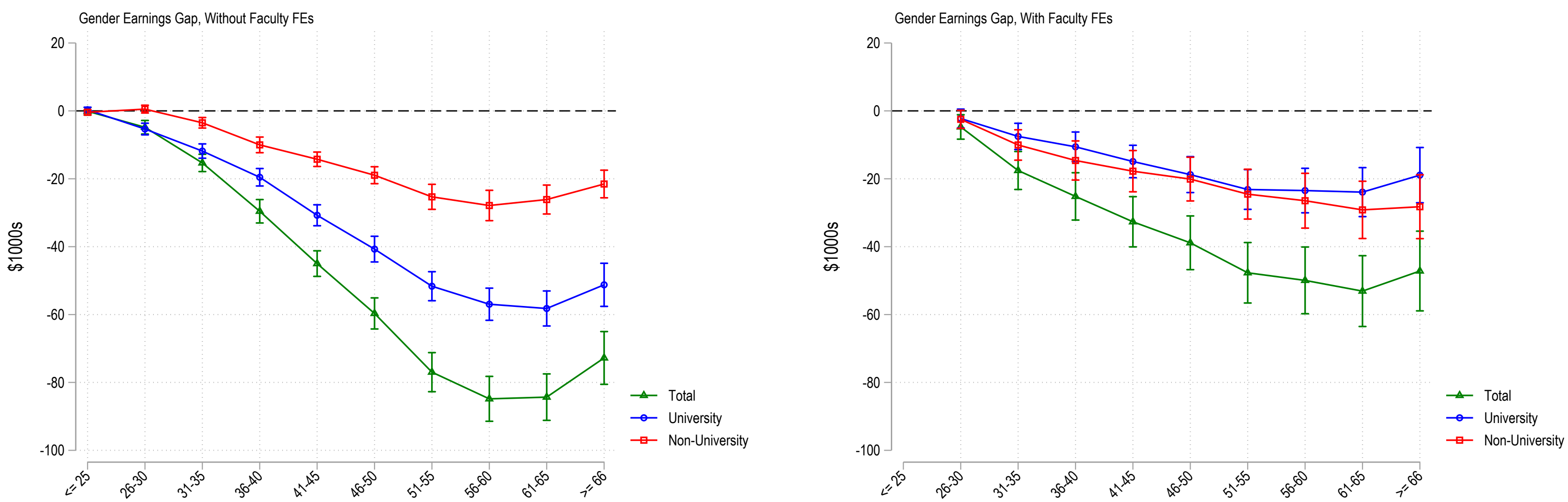
Notes – This figure shows the factions of female and male UMETRICS faculty that receive positive earnings from self-employment (left plot) and from an employer firm (right plot). Earnings from self-employment are equivalent to 1099/ILBD earnings. Earnings from an employer firm are defined as W2/LEHD earnings from a non-IPEDS EIN.

Figure 3: Contribution of University and Non-University Earnings to the Total Gender Earnings Gap by Quantile



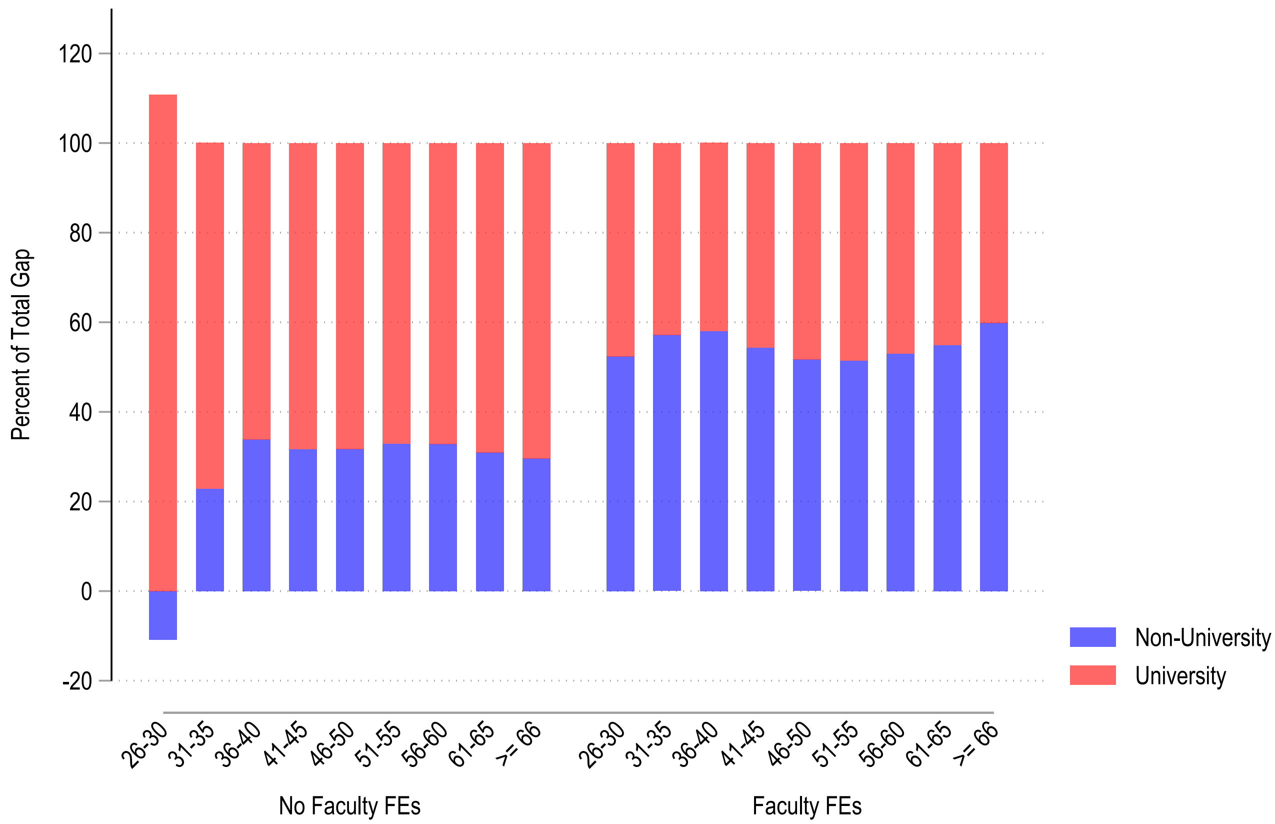
Notes – This figure displays ratios of coefficients from Table 6. These ratios measure the relative contributions of university and non-university earnings gaps to the total earnings gap at the 50th, 75th, and 90th quantiles. The left plot contains the ratios of the university and non-university earnings gaps to the total earnings gap. The right plot contains the ratios of the university and non-university earnings gap to the sum of these two gaps (thus, these sum to 100% by construction). "Total Earnings" are earnings from all sources received by a faculty member in a given year. "University Earnings" are W2 or LEHD earnings from an EIN contained in IPEDS. "Non-University Earnings" are W2/LEHD earnings from a non-IPEDS EIN plus 1099/ILBD earnings.

Figure 4: Gender Earnings Gaps by Age Group



Notes – This figure displays OLS regressions of earnings (levels) from a given source on a female faculty indicator interacted with indicators for different faculty age groups: 25 and under, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, and 66 and older. The left plot omits faculty fixed effects and the right plot includes faculty fixed effects. All regressions include year fixed effects and age fixed effects. “Total Earnings” are earnings from all sources received by a faculty member in a given year. “University Earnings” are W2 or LEHD earnings from an EIN contained in IPEDS. “Non-University Earnings” are W2/LEHD earnings from a non-IPEDS EIN plus 1099/ILBD earnings. Standard errors are clustered at the faculty level.

Figure 5: Contribution of University and Non-University Earnings to the Total Gender Earnings Gap by Age



Notes – This figure displays ratios of coefficients from Figure 4. These coefficients measure the relative contributions of university and non-university earnings gaps to the total earnings gap for each age group: 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, and 66 and older. "Total Earnings" are earnings from all sources received by a faculty member in a given year. "University Earnings" are W2 or LEHD earnings from an EIN contained in IPEDS. "Non-University Earnings" are W2/LEHD earnings from a non-IPEDS EIN plus 1099/ILBD earnings.

Table 1: Summary Statistics for Earnings by Source

	1[Earnings > 0]		Earnings ($)	
	Mean	SD	Mean	SD
Earnings Source				
Total	1	0	161,600	170,400
University	1	0	137,500	119,100
Non-University	0.426	0.495	24,100	116,500
Self-Employment	0.319	0.466	8,624	63,000
Employer Firm	0.156	0.363	15,480	96,650
Incumbent Firm	0.142	0.349	14,090	85,470
Young/Startup Firm	0.026	0.160	1,391	27,620
High-Tech Firm	0.084	0.277	9,865	87,610
Low-Tech Firm	0.093	0.290	5,613	39,850
Faculty Count: 59,500				

Notes – This table shows summary statistics for UMETRICS faculty. The unit of observation is a person-year, but only the person (faculty) counts are reported. A faculty member is included in the sample for a given calendar year if they: 1) receive positive W2/LEHD earnings from an IPEDS EIN (i.e. a university) in that calendar year and 2) the calendar year is in or after the first year they are classified as a faculty member in UMETRICS. These restrictions help to ensure that I only observe commercial engagement of faculty *while they are faculty*. Earnings are measured in real 2018 dollars.

Table 2: Female-Male Participation Gap – Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Non-University	Self-Employment	Employer	Incumbent	Young/Startup	High-Tech	Low-Tech
Female Faculty Indicator	-0.2128***	-0.2577***	0.0046	0.006791*	-0.000655	-0.01451***	0.02036***
	(0.003612)	(0.003192)	(0.002742)	(0.002657)	(0.000882)	(0.002032)	(0.002104)
Percent of Mean	-49.92	-80.78	2.95	4.77	-2.48	-17.37	21.89
Faculty Count	59,500	59,500	59,500	59,500	59,500	59,500	59,500
Year × Age FEs	×	×	×	×	×	×	×

Notes – This table displays OLS regressions of indicators for whether a source of earnings is positive on a female faculty indicator – i.e., extensive margin regressions. All regressions include age by year fixed effects. "Non-University" is an indicator for whether the faculty member received positive W2/LEHD earnings from a non-IPEDS EIN or positive 1099/ILBD earnings. "Self-Employment" is an indicator for positive 1099/ILBD earnings. "Employer" is an indicator for positive W2/LEHD earnings from a non-IPEDS EIN. "Incumbent" and "Young/Startup" are indicators for positive W2/LEHD earnings from a non-IPEDS EIN that belongs to a firm that is older than 5 years (incumbent) and five years old or younger (young/startup). "High-Tech" and "Low-Tech" are indicators for positive W2/LEHD earnings form a non-IPEDS EIN that belongs to a firm with a high-tech/low-tech NAICS code as defined by Goldschlag and Miranda (2020). The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university wages is 1 for all time periods. Standard errors are clustered at the faculty level.

Table 3: Female-Male Earnings Gaps at the Mean

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Earnings		University Earnings		Non-University Earnings	
Panel A: Level Earnings (OLS)						
Female Faculty Indicator	-63,240***	-50,610***	-45,060***	-32,730***	-18,180***	-17,890***
	(1,242)	(1,189)	(974)	(938.1)	(709.2)	(668.7)
Panel B: Level Earnings (PPML)						
Female Faculty Indicator	-0.4164***	-0.3284***	-0.3444***	-0.2466***	-0.8811***	-0.8537***
	(0.007976)	(0.007604)	(0.00746)	(0.007064)	(0.03241)	(0.03166)
Panel C: Log Earnings (OLS)						
Female Faculty Indicator	-0.4096***	-0.2875***	-0.3731***	-0.2197***		
	(0.007801)	(0.006892)	(0.008876)	(0.007444)		
Year FEs	×	×	×	×	×	×
Covariates		×		×		×
Faculty Count	59,500	59,500	59,500	59,500	59,500	59,500

Notes – This table displays regressions of earnings on a female faculty indicator. Each cell contains the coefficient on the female faculty indicator from a separate regression. Panel A displays OLS estimates using the level of earnings as the outcome. Panel B displays PPML estimates. Panel C displays OLS estimates using the log of earnings as the outcome. The coefficients from the PPML and log earnings regressions have a semi-elasticity interpretation. All regressions include year fixed effects. The regressions in even-numbered columns include controls for field, university, access to scientific resources, age, race, ethnicity, and place of birth. “Total Earnings” are earnings from all sources received by a faculty member in a given year. “University Earnings” are W2 or LEHD earnings from an EIN contained in IPEDS. “Non-University Earnings” are W2/LEHD earnings from a non-IPEDS EIN or 1099/ILBD earnings. The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university wages is 1 for all time periods. Earnings are measured in real 2018 dollars. Standard errors are clustered at the faculty level.

Table 4: Components of Non-University Female-Male Earnings Gaps

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employment Earnings	Employer Earnings	Incumbent Earnings	Young/Startup Earnings	High-Tech Earnings	Low-Tech Earnings
Panel A: Level Earnings (OLS)						
Female Faculty Indicator	-10,280***	-7,902***	-7,124***	-778.2***	-6,550***	-1,352***
	(356.1)	(600.5)	(545.4)	(113)	(513.9)	(273.5)
Panel B: Level Earnings (PPML)						
Female Faculty Indicator	-1.727***	-0.556***	-0.5498***	-0.6201***	-0.7525***	-0.2485***
	(0.05956)	(0.03989)	(0.04021)	(0.08253)	(0.05363)	(0.05051)
Year FEs	×	×	×	×	×	×
Faculty Count	59,500	59,500	59,500	59,500	59,500	59,500

Notes – This table displays regressions of earnings on a female faculty indicator. Each cell contains the coefficient on the female faculty indicator from a separate regression. Panel A displays OLS estimates using the level of earnings as the outcome. Panel B displays PPML estimates. The coefficients from the PPML regressions have a semi-elasticity interpretation. All regressions include year fixed effects. "Self-Employment Earnings" are 1099/ILBD earnings. "Employer Earnings" are W2/LEHD earnings from a non-IPEDS EIN. "Incumbent Earnings" and "Young/Startup Earnings" are W2/LEHD earnings from a non-IPEDS EIN that belongs to a firm that is older than 5 years (incumbent) and five years old or younger (young/startup). "High-Tech Earnings" and "Low-Tech Earnings" are W2/LEHD earnings form a non-IPEDS EIN that belongs to a firm with a high-tech/low-tech NAICS code as defined by Goldschlag and Miranda (2020). The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university wages is 1 for all time periods. Earnings are measured in real 2018 dollars. Standard errors are clustered at the faculty level.

Table 5: Percent Contribution of Covariates to Gender Earnings Gaps

	(1)	(2)	(3)
	Total Earnings	University Earnings	Non-University Earnings
Age FEs	17.01	19.73	10.27
Field FEs	7.887	11.58	-1.263
Race/Eth FEs	0.855	0.6041	1.477
Scientific Resources	0.5792	0.9542	-.3509
University FEs	0.3126	1.671	-3.057
Year FEs	-.4078	-.2832	-.7169
Place of Birth FEs	-4.071	-3.589	-5.265
All Covariates	22.16	30.66	1.094
Unexplained	77.83	69.33	98.90
Faculty Count	59,500	59,500	59,500

Notes – This table displays the percent contributions of covariate groups to the raw gender gaps in total, university, and non-university earnings. They are derived from Oaxaca-Blinder decompositions. "Total Earnings" are earnings from all sources received by a faculty member in a given year. "University Earnings" are W2 or LEHD earnings from an EIN contained in IPEDS. "Non-University Earnings" are W2/LEHD earnings from a non-IPEDS EIN or 1099/ILBD earnings. The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university wages is 1 for all time periods. Earnings are measured in real 2018 dollars.

Table 6: Female-Male Earnings Gaps Across the Faculty Earnings Distribution

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Earnings		University Earnings		Non-University Earnings	
Panel A: Level Earnings (50th Percentile)						
Female Faculty Indicator	-40,750***	-28,140***	-32,100***	-19,240***	-39.23	-27.44
	(843.5)	(794.9)	(755.2)	(696.5)	(55.31)	(41.46)
Panel B: Level Earnings (75th Percentile)						
Female Faculty Indicator	-72,880***	-58,360***	-54,450***	-38,950***	-12,170***	-12,500***
	(1,609)	(1,551)	(1,386)	(1,333)	(321.8)	(320.3)
Panel C: Level Earnings (90th Percentile)						
Female Faculty Indicator	-121,700***	-108,600***	-81,520***	-67,480***	-47,110***	-49,730***
	(3,128)	(3,222)	(2,552)	(2,612)	(1,827)	(1,836)
Year FEs	×	×	×	×	×	×
Covariates		×		×		×
Faculty Count	59,500	59,500	59,500	59,500	59,500	59,500

Notes – This table displays regressions, using recentered influence functions (RIFs), of earnings on a female faculty indicator. Each cell contains the coefficient on the female faculty indicator from a separate regression. Panel A displays RIF estimates at the 50th quantile of the faculty earnings distribution. Panels B and C display RIF estimates at the 75th and 90th quantiles of the faculty earnings distribution. All regressions include year fixed effects. The regressions in even-numbered columns include controls for field, university, access to scientific resources, age, race, ethnicity, and place of birth. "Total Earnings" are earnings from all sources received by a faculty member in a given year. "University Earnings" are W2 or LEHD earnings from an EIN contained in IPEDS. "Non-University Earnings" are W2/LEHD earnings from a non-IPEDS EIN plus 1099/ILBD earnings. The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university wages is 1 for all time periods. Earnings are measured in real 2018 dollars. Standard errors are clustered at the faculty level and are obtained using a Bayesian bootstrap.

Table 7: Components of Non-University Female-Male Earnings Gaps Across the Faculty Earnings Distribution

	(1)	(2)	(3)	(4)	(5)	(6)
	Self-Employment Earnings	Employer Earnings	Incumbent Earnings	Young/Startup Earnings	High-Tech Earnings	Low-Tech Earnings
Panel A: Level Earnings (50th Percentile)						
Female Faculty Indicator	1,594***	-5,637**	-4,327**	-2,076***	-5,463**	-1,194***
	(219.6)	(2,225)	(1,833)	(722.4)	(2,347)	(232.1)
Panel B: Level Earnings (75th Percentile)						
Female Faculty Indicator	-1,144***	-8,456**	-6,490**	-3,114***	-8,194**	-1,791***
	(348.9)	(3,337)	(2,750)	(1,084)	(3,521)	(348.2)
Panel C: Level Earnings (90th Percentile)						
Female Faculty Indicator	-24,410***	-7,932***	-4,156***	-3,737***	-9,833**	-7,742***
	(514.1)	(1,614)	(1,593)	(1,300)	(4,225)	(352)
Year FEs	×	×	×	×	×	×
Faculty Count	59,500	59,500	59,500	59,500	59,500	59,500

Notes – This table displays regressions, using recentered influence functions (RIFs), of earnings on a female faculty indicator. Each cell contains the coefficient on the female faculty indicator from a separate regression. Panel A displays RIF estimates at the 50th quantile of the faculty earnings distribution. Panels B and C display RIF estimates at the 75th and 90th quantiles of the faculty earnings distribution. All regressions include year fixed effects. "Self-Employment Earnings" are 1099/ILBD earnings. "Employer Earnings" are W2/LEHD earnings from a non-IPEDS EIN. "Incumbent Earnings" and "Young/Startup Earnings" are W2/LEHD earnings from a non-IPEDS EIN that belongs to a firm that is older than 5 years (incumbent) and five years old or younger (young/startup). "High-Tech Earnings" and "Low-Tech Earnings" are W2/LEHD earnings form a non-IPEDS EIN that belongs to a firm with a high-tech/low-tech NAICS code as defined by Goldschlag and Miranda (2020). The sample is defined so that only faculty with positive university earnings in a given year are included. Thus, by definition, the fraction of faculty receiving positive university wages is 1 for all time periods. Earnings are measured in real 2018 dollars. Standard errors are clustered at the faculty level and are obtained using a Bayesian bootstrap.

.

.

A Appendix

Figure A.1: Relationships Among Earnings Variables