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Social Sciences - Article

Keywords:

Posted Date: May 15th, 2025

DOI: <https://doi.org/10.21203/rs.3.rs-4214208/v2>

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Additional Declarations: The authors declare no competing interests.

Childcare Deserts Impede Scientists' Career Development and Undermine Gender Equity

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SUMMARY

For decades, the United States grappled with a childcare shortage that has left American families struggling to secure quality care, compromising both children's development and parental career progress. Here we investigate the impact of childcare availability—and the lack thereof—on US scientists' career advancement and gender equity in science. We construct a longitudinal database of childcare facilities and their capacities spanning the last twenty years. Leveraging the biennial survey of US scientists and engineers sponsored by the National Science Foundation (NSF) and the National Institutes of Health (NIH), we uncover that over half of US scientists employed at universities and research institutions work in childcare deserts, that is, areas where the supply of childcare falls significantly short of demand. Despite similar exposure to childcare deserts, the career consequences for male and female scientists differ starkly. Women scientists with young children (under six years old within the first six years post PhD) are 5.2 percentage points less likely to achieve tenure in childcare deserts, while no significant effect is observed for men with young children. Meanwhile, we observe no association between childcare deserts and tenure outcomes for scientists without children, regardless of gender. While reduced available work time partly explains this disparity, there are likely other factors, such as increased fatigue and frequent work disruptions, that could also contribute. Finally, we observe that the effect of childcare deserts is the largest when an individual's primary work activity involves applied research or teaching, which offer less flexibility in work hours and locations than does basic or theoretical research. This finding partly explains the varying effects of childcare availability across scientific disciplines. Overall, our findings highlight the critical role of expanding childcare availability to enhance research productivity and to reduce the tenure gender gap in science.

The US childcare system is plagued by limited access, high cost, and low quality. While the childcare crisis was brought into sharp focus during the COVID-19 pandemic¹⁻³, the problem is decades old^{4,5}. For years, the lack of affordable, quality childcare has strained American families⁶. To date, the US government has made little public commitment to support child care⁷. It provides almost scant childcare support to families, a mere 0.3 percent of its GDP, compared to an average of 0.8 percent among all Organisation of Economic Co-operation and Development (OECD) countries⁸. Only a handful of US states provide publicly funded, universal preschool programs, and only for 4-year-olds⁹. For younger children, public provision of care and education is almost non-existent¹⁰, leaving it almost entirely to the private sector. Lack of economies of scale, high regulatory costs, and labor intensive work lead to an overall undersupply of childcare options across the country. It is thus estimated that over half of the US population lives in childcare care deserts, areas where there are no or too few licensed childcare options for the number of children who need care¹¹. Childcare businesses struggle to survive despite paying minimal wages to childcare workers and imposing significant expenses on families.

A lack of child care can hurt workforce participation and labor productivity¹²⁻¹⁵. Moreover, because the burden of care for young children falls disproportionately on women^{16,17}, a lack of childcare likely impacts women's educational attainment and career development more than it does those of men. Recent studies have shown that having children significantly impacts researchers' career trajectories and outcomes¹⁸⁻²². However, little research has investigated how the society and institutions can better support parents in science and improve gender equity. While researchers often have access to parental leaves, short family leaves do little to mitigate this issue because the impact of parenthood on a career lasts much longer than the initial months after a child's birth. In fact, as the public provision of care and education for children does not start until a child is five or six years old in most states, parents are substantially constrained by the availability of childcare in the first five years of their children's life. Left with limited choices, young researchers can be forced to leave their profession, voluntarily or involuntarily, or delay or even give up on starting a family.

We study the impact of childcare availability (and the lack thereof) on scientists' career advancement and gender equity in science. In many high-skilled professions, women are underrepresented at entry and even more so at the top²³⁻²⁶. Becoming a scientist at research-intensive universities and institutions requires many years of training through doctoral and sometimes post-doctoral programs. It is a significant cost borne by the individual who chooses this career path and the society that funds universities and research institutions. The early years of a scientific career are particularly intense and demanding due to the

steep promotion track during this time—tenure track with an “up-or-out” trajectory²⁷. These years also typically coincide with the onset of parenthood. Career versus children thus becomes an almost unavoidable trade off for young researchers. We thus aim to answer the following questions: (1) Does the lack of childcare (i.e., childcare deserts) impact scientists’ career achievement, particularly in attaining tenure promotions? (2) Does the lack of childcare impact men and women differently, and if so, (3) how much does it contribute to the female-versus-male tenure achievement gap?

Studying tenure attainment as an outcome is important for several reasons. First, for individual researchers, tenure promotion is likely the most significant milestone in their academic careers as it nearly guarantees professional stability. This stability in turn offers them opportunities to pursue longer-term, higher-risk, higher-impact research. For research institutions, tenure promotion is critical for retaining talented researchers²⁶. Despite recent debates surrounding its relevance, tenure is a long-standing practice and remains the primary means used by US research institutions to recognize and promote junior researchers who have made significant contributions to their fields. Last but not least, while the gender gap between men and women pursuing and obtaining advanced graduate degrees in science and engineering has been narrowing, the gender gap in tenured professorships persists²⁸.

Measuring childcare availability nationally and longitudinally is challenging due to the fragmented nature of the industry and a lack of unified databases. We overcome this challenge by compiling childcare facility and employment information using the Infogroup Historical Business Data, a database of US business and organization locations dating back more than 20 years. Our sample contains 12,276 doctoral degree recipients who graduated between 1997 and 2014 with degrees in science, engineering, and health (SEH) who were employed by US universities and research institutions after graduation. We find over 56% of the scientists in our study sample work in locations classified as childcare deserts. This percentage is nearly identical for male and female researchers, each comprising approximately half of our sample. Despite equal exposure to childcare deserts, the impacts felt by female and male researchers differ significantly. While childcare deserts have no impact on men, they significantly reduce women’s propensity to obtain tenure. As a result, childcare deserts widen the gender gap in achieving tenure by 5.2 percentage points (pp), a substantial impact given the average tenure rate of 32%. This explains a significant portion (over 60%) of the gender tenure gap among researchers with children.

A placebo test shows that childcare deserts have no impact on the tenure rate of either men or women without children, further validating our methodology and findings. By studying those who are already parents at the time of graduation versus those who become parents later, we find the moderating effect of childcare deserts is the largest (-7.2 percentage points) among those who newly become parents after doctoral graduation. The moderating effect of childcare deserts on the tenure gender gap is small and insignificant for those who are parents at the time they graduate, possibly due to selection. Moreover, the moderating effect of childcare is most significant during the early stage of one’s career: -11.3 percentage points (p-value < 0.05) versus -3.1 percentage points (p-value > 0.1) when becoming parents in the first three years after graduation compared to years four to six, likely due to the prolonged loss of productivity due to the lack of childcare during the pre-tenure period.

Finally, we observe that the effect is only partially explained by less available time (-3.0%) for women when working in childcare deserts, indicating that additional factors, such as fatigue and work disruptions, likely contribute to decreased productivity in the absence of reliable childcare. Moreover, the impact of childcare deserts is most pronounced in roles primarily involving applied research and development (-15.5 percentage points, p-value < 0.01) and teaching or clinical work (-8.4 percentage points, p-value < 0.1), compared to basic and theoretical research (2.9 percentage points, p-value > 0.1). This discrepancy is likely because applied research and teaching typically require more rigid schedules and fixed working locations, making them more susceptible to workflow disruptions caused by the lack of childcare. This finding helps explain the varying effects of childcare deserts across academic disciplines.

Overall, while the US childcare system faces numerous challenges, the lack of availability is particularly pressing, as it poses an immediate obstacle for American families. Nearly three-quarters of childcare centers experience excess demand for childcare care slots in 2019²⁹, and over 75% of families report having difficulty finding care in 2023³⁰. The average waiting list length for childcare centers managed by or affiliated to top 50 US research institutions is 20.6 months (SD 7.4 months) based on our data collection. Without sufficient availability, families cannot make informed decisions based on price and quality. Parents are sometimes forced to choose suboptimal options paying more than what they would like to or compromising on desired quality. As recent literature suggests, child care decisions may be best described as accommodations rather than choices, as parents have to constantly accommodate their preferences because of a series of barriers such as restricted child care supply, work schedules, and family and child characteristics^{31,32}. Limited supply also reduces healthy competition among childcare providers, which is essential for driving down prices and improving service quality. Our findings highlight the critical role of expanding childcare availability in retaining talented scientists, maintaining research productivity, and reducing the gender gap in science. However, addressing availability alone, without also ensuring affordability and high quality, will not resolve the broader childcare crisis. We hope this study encourages further research into all dimensions of childcare, ultimately making it more accessible for all American families.

Results

Childcare Deserts

Measuring childcare availability presents several challenges. First, lacking economies of scale, the childcare industry is highly fragmented with the majority of its capacity provided by small businesses. Second, there is no national database of licensed childcare as licensing is managed individually by state agencies, making it difficult to compile a longitudinal, national database of childcare providers. Third, the capacity of childcare facilities varies significantly from small group setups (2 to 3 employees and less than 20 children) to larger centers (20 to 30 employees and hundreds of children). Accurate assessment of childcare supply therefore requires not only counting the number of facilities within a region but also considering the capacity of each to determine overall childcare availability. Finally, the adequacy of childcare supply must be evaluated in relation to demand. What may seem adequate in a sparsely populated rural area might be insufficient in a densely populated urban area.

We overcome these challenges with the Infogroup US Historical Business Data. This database offers two advantages in measuring childcare availability locally. It is a longitudinal, national database that provides granular information on US business and organization locations dating back to 1997. It also provides the number of employees working at each facility. Because the staff-to-child ratio is tightly regulated in this industry (with minor variations across states over time), the number of employees working at a facility approximates its capacity.

We measure childcare deserts at the census tract level. We choose census tracts over larger geographical units such as counties because childcare demand is local. The median land area of a census tract is about 1.8 square miles, and it varies based on local population and economic densities (25th percentile: 0.7 square mile; 75 percentile: 12 square miles). We choose census tracts over distance-based measures (e.g., one-mile radius from a workplace) because census tracts are designed to be relatively homogeneous with respect to population characteristics, economic status, and living conditions, whereas distance-based measures may fail to account for these variations. For example, traveling one mile in a college town differs significantly in time and convenience from traveling the same distance in a large city. We have also considered different ways to augment distance-based measures using the Urban Influence Code (UIC) and Rural-Urban Commuting Codes (RUCA) defined by the US Department of Agriculture (USDA)'s Economic Research Service. The results are consistent, but they are noisier than using the census-tract based measures likely because the choices of urban and rural codes and the associated distance cutoffs can be coarse and arbitrary. Our use of census tracts aligns with the definition of childcare deserts by the American Center of Progress. Similar concepts, such as food deserts and pharmacy deserts, are also defined at the census tract level^{33,34}.

We calculate childcare supply in a census tract as the total number of employees working in childcare facilities in the tract. To ensure data quality, we compare the total number of childcare facilities and employees identified from the Infogroup database with those reported in the US Census Bureau's County Business Patterns (CBP) database (available only at the county level). The correlations are as high as 96% to 97%. We next quantify childcare demand. Workplace locations in our study are primarily university campuses, where the majority of residents are college students. Therefore, the primary source of childcare demand in these areas comes from the workforce rather than the residents. We thus define childcare demand as proportional to the number of employees working in a census tract, again using the Infogroup database. Ideally, an accurate measure of demand would entail counting the number of children aged 0 to 5 of these employees. Unfortunately, data of this granularity and longitudinal span are unavailable. The most relevant is the American Community Survey (ACS) 2000–2005 snapshot which contains a five-year estimate of the total number of workers with children under age 6 at the census tract level. We find the two estimates—our measure derived from the Infogroup database and the ACS five-year estimates—are highly consistent, with correlations as high as 87.0% at the census tract level and 98.9% at the county level.

We then calculate the childcare supply-to-demand ratio for each census tract and adopt a threshold to define childcare deserts. The threshold is chosen such that a childcare desert is characterized as an area with no or extremely low child care supply, i.e., less than one third of demand, following the criterion adopted by the Center of American Progress¹¹. The findings are more pronounced when we adopt stricter thresholds.

Figure 1 shows workplace childcare deserts in the United States in 2019 as an illustration. Approximately half of the country (54.6% of census tracts) is considered workplace childcare deserts, a persistent trend observed over the more than 20 years covered by our study. According to our data, 56.4% of researchers are employed in regions classified as childcare deserts, as shown in Table 1. The analysis indicates no statistically significant difference in the proportion of male and female researchers working in childcare deserts (56.2% for males and 56.6% for females, p -value = 0.640). These data underscore the widespread nature of childcare scarcity and its uniform distribution across gender. Despite this uniform exposure, it remains to be seen whether it has the same impact on male and female scientists.

Gender Disparity in Scientists' Careers

Our sample contains 12,276 SEH doctoral recipients from 1997 to 2014 who were employed at US universities or research institutions after graduation. These data are derived from the Survey of Doctorate Recipients (SDR), a biennial survey of US-trained doctoral scientists and engineers sponsored by the National Science Foundation (NSF) and the National Institutes of

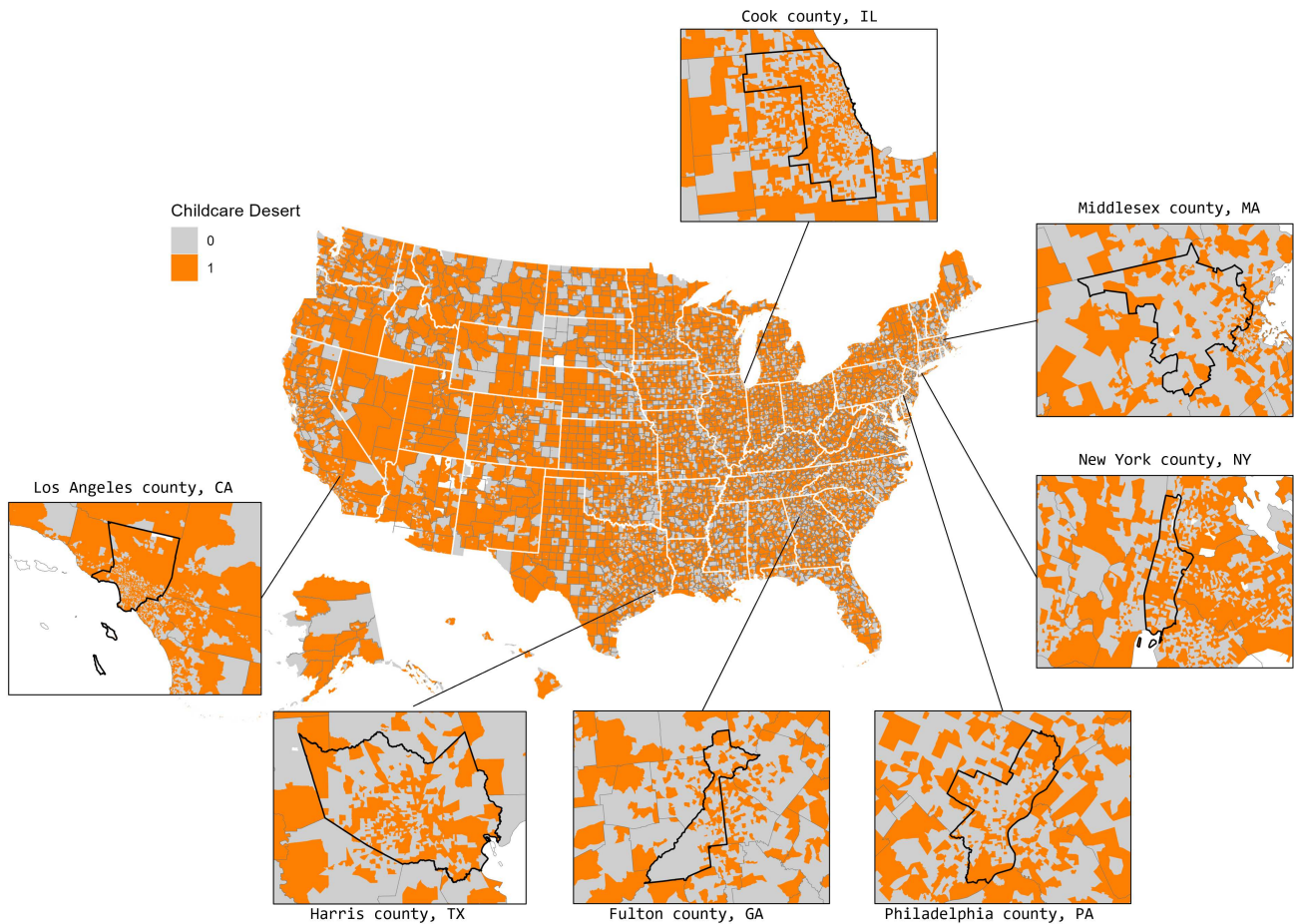


Figure 1. Workplace Childcare Deserts at The Census Tract Level: 2019. Workplace childcare deserts (shown in orange) are defined as census tracts in which there is no or very low childcare supply, i.e., a supply-to-demand ratio less than one third. Workplace childcare supply is approximated as proportional to the number of employees working in childcare facilities (primary SIC code: 8351) in a census tract based on the Infogroup US Historical Business Data. Workplace childcare demand is approximated as proportional to the total number of employees working in a census tract also based on the Infogroup US Historical Business Data. Refer to Section **Methods–Variables** for details of how these two measures are then used to obtain an estimate of the childcare supply-to-demand ratio in a census tract.

Health (NIH). The dataset provides two benefits for studying the impact of childcare availability on the career progression of researchers. First, it tracks the career transitions of US doctoral scientists and engineers through longitudinal surveys conducted every two years, achieving a high response rate of 65% as of 2021³⁵. Second, in addition to tracking educational and career achievements, the survey gathers data on family background, specifically marital status, parenthood status, and, if applicable, the age brackets of children. The relevant age categories for this study are under two years and between two and five years.

We match our sample with the Infogroup database to define whether someone works in a childcare desert. We then match our sample with the Integrated Postsecondary Education Data System (IPEDS) database to obtain institutional characteristics including student enrollments, faculty counts, and percentages of women faculty at different ranks. Last, we match our sample with the Census Bureau databases to incorporate regional economic controls. In particular, we account for population, business and employment densities, and median household income and unemployment rate at the commuting zone level, which more accurately reflect the local economy where people live and work than do county level data^{36,37}. Detailed definitions of these variables can be found in the Methods section. These controls are included in subsequent analyses, as local demographic and economic conditions may correlate with job mobility. Notably, our results remain consistent when using county or census tract-level measures.

Table 1 presents the demographic and professional characteristics of the study cohort, comprising 12,276 individuals, almost evenly divided between males (6,097) and females (6,179). The average tenure rate is approximately one third (32%). Notably, there exists a gender disparity in tenure achievement: female researchers are 5.6 percentage points less likely to obtain tenure than their male counterparts, with a rate of 29.2% for females versus 34.8% for males (p -value < 0.001). Furthermore, the data indicate a difference in family formation patterns after doctoral graduation: 46.5% of male researchers report having at least one child aged 0 to 5 years within six years from their graduation, in contrast to 39.7% of female researchers (p -value < 0.001). This study focuses on children within the 0 to 5 age range due to the significant childcare needs and the lack of public support during this period. The selection of the six-year post-graduation time frame aligns with the typical duration of the tenure track. Familial responsibilities, particularly those involving young children, may influence tenure outcomes during this critical phase.

We note a few more differences between female and male researchers. Female researchers have a lower marriage rate (64.1% versus 69.1%, p -value < 0.001). The spouses of female researchers are more likely to work full time (83.1% versus 54.2%, p -value < 0.001) and less likely to work part time (7.4% versus 14.6%, p -value < 0.001) or not work (9.5% versus 31.2%, p -value < 0.001). Compared with males, female obtain their PhD at a slightly older age (32.8 versus 32.1, p -value < 0.001) and are slightly less likely to graduate from a “highest research activity institution” based on the Carnegie Classification of Institutions of Higher Education (74.3% versus 76.6%, p -value = 0.004). In terms of PhD field of study, a higher percentage of women than men obtained doctoral degrees in biological and biomedical sciences, health sciences, and psychology, social Sciences, humanities and other (all p -values < 0.001). A lower percentage of women than men obtained doctoral degrees in other fields including, engineering, mathematics and computer sciences, and physical sciences (all p -values < 0.001). About the same percentages of women and men obtain PhDs in the field of agricultural and natural sciences (p -value = 0.391). Finally, compared to male researchers, female researchers are slightly less likely to be employed at the highest research activity institutions (53.3% versus 57.4%, p -value < 0.001). Female researchers’ employer institutions tend to be smaller in size, and located in regions (i.e., commuting zones) with higher population, business and employment densities, and higher median income levels (p -values < 0.001).

Working in Childcare Deserts Means Lower Tenure Promotion Rate for Women but Not Men

We next analyze the association between working in childcare deserts and tenure promotion using the linear probability model (LPM). LPM offers unbiased and interpretable estimates compared to nonlinear models, especially when the main variable of interest or the outcome variable is binary^{38,39}. The results are consistent under the Logit model. In all models, we control for individual, employer and regional characteristics presented in Table 1, PhD graduation year dummies, and first SDR response year dummies. State fixed effects are included in all models to account for variations in childcare-related policies across states. Standard errors are clustered at the state level. The results remain consistent when controlling for fixed effects at the county and institution levels.

We observe that the gender gap in tenure probability previously observed in the summary statistics persists, even after accounting for marital status, PhD graduation age, year, institutions and fields of study, employment institution characteristics, and regional economic controls. All else equal, female researchers have a 4.5 percentage points lower probability of obtaining tenure than their male colleagues as shown in Column (1) of Table 2, consistent with what we observe in the summary statistics in Table 1. Having a child aged 0 to 5 years in the first six years after graduation further widens the gender gap. While having a child does not affect male researchers’ probability of obtaining tenure, it significantly lowers female researchers’ probability of earning tenure by 4.8 percentage points based on Column (2), a sizable impact given the sample mean of the 32 percent tenure rate. Given the significantly lower tenure rate associated with female researchers with children, it is unsurprising that fewer women have children during their pre-tenure years. While the recent literature shows that parenthood harms women’s careers

Table 1. Summary Statistics of Workplace Childcare Deserts, Familial, Educational, and Professional Characteristics of 1997–2014 SEH Doctoral Recipients Employed at US Universities and Research Institutions: Overall and by Gender

	Male	Female	Total	P-value
Childcare Desert (%)	56.2	56.6	56.4	0.640
Tenured (%)	34.8	29.2	32.0	<0.001
<i>Individual Characteristics</i>				
Has Child 0-5yr (%)	46.5	39.7	43.1	<0.001
Married (%)	69.1	64.1	66.6	<0.001
Spouse Working				
Full Time (%)	54.2	83.1	68.5	<0.001
Part Time (%)	14.6	7.4	11.0	<0.001
Not Working (%)	31.2	9.5	20.5	<0.001
PhD Age Obtained	32.1	32.8	32.5	<0.001
	(5.8)	(7.1)	(6.5)	
PhD Highest Research Inst. (%)	76.6	74.3	75.4	0.004
PhD Field of Study				
Agricultural and Natural Resources	5.5	5.2	5.3	0.391
Biological and Biomedical Sciences	24.6	27.3	25.9	<0.001
Engineering	16.0	6.0	10.9	<0.001
Health Sciences	5.3	10.5	7.9	<0.001
Mathematics and Computer Sciences	9.8	5.4	7.6	<0.001
Physical Sciences	17.4	11.6	14.5	<0.001
Psychology, Social Sciences, Humanities and Other	21.5	34.0	27.8	<0.001
<i>Employer Characteristics</i>				
Highest Research Inst. (%)	57.4	53.3	55.3	<0.001
Faculty Count (log scaled)				
Full Rank	5.55	5.44	5.49	<0.001
	(1.14)	(1.19)	(1.17)	
Associate Rank	5.14	5.10	5.12	0.014
	(0.92)	(0.96)	(0.94)	
Assistant Rank	5.14	5.10	5.12	0.006
	(0.80)	(0.84)	(0.82)	
Percentage of Women Faculty				
Full Rank	23.6	25.9	24.8	<0.001
Associate Rank	38.5	40.7	39.6	<0.001
Assistant Rank	44.6	47.0	45.8	<0.001
Student Count (log scaled)				
Undergraduate	8.93	8.82	8.87	0.006
	(2.19)	(2.35)	(2.27)	
Graduate	7.96	7.92	7.94	0.353
	(2.30)	(2.31)	(2.30)	
<i>Regional (Commuting Zone) Characteristics</i>				
Population Density (log scaled)	5.76	5.88	5.82	<0.001
	(1.30)	(1.26)	(1.28)	
Business Density (log scaled)	2.27	2.36	2.31	<0.001
	(1.12)	(1.11)	(1.12)	
Employment Density (log scaled)	4.83	4.94	4.88	<0.001
	(1.39)	(1.34)	(1.37)	
Median Household Income (log scaled)	10.86	10.89	10.87	<0.001
	(0.24)	(0.23)	(0.23)	
Unemployment Rate	5.37	5.41	5.39	0.168
	(1.67)	(1.60)	(1.63)	
No. of Observations	6,097	6,179	12,276	

Notes. Data sources: (1) Childcare Desert: Infogroup US Historical Business Data. (2) Tenured and individual characteristics: The Survey of Doctorate Recipients (SDR) and The Doctorate Records File (DRF). (3) Employer characteristics: Integrated Postsecondary Education Data Systems (IPEDS). (4) Regional characteristics: the Census Bureau. Childcare deserts are defined as census tracts in which there are no or very low childcare supply with demand to supply ratio lower than one third. Has Child 0-5yr is measured within first six years after doctoral graduation. Tenure is observed at at least seven years after doctoral graduation. Highest research inst., highest research activity institution is defined by the Carnegie Classification of Institutions of Higher Education. Regional characteristics are measured at the commuting zone level. See Methods section for details of sample construction and variables definitions. Standard deviations for continuous variables are shown in parentheses.

Table 2. Gender Gap in Tenure Promotion (Column 1), Gendered Effect of Parenthood (Has Children Under Age 6) on Tenure Promotion, (Column 2), Gender Gap in Tenure Promotion Among Researchers With Children (Column 3), and Gendered Effect of Working in Childcare Deserts on Tenure Promotion for Researchers With Children (Column 4)

Sample:	All		If Has Child	
	(1)	(2)	(3)	(4)
Female	-0.045*** (0.010)	-0.026** (0.011)	-0.061*** (0.013)	-0.032* (0.017)
Has Child		0.015 (0.014)		
Female X Has Child		-0.048*** (0.014)		
Desert				0.016 (0.019)
Female X Desert				-0.052** (0.021)
Controls	Yes	Yes	Yes	Yes
No. of Observations	11,941 [†]	11,941	5,147	5,125 [‡]
Adj. R-squared	0.19	0.19	0.20	0.21

Notes: The model is ordinary least squares (OLS) regression. The outcome variable is the binary indicator of whether an individual has attained tenure promotion observed at least seven years after doctoral graduation. The controls include individual, employer, and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

Columns (1) and (2) analyze gendered effects of having children on tenure rate, where having children is defined as having children under the age of six during the first six years after doctoral graduation. Columns (3) and (4) analyze gendered effects of childcare deserts, i.e., areas with no or very low childcare supply relative to demand, on tenure rate for researchers with children.

[†] 335 (2.7%) observations are dropped due to missing values for employer characteristics: some institutions did not report faculty counts or enrollments in certain years. [‡] 23 (0.4%) observations are dropped due to missing child care availability data caused by missing or inaccurate facility location information. For complete estimation results, see Extended Data Table 1. For results from the Logit model, see Extended Data Table 2.

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

more (e.g., leaving full time employment¹⁹ or lowering productivity²⁰), this set of analyses offers new, yet consistent, evidence that parenthood contributes significantly to the gender gap in tenure achievement.

To analyze the impact of lack of childcare support on the tenure rate, we next focus on the subsample of researchers who have children between 0 and 5 years old during the first six years after graduation. Column (3) shows that the gender gap for this subsample is 6.1 percentage points. Column (4) further shows that there is a differential impact of lack of childcare on male and female researchers—working in a childcare desert further reduces female researchers’ tenure rate by 5.2 percentage points, while having no impact on male researchers’ tenure rate. Additionally, the tenure gap in non-desert areas is much smaller (3.2 percentage points, $p\text{-value} < 0.1$), while the gap in desert areas is as much as 8.4 percentage points ($3.2 + 5.2$ percentage points). In other words, childcare deserts explain over 60% of the tenure gender gap among researchers with children.

Placebo Test: Childcare Deserts are Not Associated with Tenure Outcomes for Researchers Without Children, Regardless of Gender

To further validate the results, we estimate the impact of childcare desert on tenure promotion on the following four subsamples: (1) female researchers with children ($N=2,379$), (2) male researchers with children ($N=2,746$), (3) female researchers without children ($N=3,618$), and (4) male researchers without children ($N=3,140$), where “children” refers to those between age 0 and 5 during the first six years after a respondent’s PhD graduation. The results are shown in Figure 2. With these more granular subsamples, we continued to find that childcare deserts harm female researchers’ likelihood of receiving tenure (-0.039 ; $p\text{-value} < 0.01$), but have no effect on male researchers (0.018 ; $p\text{-value} > 0.1$), indicating a 5.7 percentage points gender gap, consistent with the previous estimate using the interaction effect model. As a placebo test, we further investigate whether a childcare desert affects male and female researchers without children. We expect that there should be no effect of childcare deserts in this subsample, otherwise it may suggest our measure of childcare availability captures other hidden factors (for example, local economic factors) that affect job promotions in general. We do not find an effect for either female or male researchers (-0.007 and 0.013 ; $p\text{-values} > 0.1$), confirming the validity of our childcare desert measure.

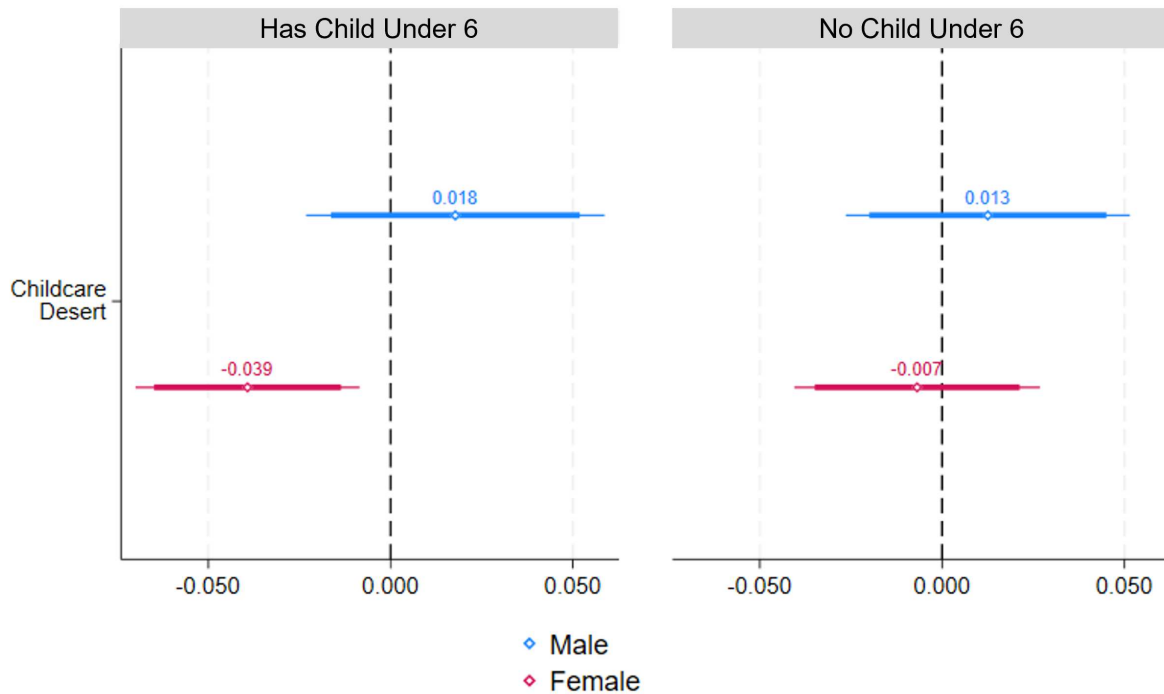


Figure 2. Effect of Childcare Deserts on Tenure Promotion: By Gender and By Parenthood Status | Shown in the figure are estimated effects of childcare deserts on researchers’ tenure attainment, as well as their confidence intervals (90% and 95%). The model is OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at state level. The figure on the left shows the impact of childcare deserts on subsamples of women ($N=2,379$) and men ($N=2,746$) with children (under the age of six in the first six years after doctoral graduation). The figure on the right shows the impact of childcare desert on subsamples of women ($N=3,618$) and men ($N=3,140$) without children.

Examination of Alternative Explanations

Our results are robust to (1) the alternative model specification—the Logit model (Extended Data Table 2), (2) inclusion of county or institution fixed effects (Extended Data Table 3), (3) exclusion of states that experienced significant expansions of public preschools, typically targeting four-year-olds (Extended Data Table 4), (4) different types of regional controls at commuting zone, county, and census tract levels (Extended Data Table 5), (5) alternative definitions of “having children” (under six versus under three years old, within six years versus within three years after doctoral graduation; Extended Data Table 6), (6) various cutoffs of the supply-to-demand ratio used to define deserts (i.e., one third, one fourth, one fifth, and one sixth; see Extended Data Table 7), (7) different time windows used to define childcare deserts (first response year versus first after graduation year, plus and minus one year around these years, and within three years following these periods; Extended Data Table 8), (8) defining childcare desert using both the focal census tract and its neighboring tracts (Extended Data Table 9), and (9) distance-based childcare desert measures (i.e., 1, 2, 5, and 10-mile radii, as well as radius defined based on rural versus urban areas; Extended Data Table 10 and 11). It is worthwhile noting that using census tract based childcare desert measures generate more robust and economically meaningful results than distance-based measures. While point estimates from distance-based measures are consistent, they are often statistically insignificant, as simple distance measures fail to account for variations in population and economic densities. When using tiered radius measures adjusted for UIC and RUCA codes, the estimates become statistically significant ($p\text{-value} < 0.1$). However, these tiered definitions rely on coarse and somewhat arbitrary distance cutoffs. As result, we retain census tract-based measures as our primary metric and present results from the distance-based measures in robustness analyses. Finally, our findings remain robust when excluding recent graduates as their tenure clocks could have been impacted by the exposure to the COVID-19 pandemic (Extended Data Figure 6).

In addition to the aforementioned model variations, our results are also robust to controlling for potential confounders including (1) post doc status upon graduation (Extended Data Table 12), (2) the institution-level tenure stoppage policy (gender neutral versus female only; see Extended Data Table 13 and 14), (3) county-level voting patterns in presidential elections (Extended Data Table 15), (4) childcare facility density, capacity concentration, and density by facility types (service-based versus school-based centers; see Extended Data Table 16), and (5) county-level median childcare prices and 75th percentile prices (Extended Data Table 17). Note childcare prices data are only available at county level from 2008–2018 and many data points are imputed or missing due to inconsistent reporting and low response rate. Results from this subsample with county-level childcare prices data are statistically insignificant. However, the point estimates (-4.8 to -4.9 percentage points) are highly consistent with the main results, with and without childcare price controls.

Finally, we examine whether selection and parenthood timing may moderate the associations we observe. Specifically, if researchers choose their employers based on childcare availability, and in particular, if female researchers are more likely to do so, such selection may bias the estimates. To isolate the effects from potential selection biases, we study two separate subsamples: those who are already parents at the time of their doctoral graduation and those who are not parents yet but will become parents later. Those who are already parents are more likely to factor childcare availability into their choices of employers, while those who are not yet parents are less likely to do so. Results are shown in Table 3. For the already parents, we observe no statistically significant association between childcare deserts and the tenure gender gap (-1.4 to -2.7 percentage points, $p\text{-values} > 0.1$). On the other hand, for new parents, who are less likely to be impacted by selection, we observe an even larger and statistically significant association between childcare deserts and the tenure gender gap (-7.2 percentage points, $p\text{-value} < 0.05$).

We further study when respondents become parents: early (years one to three) versus late (years four to six) parenthood during the pre-tenure period. Results in Table 3 Columns (4) and (5) indicate that childcare desert significantly increases the tenure gender gap when researchers become parents early in the pre-tenure period (-11.3 percentage points, $p\text{-value} < 0.05$). In contrast, no statistically significant effect is observed for those who become parents later in the pre-tenure period (-3.1 percentage points, $p\text{-value} > 0.1$). The greater moderating effect of childcare deserts for earlier-career parents is likely a result of prolonged loss of productivity caused by the lack of reliable childcare. Also note that the gender gap in non-deserts is significant for later-career parents (-9.5 percentage points, $p\text{-value} < 0.1$), which could suggest that the effect of parenthood is not sufficiently moderated by childcare as the onset of parenthood is close to the tenure evaluation point.

Lack of Childcare Means Less Time Available for Mothers, while Other Mechanisms Are Also Possible

Why does the lack of childcare hurts female scientists’ tenure attainment more than male scientists? Recent studies²⁰ suggest that the gendered impact of parenthood could be caused by women having less time available for research than men due to greater childcare responsibilities, and hence have lower productivity than men. Therefore, one potential hypothesis is that the lack of childcare means women have less time for research as they spend more time caring for young children due to lack of childcare options.

We test this hypothesis leveraging responses to the SDR survey question “During a typical week on your principal job, how many hours did you work?” The average reported hours per week in our sample is 48.7 hours (SD 12.5 hours). We first analyze

Table 3. Effects of Childcare Deserts on Tenure Promotion: Timing of Parenthood

Sample:	Already Parent	Already Parent	New Parent	New Parent	New Parent
	(1)	(2)	(3)	Yr 1-3 (4)	Yr 4-6 (5)
Female	0.034 (0.066)	0.026 (0.06)	-0.051* (0.027)	-0.012 (0.030)	-0.095* (0.051)
Desert	0.026 (0.049)	0.022 (0.049)	0.015 (0.031)	0.049 (0.038)	-0.018 (0.049)
Female X Desert	-0.027 (0.077)	-0.014 (0.074)	-0.072** (0.035)	-0.113** (0.045)	-0.031 (0.066)
Controls	Yes	Yes	Yes	Yes	Yes
No. of Observations	803	845	2,868	1,774	771
Adj. R-squared	0.22	0.22	0.22	0.23	0.21

Notes: The model is OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

Columns 1 and 2 analyze the gendered effects of working in childcare deserts on tenure promotion for those who are already parents at the time of doctoral graduation. Already parents in Column 1 are defined as individuals who report having children of age 6 to 11 within six years after their doctoral graduation. Already parents in Column 2 are defined as individuals who report having children of age 6 to 18 within six years after their doctoral graduation.

Columns 3 to 5 analyze the same effect for those who become parents only after graduation. New parents in Column 3 are defined as individuals who report having no children of any age in the first response after graduation, or those who report having children under age 2 at least two years after graduation, or those who report having children 2 to 5 at least five years after graduation. New parents in Column 4 are defined as those who report having children under the age of 2 in the first three years after graduation and no older children below age 12. New parents in Column 5 are defined as those who report having children under the age of 2 in years four to six after graduation but not no older children below age 12, and meanwhile report no children below age 12 in years one to three after graduation.

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

whether having a child reduces researchers' working hours and whether this effect differs for men and women. Similarly, we also examine whether working in childcare deserts further exacerbates the negative impact of parenthood and whether this moderating effect differs by gender. The results are reported in Table 4. Column 1 indicates that having a child has no statistically significant association with time available for men (-1% , $p\text{-value} > 0.1$). However, it is associated with 10.4% less time for women ($p\text{-value} < 0.01$). In other words, this suggests women with children on average have 5.1 fewer hours available per week for work than men with children. Column 2 indicates that working in a childcare desert further reduces women's working hours by 3.2% ($p\text{-value} < 0.1$) relative to men. Note, however, the magnitude is relatively moderate, i.e., 1.6 hours per week.

We next see whether the gendered effect of childcare deserts on working hours can explain the observed gender disparities in tenure rate. Column (3) in Table 2 shows that after controlling for average weekly working hours, the estimated effect of childcare deserts on the gender gap in tenure rates decreases moderately, from 5.1 percentage points ($p\text{-value} < 0.01$) to 4.5 percentage points ($p\text{-value} < 0.1$). Note weekly working hours have a positive and statistically significant impact on tenure rate, consistent with our expectation. In sum, the observed effect of childcare deserts on the tenure gender gap is only partially explained by on average less time available for women than men. This suggests that additional factors likely influence the research productivity of parents, particularly women, in the absence of reliable childcare. One potential explanation is that female researchers compensate for lost research time during conventional work hours by working at less desirable times, significantly reducing their leisure and sleep. Studies have documented substantial, prolonged sleep deprivation of up to six years among mothers of young children⁴⁰, which could undermine productivity and, over time, lead to adverse health outcomes⁴¹.

Another plausible mechanism is that, despite only a moderate reduction in total working hours, frequent disruptions due to childcare responsibilities fragment women's work schedules. This fragmentation may impair workflow continuity and reduce productivity. Beyond burnout and disrupted workflows, other factors such as the need for multitasking, diminished synchronization with colleagues, and increased domestic tension may also contribute. Note, too, that working hours are self-reported, which introduces the potential for reporting bias. Furthermore, while the SDR survey collects data on average hours available for work, variability in the distribution of these hours may also impact research productivity and consequently tenure attainment. Further investigation into these factors could provide valuable insights into how inadequate childcare affects mothers' work productivity and inform strategies to mitigate the impacts.

Differing Effects of Childcare Deserts by Fields of Study, Partially Explained by Differences in Work Activity Flexibility

Next we examine whether the effect of childcare deserts varies across fields of study and why. The results are shown in Figure 3. The fields in which we observe the largest impact of childcare deserts on the tenure gender gap are agricultural and natural resources (-5.0 to -12.8 percentage points) and engineering (-6.3 to -11.8 percentage points), followed by biological and biomedical sciences (-3.8 to -7.3 percentage points), psychology and social sciences (-4.8 to -5.7 percentage points), and mathematics and computer sciences (-5.8 to -6.9 percentage points). We observe almost no moderating effect of childcare deserts on the tenure gender gap in health sciences and physical sciences.

To better understand why the effects of childcare deserts differ by academic disciplines, we analyze how the nature of work differs across fields and assess whether these differences could partially explain the observed disparities. To do so, we leverage the SDR survey item that asks respondents about their primary work activities in the principal jobs. The survey classifies primary work activities into 14 categories such as basic research, applied research, managing and supervising people or projects, teaching, professional work (e.g., clinical and legal work), accounting, human resources, etc. We identify the most relevant categories for our sample and group them into the following major work activity groups: basic research (28.2%), applied research and development (28.7%), teaching or clinical work (37.1%), and administrative work (5%).

We begin by investigating whether the impact of childcare deserts varies across researchers based on their primary work activity group. The results, presented in Figure 4, reveal that childcare deserts have the greatest impact on the tenure gender gap among individuals primarily engaged in applied research and development, with an estimated effect of -15.0 to -15.5 percentage points ($p\text{-value} < 0.01$). This is followed by those whose primary work involves teaching or clinical duties, where the effect ranges from -8.2 to -8.4 percentage points ($p\text{-value} < 0.1$). In contrast, no significant impact is observed for researchers whose primary activities are basic research or administrative work. Note these results are obtained while controlling for holding post-doc positions and its interactions with gender and childcare desert, as post-doc positions could correlate with primary work activities. We find no significant association between postdoc and childcare-moderated tenure gender gap in these specifications.

These findings suggest that the inflexibility of certain work activities can amplify the challenges of childcare deserts. Applied research and development often require access to labs, specialized equipment, or field work, which limits flexibility in work hours and locations. This aligns with previous research indicating that equipment-intensive fields suffered more significant loss in research time during the COVID-19 pandemic²¹. Similarly, teaching and clinical roles typically involve fixed schedules

Table 4. Gendered Effects of Parenthood and Childcare Deserts on Reported Working Hours Per Week (Column 1 and 2), and Gendered Effect of Childcare Deserts on Tenure Controlling for Average Weekly Working Hours (Column 3)

Sample: Outcome Variable:	All Hrs Per Wk (log scaled) (1)	If Has Child Hrs Per Wk (log scaled) (2)	If Has Child Tenure (3)
Female	-0.015* (0.008)	-0.101*** (0.011)	-0.006 (0.018)
Has Child	-0.009 (0.007)		
Female X Has Child	-0.104*** (0.008)		
Desert		0.016 (0.010)	0.012 (0.019)
Female X Desert		-0.032* (0.017)	-0.045* (0.022)
Hrs Per Wk (log scaled)			0.219*** (0.017)
Controls	Yes	Yes	Yes
No. of Obs	11941	5125	5125
Adj. R-Sq	0.07	0.07	0.23

Notes: The model is OLS regression. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

Column (1) uses the full sample and studies the impact of parenthood on reported working hours per week. Column (2) uses the subsample of researchers with children (i.e., those with children under six years of age in the first six years after doctoral graduation) and studies the impacts of childcare deserts on reported working hours per week. The outcome variables in Columns (1) and (2) (i.e., working hours per week) are log scaled, so the coefficients should be interpreted as percentages. Column (3) uses the subsample of researchers with children and studies the impact of childcare deserts on tenure while controlling for average working hours per week.

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

and locations, further constraining flexibility in managing work and caregiving responsibilities.

Further supporting our hypothesis, we observe in Figure 5 the highest percentages of respondents identifying their primary work activities as applied research and development are in engineering (45.9%) and agricultural and natural resources (39.1%), compared to the overall average of 28.7% across all fields. Similarly, the highest percentages of respondents reporting their primary work activities as teaching or clinical work are in psychology, social sciences, humanities, and other (55.5%) and mathematics and computer science (55.4%), relative to the average of 37.1% across all fields. Recall these are also the fields where we observe the greatest impact of childcare deserts on gender gap in tenure rates.

In summary, these patterns shed light on the differential impacts of childcare deserts across fields of study. Notably, disciplines with a higher proportion of work in applied research and development or teaching and clinical roles—activities typically associated with lower flexibility—exhibit stronger effects. These findings align with our hypothesis that disruptions to work, beyond the general reduction in available time, significantly impact research productivity and, consequently, tenure outcomes for mothers without reliable childcare.

However, note that this is not the only factor at play. For instance, researchers in health sciences report the third-highest percentages of both applied research and development and teaching or clinical work, yet we do not observe a statistically significant moderating effect of childcare deserts on gender disparities in this field. Conversely, a substantial proportion of respondents in biological and biomedical sciences report basic research as their primary work activity, yet this field shows a somewhat significant effect of childcare deserts. It can be due to the fact that basic research in biological and biomedical sciences also involves lab work with little scheduling flexibility. More detailed work activity data can deepen our understanding of how childcare deserts affect productivity and tenure outcomes, and allow us to better identify mitigation strategies.

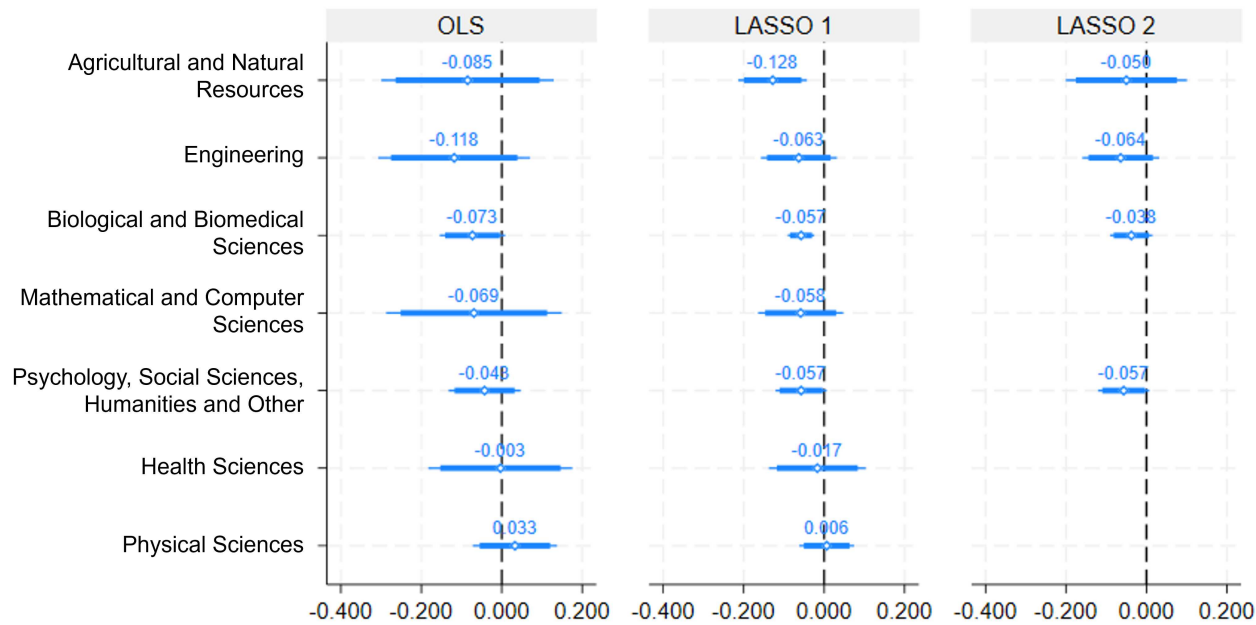


Figure 3. Effect of the Childcare Deserts on Tenure Promotion: By Field of Study | This figure illustrates the impact of childcare deserts on the tenure gender gap across different fields of study, along with their 90% and 95% confidence intervals. Fields of study are categorized based on the NSF’s definitions⁴². The outcome variable is tenure promotion. Standard errors are clustered at the state level. The figure on the left shows the results from the OLS regression including the full set of two-way and three-way interaction terms for field of study, childcare desert, and gender, alongside the same control variables in Table 2. The figure in the middle shows the results from the least absolute shrinkage and selection operator (LASSO) regression, which retains the full set of three-way interactions but selects among other variables (including two-way interactions and controls) using the Adaptive LASSO method. The figure on the right shows the results from the LASSO regression that selects variables among all variables using the Adaptive LASSO method. Estimates shown in the middle and the right figures are bias-corrected using the post-LASSO regressions.

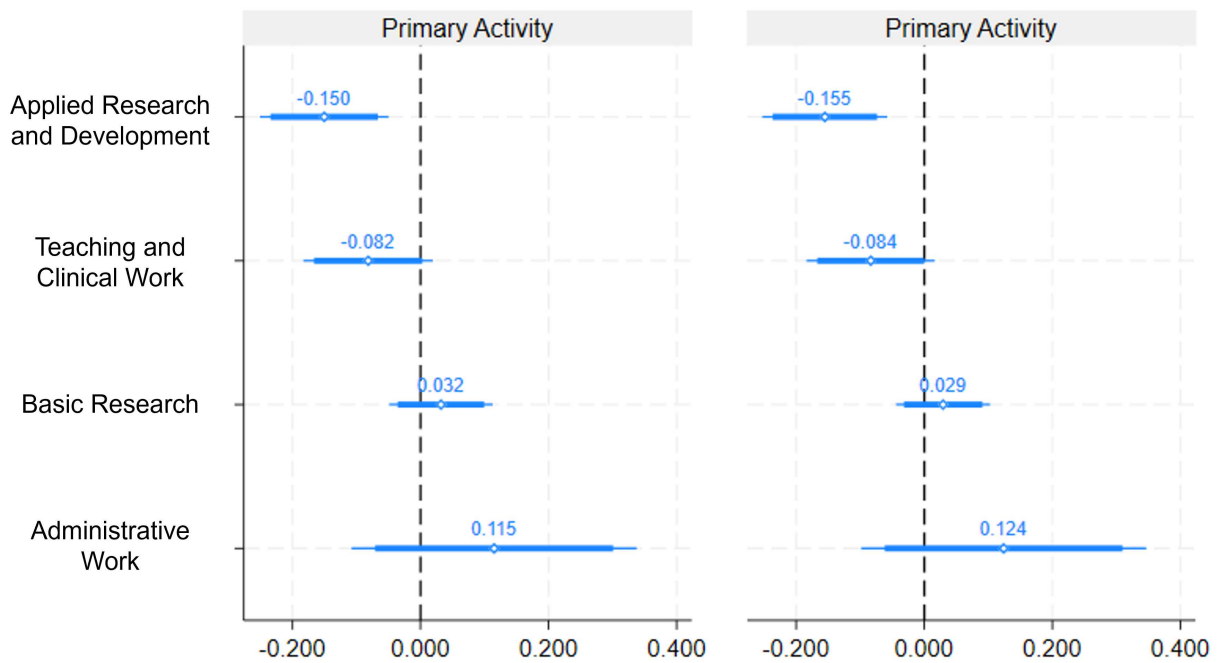


Figure 4. Effect of the Childcare Deserts on Tenure Promotion: By Primary Work Activity | This figure illustrates the effects of childcare deserts for researchers whose primary work activity falls into one of the following four categories: basic research (28.2%), applied research and development (28.7%), teaching and clinical work (37.1%), and administrative work (5%). The SDR asks respondents to report their primary work activity in their principal jobs and classifies them into 14 categories including basic research, applied research, managing and supervising people or projects, teaching, professional work (e.g., clinical, legal services), accounting, sales, human resources, etc. We then group them into the above mentioned four major groups that are most relevant for our sample—SEH doctoral recipients employed at US universities or research institutions. The model is OLS regression. The outcome variable is tenure promotion. The controls include individual, employer, and regional characteristics listed in Table 1, as well as PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Additionally, we account for the gendered impact of postdoc positions on tenure, as postdoc positions can correlate with primary work activities. For example, postdocs are often not required to teach. The left figure controls for reported postdoc plans upon graduation, while the right figure controls for reported postdoc commitments upon graduation. We do not find a statistically significant impact of postdoc status on tenure gender gap.

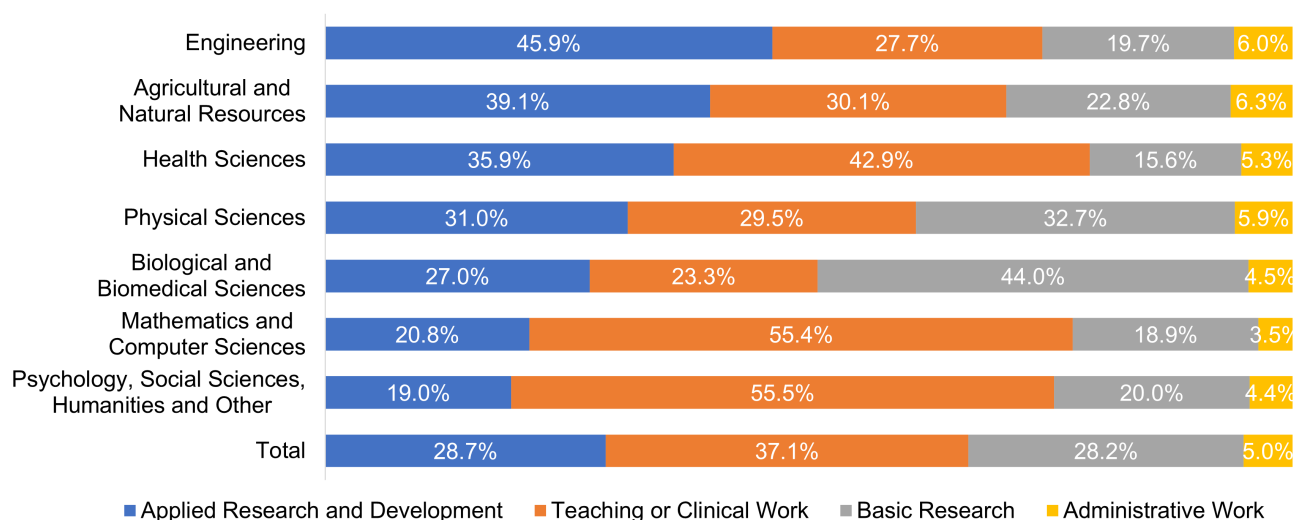


Figure 5. Primary Work Activity By Field of Study | The figure displays the percentage of respondents reporting each type of primary work activity by field of study, as well as the overall percentages across all fields (total). Fields of study are based on the NSF’s definition⁴². The SDR asks respondents to report their primary work activity in their principal jobs and classifies them into 14 categories including basic research, applied research, managing and supervising people or projects, teaching, professional work (e.g., clinical, legal services), accounting, sales, human resources, etc. We then group them into four major groups that are most relevant for our sample—SEH doctoral recipients employed at US universities or research institutions. The four major groups are: basic research (28.2%), applied research and development (28.7%), teaching or clinical work (37.1%), and administrative work (5%).

Discussion

Over 50,000 individuals obtain science, engineering, and health doctoral degrees from US colleges and universities annually⁴³, while only a small percentage progress to tenured positions years later. Based on data from IPEDS, women constitute more than half of tenure-track assistant professors and non-tenure track professors, yet they represent only 45% percent of associate professors and 32.5% of full professors within research universities and institutions²⁸. The recent literature shows that parenthood, whether through childbirth or adoption, significantly affects researchers’ career trajectories— particularly those of female researchers^{19,20}. However, this does not mean that researchers, and American families more broadly, should stop having children⁴⁴. Rather, society should find ways to better support young families. This paper investigates how childcare availability (and the lack thereof) moderates the impact of parenthood on scientists’ careers and gender equity in the profession. We find that childcare deserts, defined as areas with no or an extremely low supply of childcare relative to demand, reduce researchers’, particularly women’s, prospects of attaining tenure, and widen the gender tenure gap by 5.2 percentage points, a substantial effect given the average tenure attainment rate of 32 percent. Importantly, this effect is observed only for women with children, and not for men with children or either men or women without children. Our results are robust to many alternative model and variable specifications, and controlling for multiple potential confounding factors, as well as potential selection.

Further analysis reveals that the gendered impact of childcare deserts can be partly attributed to reductions in mothers’ time available for work. However, the magnitude of the effect is only moderate, which suggests other factors could be at play, including burnout, workflow disruptions, demands for multitasking, and difficulties in synchronizing with collaborators, among others. We further find that fields where primary work activities have more rigid requirements for work hours and locations (e.g., applied research and teaching) are the most affected by childcare deserts. These positions, offering limited flexibility, are more vulnerable to work disruptions caused by inadequate childcare. For instance, fields like engineering and agricultural and natural sciences, where applied research is more prevalent than basic research, experience the greatest impact. Similarly, fields such as mathematics and computer science, psychology, social sciences, and humanities, where teaching constitutes a significant portion of primary activities, are also highly affected by childcare deserts. Although our findings do not address all the factors contributing to these impacts, they support the hypothesis that work disruptions can be a key driver of lower productivity and tenure rates in the absence of reliable childcare.

We would also highlight that the lack of childcare presents significant challenges not only to researchers, but also to many

American families, as childcare availability has remained low for many decades. This scarcity also has broader and long-term economic and societal impacts. To address these issues, the US government might invest in enhancing childcare availability for American families⁴⁵. This could include infrastructure investment, tax benefits for childcare businesses, and better support for childcare workers, particularly in regions where supply significantly falls short of demand. The president's executive order on increasing access to high-quality care and supporting caregivers⁴⁶, and the effort announced to reduce costs for families receiving childcare subsidies⁴⁷, are examples. In addition to federal proposals, states might also find new ways to support the childcare sector, especially since childcare businesses are no longer receiving the financial relief that they had during the COVID-19 pandemic⁴⁸.

Moreover, addressing the childcare needs of American families is not just a social imperative but also a strategy that can be leveraged by businesses and organizations to enhance workforce productivity and diversity⁴⁹. Universities and other organizations should consider providing on-site childcare and backup childcare or implementing other forms of childcare subsidies to attract and retain talented workers and support high productivity⁵⁰. Currently, less than half of US universities offer on campus childcare, a figure that declined by 10 percentage points from 2004 to 2019^{51,52}. Moreover, even when on-campus childcare is available, its capacity often fails to meet demand, resulting in extensive waiting lists. We hand-collected data on waiting list lengths for childcare centers from the top 50 US research institutions, ranked by total research and development (R&D) expenditures. Among these institutions, 60% have university-managed childcare centers while 40% do not. Some institutions offer childcare benefits, such as priority enrollment and tuition discounts, through partner centers, where the capacity is shared among university affiliates and others. Regardless of whether the center is university-managed or partnered, and irrespective of the benefits provided, waiting lists remain long with 46.5% of centers (N=157) reporting an average waiting list length of one (incl.) to two years. Another 27.4% report wait times of two (incl.) to three years, while 12.7% indicated waits of six months (incl.) to one year. One center had a waiting list of three years or longer. Expanding childcare capacity on or near university campuses could reduce these waiting times, thereby improving access to childcare, enhancing research productivity, and mitigating gender disparities in academia. For a detailed analysis of center types, enrollment eligibility, associated benefits, and the distribution of average waiting list lengths, refer to Extended Data Figure 7, 8 and 9.

We note a few limitations of this study and potential areas for future research. First, our findings should be interpreted as observational rather than causal. While we have accounted for numerous confounding factors at the individual, institutional, and regional levels, childcare availability may remain correlated with other unobserved variables that simultaneously influence mobility or career advancement. Causal analyses leveraging exogenous variations in childcare availability provide more robust evidence.

Second, derived from the Infogroup Historical Business data, our childcare data capture only center- and group-based care. More than 80% of all licensed slots are in child care centers⁵³, and an estimated 62% of families use these formal care arrangements⁵⁴. We do not have visibility of family-based care (i.e., care provided in private homes or apartments) or other arrangements of care (e.g., nannies, neighbors, and family relatives). Incorporating these semi-formal or informal care options will provide a more comprehensive view of childcare availability and its potential impact.

Third, while our findings provide partial support for the disproportionate impact of childcare deserts on women—such as reduced available work time and increased disruptions, particularly in environments with limited work flexibility—additional mechanisms are likely at play. These may include burnout, increased multitasking demands, and greater challenges in team coordination, among others. Investigating these hypotheses requires more granular time-use data. Such analyses could not only enhance our understanding of how inadequate childcare affects parents'—particularly mothers'—research productivity but also offer valuable insights into strategies for supporting families.

Finally, while this research studies the impact of childcare deserts on scientists' careers, lack of childcare availability is only one of the challenges faced by young families. Affordability and quality are equally important considerations. Increasing supply without making it affordable will not truly increase accessibility^{55,56}. At the same time, making childcare universal without investing in quality could have negative short- and long-term impacts on children^{12,57,58}, which could in turn lead to negative economic and societal outcomes⁵⁹. A primary challenge to studying childcare affordability and quality at scale is lack of granular, nationwide data. While the US Department of Labor has compiled a national database of childcare prices from 2008 to 2018, this data is published only at county level and a significant portion of data are imputed or missing. In terms of childcare quality, there is no database that provides detailed ratings of providers nationwide. Although most states have implemented childcare quality assurance programs, participation is typically voluntary. For example, only 50% of licensed childcare providers in Michigan participate in the state's Great Start to Quality program. Moreover, states follow different protocols in data collection leading to significant variations in types of data collected and standards used to assess quality. Therefore, a significant effort is required to acquire and standardize data to evaluate childcare quality consistently. Despite the challenges, research in these areas will allow us to better understand the reasons and consequences of the US childcare crisis and identify sustainable solutions.

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518 **Methods**

519 **Ethics**

520 The University of Michigan's Institutional Review Board approved the study as Not Regulated (category: Research Involving
521 Coded Private Information/Research, and Research Involving De-identified Biological Specimens or Information). The PI (and
522 the Regents of the University of Michigan) obtained the license for restricted-use data from NCSSES in February 2022 following
523 the NCSSES's licensing procedure. The license is effective till June 2026. The PI is the only person with access to the licensed
524 data. The data are stored, accessed and analyzed within the NCSSES Virtual Data Enclave. The PI has completed annual data
525 security training, undergone periodic data security audits, and maintained continued compliance per the license agreement. The
526 tables and figures presented in this manuscript comply with the data privacy and confidentiality guidelines of the NCSSES and
527 have been reviewed and approved by the NCSSES Data Enclave staff for export and publication.

528 **Data**

529 This study uses the following datasets:

530 (1) *Infogroup US Historical Business Data*: This dataset contains detailed facility-level information on US businesses and
531 organizations since 1997. It includes data on the facility's name, location, its parent company, industry classifications (with
532 primary SIC and NAICS codes, and up to six secondary SIC codes), number of employees, and sales volume. This dataset is
533 integral to our research because it enables us to identify childcare facilities, as well as their approximate capacities, using the
534 primary SIC code 8351. Childcare facilities under this classification include childcare centers, day care centers, group day care
535 centers, Head Start centers, nursery schools, and preschool centers.

536 (2) *Survey of Doctorate Recipients (SDR) Linked with the Doctorate Records File (DRF)*: The SDR, a biennial survey,
537 targets individuals under 76 years old who have earned a research doctoral degree in a science, engineering, or health field
538 from a US institution. The survey's population includes roughly 1.2 million individuals, with about 120,000 participants in the
539 sample. It gathers data on demographics, education, family, and career histories, and is co-sponsored by the National Center for
540 Science and Engineering Statistics (NCSSES) within the National Science Foundation and the National Institutes of Health. The
541 most recent data available are from 2021. The DRF complements this by being a cumulative record of all US research doctorate
542 recipients since the 1920s. Updated annually on the basis of the Survey of Earned Doctorates (SED), DRF provides data on
543 educational history, demographic characteristics, and post-graduation plans. The SED is sponsored by the NCSSES, as well as
544 three federal agencies (the National Institutes of Health, US Department of Education, and the National Endowment for the
545 Humanities), and the most recent data available are from the academic year 2022. Access to these data is obtained through an
546 NSF/NCSSES restricted-use data license.

547 (3) *Integrated Postsecondary Education Data System (IPEDS) Data*: IPEDS is a system that gathers data from every US
548 college and university through twelve interrelated survey components conducted annually. In this study, we use institutional
549 characteristics, enrollment statistics, and human resources metrics from the database. Each postsecondary institution in the
550 survey is designated a unique UNITID, which is used to link the IPEDS data and the SDR data based on employer institution
551 UNITIDs.

552 (4) *Census Bureau Data*: The Census Bureau provides annual estimates of population, economic establishments, total
553 employment, median household income, and unemployment rate at the county level, as well as the land area of each county.
554 We aggregate these measures from the county level to commuting zone level. We perform this aggregation because county
555 boundaries do not adequately define a local economy but rather often reflect political boundaries. Commuting zones, on the
556 other hand, are geographic units of analysis intended to more closely reflect the local economy where people live and work^{36,37}.
557 Delineations of commuting zones before 2010 are obtained from USDA's Economic Research Service website, and those after
558 2010 are obtained from the Pennsylvania State University's Labor-sheds for Regional Analysis website.

559 **Data Merging Process**

560 We take the following three steps to integrate the datasets mentioned above.

Step 1: Our initial step involves combining the IPEDS data, which include geo-coded institutional locations, with census tract level childcare availability data derived from the Infogroup US Historical Business data. IPEDS data provide geo-coded locations for institutions. Using R's tigris package, we first identify the 2020 census tracts associated with these geo-locations. When necessary, we convert the 2020 census tracts to 2010 and 2000 census tracts using the relationship files provided by the Census Bureau. Then, we merge the IPEDS data with the childcare availability data based on each institution's census tract location.

Step 2: In the second step, we proceed to link the combined IPEDS and childcare data with the regional economic metrics at the commuting zone level.

Step 3: For the final step, we integrate the previously merged datasets with the SDR/DRF dataset. The merging is conducted at the institution level using unique institutional identifiers, known as UNITIDs.

Sample

We start from 81,076 individuals who received doctoral degrees between 1997 and 2014 according to the SDR survey. The most recent SDR survey available is from 2021. Given that the typical tenure track is approximately six years, it is unlikely that individuals who graduated after 2014 have undergone tenure evaluation and obtained their tenure promotion decisions. Within this group, 38.2% (or 30,941 individuals) responded to at least one survey within six years of their PhD graduation, and their most recent responses occurred more than six years post-graduation. This selection criterion enables us to track employment locations shortly after graduation—specifically, whether respondents are working at a university or research institution—and observe their tenure outcomes. We acknowledge that tenure track lengths vary across institutions as well as due to individual extensions. Therefore, our sample may include recent graduates who are still in tenure-track positions and have not yet reached the tenure evaluation phase as of the 2021 survey. We account for the year dummies of PhD attainment in our analysis to control for the potentially lower likelihood of observing tenure outcomes for more recent graduates.

Among these respondents, about 41.0% (12,700 individuals) were employed at four-year colleges or universities, medical schools, and university-affiliated research institutions in the US based on their first reported employment positions. We match 96.7% (12,276) of them with the IPEDS data and the childcare availability data. The remaining unmatched individuals either lack valid employment institution codes or are employed by institutions located in US territories (e.g., Guam, Puerto Rico) for which no childcare data are available.

Variables

- **Workplace Childcare Desert:** defined as an area (i.e., a census tract) where the childcare supply-to-demand ratio is lower than a threshold. Specifically,

$$\begin{aligned} & \text{Workplace Childcare Supply-to-Demand Ratio} \\ & \approx \frac{\text{Childcare Employee Count} * \% \text{ Direct Labor} * \text{Children-to-Staff Ratio} * \% \text{ Center Based Childcare Slots}}{\text{Total Employee Count} * \text{Average Number of Children Aged 0-5yrs Per Employee}} \\ & \approx a * \frac{\text{Number of Childcare Employees}}{\text{Total Number of Employees}}. \end{aligned}$$

That is, our workplace childcare supply-to-demand ratio is defined as proportional to the percentage of the workforce in a census tract working in the childcare industry. Intuitively, a greater percentage of the workforce working in the childcare industry indicates higher childcare availability in an area, and a lower percentage indicates lower availability. The multiplier a can be approximated using the following statistics: (1) average percentage of direct labor in the childcare industry (84%)⁶², (2) average child-to-staff ratio (8:1)⁶³, (3) market share of center or group based childcare slots (85%)⁵³, and (4) average number of children aged 0-5 years per worker (1/9), which is calculated by the average population aged 0-5 years / (average population aged between 20 and 65 years * (1 - average unemployment rate)).

We then define workplace childcare deserts as follows:

$$\text{Workplace Childcare Desert} = \begin{cases} 1, & \text{if Workplace Childcare Supply-to-Demand Ratio} < \frac{1}{3}, \\ 0, & \text{otherwise.} \end{cases}$$

The threshold of one third is chosen to be consistent with the Center for American Progress measure¹¹. To ensure the robustness of our measure, we adjust the threshold at various levels, including 1/4, 1/5, and 1/6, in addition to our initial setting. The results from these analyses are shown in Extended Data Table 7.

We note a key difference of our childcare desert measure compared to the one used by the Center for American Progress is that we measure *workplace* childcare desert instead of residential childcare desert. Given that college campus populations

predominantly consist of students, a definition of childcare deserts based on the workforce population is more relevant in our context. While the proximity of childcare services to the respondent's home may also be of interest, home locations are not disclosed in the SDR data to maintain respondents' privacy.

- **Tenured:** equals 1 if the respondent ever chose "tenured" in the tenure status question in the SDR, 0 otherwise.
- **Has Child 0-5yrs Within six Years After Graduation** (or in short, **Has Child**): equals 1 if the respondent responded having children either under two or between two and five years when responding within the first six years after PhD graduation.
- The variables **Female**, **Married**, **Spouse Working Full Time**, and **Spouse Working Part Time** are directly obtained from the SDR data.
- The variables **PhD Degree Age Obtained**, **PhD Degree Year Obtained**, **PhD Field of Study** are directly obtained from the DRF data.
- **PhD Degree Highest Research Institution** and **Employer Highest Research Activity Institution** are defined as doctoral or employer institutions classified to have the highest research activity based on the Carnegie Classification of Institutions of Higher Education.
- The variables **Employer Professor Counts at Full, Associate and Assistant Levels**, **Employer Female Faculty Percentages at Full, Associate and Assistant Levels**, **Students Counts at Undergraduate and Graduate Levels** are directly obtained from the IPEDS data.
- **Population Density:** defined as the population divided by the land area at the commuting zone level.
- **Business Density:** defined as the number of establishments divided by the land area at the commuting zone level.
- **Employee Density:** defined as the total number of employees divided by the land area at the commuting zone level.
- **Median Household Income:** defined as weighted median household income at the commuting zone levels, where the weights are county-level populations.
- **Unemployment Rate:** defined as weighted unemployment rate e at the commuting zone levels, where the weights are county-level populations.

Empirical Specifications

We use the following two models to measure the impact of having children on tenure probability for the entire sample:

$$y_i = f(\alpha + \beta \text{Female}_i + X_i \gamma + \varepsilon_i) \quad (1)$$

$$y_i = f(\alpha + \beta \text{Female}_i + \delta \text{Has Child}_i + \eta \text{Female}_i \times \text{Has Child}_i + X_i \gamma + \varepsilon_i) \quad (2)$$

We use the following two models to measure the impact of working in a childcare desert on tenure probability in the subsample of respondents who reported having children:

$$y_i = f(\alpha + \beta \text{Female}_i + X_i \gamma + \varepsilon_i) \quad (3)$$

$$y_i = f(\alpha + \beta \text{Female}_i + \delta \text{ChildcareDesert}_i + \eta \text{Female}_i \times \text{ChildcareDesert}_i + X_i \gamma + \varepsilon_i) \quad (4)$$

Index i denotes a respondent in our sample. y_i denotes the tenure outcome of individual i . Matrix X_i includes all variables listed in the Variables section except for childcare desert, tenured, has child, and female. $f()$ denotes the link function, which can be the linear probability model (Table 2) or the Logit model (Extended Data Table 2). The linear probability model is both unbiased and more interpretable than nonlinear models like Logit, particularly when the outcome variable and/or the variable of interest is binary^{38,39}.

We further conducted subsample analyses (Figure 2) conditional on gender and parenthood status (i.e., with and without children) using the following equation:

$$y_i = f(\alpha + \beta \text{ChildcareDesert}_i + X_i \gamma + \varepsilon_i) \quad (5)$$

Finally, to study the differential impact of childcare deserts by fields of study (Figure 3), we use the following three-way interaction model,

$$y_i = f(\alpha + \beta \text{Female}_i + \delta \text{ChildcareDesert}_i + \eta \text{Female}_i \times \text{ChildcareDesert}_i + \beta \text{Female}_i \times \text{Field}_i + \delta \text{ChildcareDesert}_i \times \text{Field}_i + \eta \text{Female}_i \times \text{ChildcareDesert}_i \times \text{Field}_i + X_i \gamma + \varepsilon_i) \quad (6)$$

We use a similar model to study the differential impact of childcare deserts by primary work activity (Figure 4).

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Data Availability

The study utilizes the following datasets:

(1) The Infogroup US Historical Business Data (1997-2020) are accessed through University of Michigan’s License with Infogroup (now DataAxle). The data can be accessed from University of Michigan’s Library:
<https://search.lib.umich.edu/databases/record/9111>

(2) Survey of Doctorate Recipients (SDR) Linked with the Doctorate Records File (DRF) data files are accessed through National Center for Science and Engineering Statistics (NCSES)’s restricted-use data license. The data are stored and analyzed within NCSES’s Virtual Data Enclave. Researchers should follow the instructions listed on NCSES’s webpage below to obtain the license and to access restricted use data:

<https://nces.nsf.gov/about/licensing>

(3) The Integrated Postsecondary Education Data System (IPEDS) data are publicly available and can be downloaded directly from IPEDS’ webpage below:

<https://nces.ed.gov/ipeds/use-the-data>

(4) Census Bureau Data are publicly available and can be downloaded directly from the Census’s webpages below:

<https://www.census.gov/programs-surveys/popest.html>

<https://www.census.gov/programs-surveys/cbp/data/datasets.html>

<https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html>

The final merged data are stored and analyzed within the NCSES’s Virtual Data Enclave per NCSES’s licensing policy.

Code Availability

All STATA code (version 18) are available within the NCSES’s Virtual Data Enclave per NCSES’s licensing policy.

Author Contributions

The paper is single authored. The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

Online Content

Extended Data Table 1. Effects of Childcare Deserts on Tenure: Full Results Table

	All		If Has Child	
	(1)	(2)	(3)	(4)
Female	-0.045*** (0.010)	-0.026** (0.011)	-0.061*** (0.013)	-0.032* (0.017)
Has Child		0.015 (0.014)		
Female X Has Child		-0.048*** (0.014)		
Desert				0.016 (0.019)
Female X Desert				-0.052** (0.021)
Married	0.010 (0.013)	0.012 (0.014)	0.020 (0.028)	0.019 (0.027)
Spouse Working Full Time	0.004 (0.012)	0.008 (0.012)	-0.039** (0.018)	-0.036** (0.018)
Spouse Working Part Time	0.032 (0.021)	0.032 (0.021)	0.008 (0.028)	0.009 (0.028)
PhD Age Obtained	-0.007*** (0.001)	-0.007*** (0.001)	-0.010*** (0.002)	-0.010*** (0.002)
PhD Highest Research Inst.	0.071*** (0.009)	0.072*** (0.009)	0.048** (0.018)	0.047** (0.018)
Full Rank Faculty Count (log scaled)	-0.001 (0.021)	-0.001 (0.021)	0.021 (0.025)	0.019 (0.026)
Associate Rank Faculty Count (log scaled)	-0.005 (0.013)	-0.004 (0.013)	-0.006 (0.022)	-0.004 (0.022)
Assistant Rank Faculty Count (log scaled)	-0.012 (0.020)	-0.012 (0.020)	-0.015 (0.024)	-0.015 (0.024)
Full Rank Women Faculty Percentage	0.094 (0.084)	0.094 (0.084)	0.117 (0.094)	0.116 (0.093)
Associate Rank Women Faculty Percentage	-0.002 (0.065)	-0.002 (0.064)	-0.042 (0.120)	-0.032 (0.124)
Assistant Rank Women Faculty Percentage	0.009 (0.073)	0.009 (0.073)	0.003 (0.088)	-0.004 (0.089)
Undergraduate Student Count (log scaled)	0.021*** (0.004)	0.021*** (0.004)	0.015*** (0.005)	0.015*** (0.005)
Graduate Student Count (log scaled)	-0.012*** (0.003)	-0.012*** (0.003)	-0.010** (0.005)	-0.010** (0.005)
Highest Research Inst.	-0.189*** (0.025)	-0.189*** (0.025)	-0.228*** (0.030)	-0.228*** (0.030)
Pop. Density (log scaled)	0.046 (0.069)	0.045 (0.068)	0.116 (0.102)	0.114 (0.102)
Business Density (log scaled)	-0.002 (0.038)	-0.002 (0.038)	0.006 (0.056)	-0.002 (0.056)
Employment Density (log scaled)	-0.069 (0.067)	-0.069 (0.066)	-0.145* (0.086)	-0.138 (0.086)
Median Household Income (log scaled)	-0.085 (0.076)	-0.085 (0.075)	-0.063 (0.114)	-0.067 (0.110)
Unemployment Rate	-0.010** (0.004)	-0.010** (0.004)	-0.006 (0.008)	-0.006 (0.008)
Intercept	1.771 -0.806	1.763 -0.802	1.618 -1.221	1.643 -1.192
Other Controls	Yes	Yes	Yes	Yes
No. of Observations	11,941 [†]	11,941	5,147	5,125 [‡]
Adj. R-squared	0.19	0.19	0.20	0.21

Notes: The model is OLS regression. The outcome variable is tenure promotion. Other controls (not reported in the table): PhD graduation year dummies, PhD field of study, first SDR response year dummies, and state fixed effects. Standard errors are clustered at state level. [†] 335 (2.7%) observations are dropped due to missing values for employer characteristics: some institutions did not report faculty counts or enrollments in certain years. [‡] 23 (0.4%) observations are dropped due to missing child care availability data caused by missing or inaccurate facility location information. ***, p < 0.01. **, p < 0.05, *, p < 0.1.

Extended Data Table 2. Effects of Childcare Deserts on Tenure: Logit Model Results

	All		If Has Child	
	(1)	(2)	(3)	(4)
Female	-0.255*** (0.058)	-0.147** (0.067)	-0.347*** (0.080)	-0.163 (0.099)
Has Child		0.078 (0.076)		
Female X Has Child		-0.262*** (0.079)		
Desert				0.096 (0.106)
Female X Desert				-0.338*** (0.117)
Controls	Yes	Yes	Yes	Yes
No. of Observations	11,941	11,941	5,147	5,125
LogLik	-6210.32	-6205.79	-2640.80	-2624.29

Notes: The model is the Logit model. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

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

Extended Data Table 3. Effects of Childcare Deserts on Tenure: Robustness with County Fixed Effects and Institution Fixed Effects Instead of State Fixed Effects

Sample:	All		If Has Child	
Fixed Effects Used:	County F.E.	Institution F.E.	County F.E.	Institution F.E.
	(1)	(2)	(3)	(4)
Female	-0.028** (0.011)	-0.029** (0.012)	-0.025 (0.020)	-0.029 (0.021)
Has Child	0.010 (0.016)	0.010 (0.016)		
Female X Has Child	-0.040** (0.017)	-0.039** (0.018)		
Desert			0.025 (0.025)	0.034 (0.025)
Female X Desert			-0.058** (0.026)	-0.050* (0.027)
Controls	Yes	Yes	Yes	Yes
No. of observations	11,941	11,941	5,125	5,125
Adj. R-squared	0.22	0.24	0.24	0.27

Notes: The model is the OLS regression. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and county fixed effects (Columns 1 and 3), or institution fixed effects (Columns 2 and 4). Standard errors are clustered at the county level in Columns (1) and (3), and at the institution level in Columns (2) and (4). There are 128, 360, 155, 366 singleton observations in Columns (1), (2), (3), and (4), respectively.

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

Extended Data Table 4. Effects of Childcare Deserts on Tenure: Excluding States with Recent Public Preschool Expansions Targeting 4-Year-Old

Excluded States:	D.C. (1)	Multiple States (2)
Female	-0.031* (0.017)	-0.028 (0.019)
Has Child	0.016 (0.019)	0.016 (0.022)
Female X Has Child	-0.052** (0.021)	-0.058** (0.022)
Controls	Yes	Yes
No. of Observations	5,102	4,516
Adj. R-squared	0.21	0.21

Notes: According to The State of Preschool⁹ issued annually by the National Institute for Early Education Research, some states have started to offer public preschools in recent years, targeting primarily 4-year-old (with the exception of Washington, D.C., which offers them to both 3- and 4-year-old). However, since publicly-funded preschools often affiliate with public schools, their facilities may not appear in the Infogroup database with a *primary* SIC code for childcare facilities. Therefore, the childcare availability measure we construct may underestimate the childcare capacity, in particular, for older aged children, in these states in recent years. This table presents analyses excluding these states to ensure the robustness of the results. Column (1) excludes Washington, D.C., whereas Column (2) excludes Washington, D.C., Vermont, Oklahoma, Florida, West Virginia, Wisconsin, and Georgia. The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

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

Extended Data Table 5. Effects of Childcare Deserts on Tenure: Robustness with Different Regional Controls at Commuting Zone, County, and Census Tract Levels

Regional Controls Used:	Commuting Zone (1)	County (2)	Census Tract (3)
Female	-0.032* (0.017)	-0.032* (0.017)	-0.033* (0.018)
Desert	0.016 (0.019)	0.017 (0.019)	0.024 (0.021)
Female X Desert	-0.052** (0.021)	-0.052** (0.021)	-0.052** (0.021)
Controls	Yes	Yes	Yes
No. of Observations	5,125	5,123	5,140
Adj. R-squared	0.21	0.20	0.20

Notes: The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level. Column (1) includes regional characteristics (i.e., population density, business density, employment density, median household income, and unemployment rate) at commuting zone level, where the commuting zone delineations are obtained from the USDA's Economic Research Services for years before 2010 and the Pennsylvania State University's Labor-sheds for Regional Analysis website. Column (2) includes regional characteristics (i.e., population density, business density, employment density, median household income, and unemployment rate) at county level. Column (3) includes population density, business density, and employment density at census tract level. Note median household income and unemployment rate are not available at census tract level. The number of observations in Column (3) is slightly larger than those in Columns (1) and (2) because median income and unemployment data are not available for some observations in Columns (1) and (2).

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

Extended Data Table 6. Effects of Childcare Deserts on Tenure: Different Child Age Groups and Observation Windows Used to Define Researchers with Yong Children

Child Age: Years After Graduation:	Under Age 6 Within 6 Yrs (1)	Under Age 6 Within 3 Yrs (2)	Under Age 3 Within 3 Yrs (3)
Female	-0.032* (0.017)	-0.028 (0.023)	-0.003 (0.025)
Desert	0.016 (0.019)	0.025 (0.020)	0.030 (0.020)
Female X Desert	-0.052** (0.021)	-0.061** (0.023)	-0.067** (0.026)
Controls	Yes	Yes	Yes
No. of Observations	5,125	3,817	3,018
Adj. R-squared	0.21	0.21	0.21

Notes: The model is the OLS regression. The outcome is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level. Column (1) uses the subsample of researchers who reported having children under age six within the first six years after doctoral graduation. Column (2) uses the subsample of researchers who reported having children under age six within the first three years after doctoral graduation. Column (3) uses the subsample of researchers who reported having children under age two within the first three years after graduation.

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

Extended Data Table 7. Effects of Childcare Deserts on Tenure: Robustness with Different Childcare Desert Cutoffs

Cutoffs:	One Third (1)	One Fourth (2)	One Fifth (3)	One Sixth (4)
Female	-0.032* (0.017)	-0.034* (0.019)	-0.030* (0.017)	-0.032* (0.016)
Desert	0.016 (0.019)	0.017 (0.019)	0.019 (0.019)	0.019 (0.020)
Female X Desert	-0.052** (0.021)	-0.056** (0.024)	-0.067*** (0.021)	-0.067*** (0.022)
Controls	Yes	Yes	Yes	Yes
No. of Observations	5,125	5,125	5,125	5,125
Adj. R-squared	0.21	0.21	0.21	0.21

Notes: The model is the OLS regression. The outcome is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level. Column (1) to (4) use the following supply-to-demand ratio cutoffs to define childcare deserts: 1/3, 1/4, 1/5, and 1/6.

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

Extended Data Table 8. Effects of Childcare Deserts on Tenure: Childcare Deserts Measured Based on Supply-to-Demand Ratio in the First Response Year (Column 1) versus the First after graduation Year (Column 4), in Years Around the First Response Year (Columns 2 and 3), and in Years around the First after graduation Year (Columns 5 and 6)

Time Window Used to Measure Desert:	1st Resp. Yr (1)	1st Resp. ± 1 Yr (2)	1st Resp. within 3 Yrs (3)	Post PhD 1st Yr (4)	Post PhD ± 1 Yr (5)	Post PhD within 3 Yrs (6)
Female	-0.032* (0.017)	-0.039** (0.018)	-0.031* (0.018)	-0.038 (0.025)	-0.024 (0.025)	-0.034 (0.025)
Desert	0.016 (0.019)	-0.001 (0.019)	0.013 (0.018)	0.008 (0.022)	0.012 (0.022)	0.015 (0.022)
Female X Desert	-0.052** (0.021)	-0.041* (0.023)	-0.052** (0.024)	-0.048 (0.029)	-0.060** (0.029)	-0.055* (0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	5,125	5,134	5,097	3,808	3,607	3,819
Adj. R-squared	0.21	0.21	0.20	0.21	0.2	0.21

Notes: The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level. In Column (1), childcare desert is measured based on supply-to-demand ratio in the first response year of each respondent. In Column (2), childcare desert is measured based on the average supply-to-demand ratio ± 1 year around the first response year. In Column (3), childcare desert is measured based on the average supply-to-demand ratio within three years following the first response year. In Column (4), childcare desert is measured based on the supply-to-demand ratio in the first year after doctoral graduation and at the first reported employer location within three years after graduation. In Column (5), childcare desert is measured based on the average supply-to-demand ratio ± 1 year around the first graduation year and at the first reported employer location within three years after graduation. In Column (6), childcare desert is measured based on the average supply-to-demand ratio within three years following the doctoral graduation and at the first reported employer location within three years after graduation. ***, $p < 0.01$. **, $p < 0.05$, *, $p < 0.1$.

Extended Data Table 9. Effects of Childcare Deserts on Tenure: Childcare Deserts Measured based on Supply-to-Demand Ratio in the Focal Census Tract and Its Neighboring Tracts

Geo Areas:	Census Tract	Census Tract and Neighboring Tracts	Census Tract and Neighboring Tracts Separately Controlled
	(1)	(2)	(3)
Female	-0.032* (0.017)	-0.050*** (0.016)	-0.022 (0.019)
Desert	0.016 (0.019)	0.013 (0.024)	0.015 (0.019)
Female X Desert	-0.052** (0.021)	-0.037 (0.031)	-0.050** (0.020)
Neighbor Tract Desert			0.026 (0.021)
Female X Neighbor Tract Desert			-0.035 (0.024)
Controls	Yes	Yes	Yes
No. of Observations	5125	5147	5125
Adj. R-squared	0.21	0.20	0.21

Notes: The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

Column (1) defines childcare desert based on the supply-to-demand ratio in the focal census tract. Column (2) defines childcare desert based on the supply-to-demand ratio in the focal census tract and all of its neighboring tracts. Column (3) defines two childcare desert measures based on supply-to-demand ratios in the focal tract, and in all the neighboring tracts, respectively.

Results in Column (2) indicate that childcare desert measured based on the focal census tract and all its neighboring tract has a negative impact on the tenure gender gap (-3.1%), although statistically insignificant ($p\text{-value} > 0.1$). Results in Column (3) indicate that focal tract desert has a statistically significant impact on the tenure gender gap (-5.0%, $p\text{-value} < 0.05$) while neighboring tract desert has a smaller and statistically insignificant impact (-3.5%, $p\text{-value} > 0.05$). This suggests that childcare availability has a diminishing impact as it gets farther away from the workplace location.

Column (2) has slightly more observations than the others because childcare desert is defined based on the aggregate supply-to-demand ratio in the focal and neighboring tract. The value is non-missing as long as we have data on one of the tracts.

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

Extended Data Table 10. Effects of Childcare Deserts on Tenure: Distance-Based Childcare Deserts Measures

Radius Based Geo Areas:	1 Mile	2 Miles	5 Miles	10 Miles	UIC-based Radius	RUCA & UIC-based Radius
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.051*** (0.018)	-0.051*** (0.013)	-0.057*** (0.014)	-0.058*** (0.012)	-0.051*** (0.013)	-0.050*** (0.013)
Desert	0.023 (0.019)	0.022 (0.024)	0.010 (0.037)	0.012 (0.048)	0.022 (0.027)	0.015 (0.026)
Female X Desert	-0.022 (0.026)	-0.037 (0.026)	-0.029 (0.040)	-0.062 (0.075)	-0.063* (0.033)	-0.058* (0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	5,147	5,147	5,147	5,147	5,147	5,058
Adj. R-squared	0.20	0.20	0.20	0.20	0.20	0.20

Notes: The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level. Columns 1 to 4 define childcare desert based on the supply-to-demand ratio within 1, 2, 5, and 10-mile radius of the workplace location. Columns 5 and 6 augment these radius-based definitions based on Urban Influence Codes (UIC) and Rural-Urban Commuting Area Codes (RUCA) published by the USDA's Economic Research Service. Different radius cutoffs are used under different UIC and/or RUCA codes. See Extended Data Table 11 for how cutoffs are chosen based on UIC and RUCA categories.

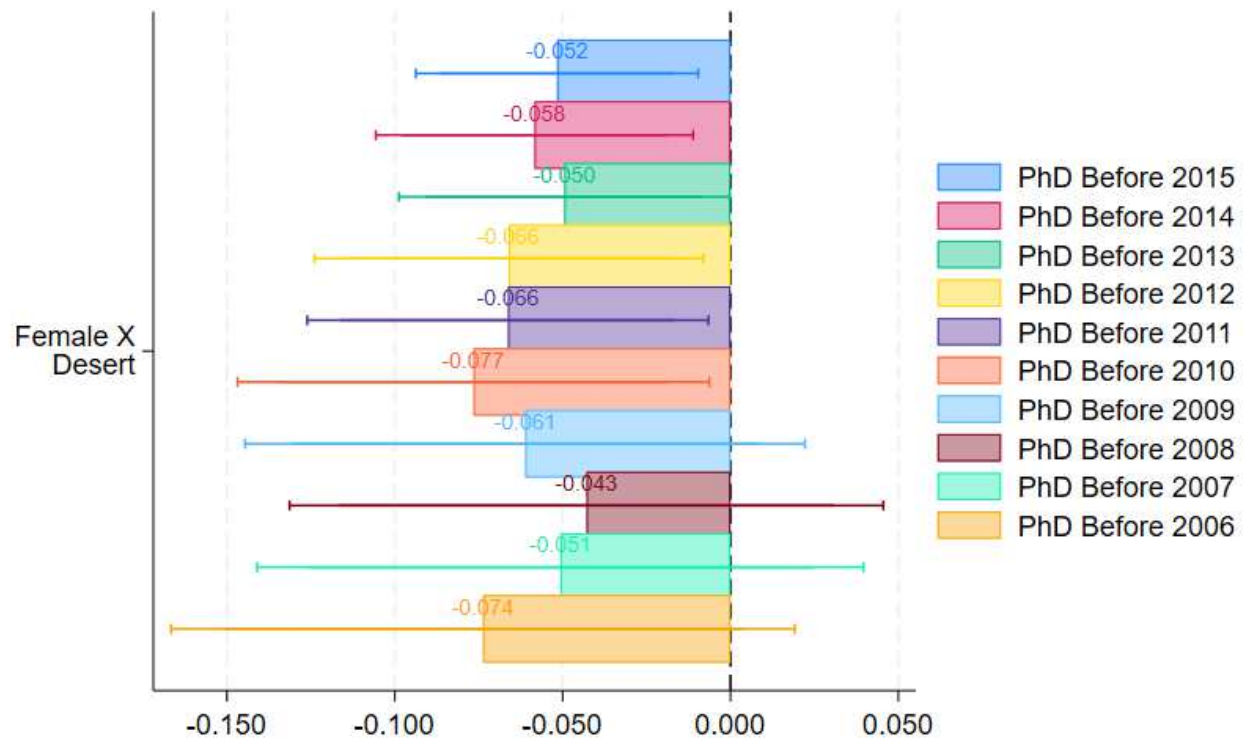
***, $p < 0.01$. **, $p < 0.05$, *, $p < 0.1$.

Extended Data Table 11. Radius Measures based on Urban Influence Codes (UIC) and Rural-Urban Commuting Area Codes (RUCA)

UIC Based Radius Measure		
UIC Codes	UIC Descriptions	Radius Used
1	Large Metropolitan Counties	2.5 miles
2	Small Metropolitan Counties	5 miles
3 and above	Non-metropolitan Counties	10 miles

RUCA and UIC Based Radius Measure		
UIC and RUCA Codes	Descriptions	Radius Used
UIC=1 and RUCA<4	Large Metropolitan Counties, Non Rural Tracts	2.5 miles
UIC=2 and RUCA<4	Small Metropolitan Counties, Non Rural Tracts	5 miles
UIC≥3 or RUCA≥4	Non Metropolitan Counties, or Rural Tracts	10 miles

Notes: These cutoffs are used in Extended Data Table 10 Columns 5 and 6 to define childcare deserts. Data are obtained from the USDA's Economic Research Service. Urban Influence Code (UIC) is a classification scheme that distinguishes metropolitan counties by population size of their metro area, and nonmetropolitan counties by size of the largest city or town and proximity to metro and micropolitan areas. The metro and nonmetro categories are further divided into two metro and 10 nonmetro categories, resulting in a 12-part county classification. UIC was updated in 1993, 2003, and 2013. The rural-urban commuting area (RUCA) codes classify US census tracts using measures of population density, urbanization, and daily commuting. Whole numbers (1–10) delineate metropolitan, micropolitan, small town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows. A number greater than equal to 4 typically indicates rural areas. RUCA was updated in 1990, 2000, and 2010.



Extended Data Figure 6. Effects of Childcare Deserts on the Tenure Gender Gap: Exclude Recent PhD Graduates by Graduation Year | Shown in the figure are the effects (point estimates and 95% confidence intervals) of childcare deserts on the tenure gender gap when excluding recent doctoral graduates based on their graduation years. Those who graduated more recently may have their tenure clock or tenure outcome impacted by the COVID-19 pandemic, which placed significant childcare burden on young families. These results shown in the figure demonstrate our findings are robust to such concerns. Note as more years' of data are excluded (for example, excluding all those who graduated 2009 and after), the estimates become statistically insignificant, but the effect sizes are still consistent. The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

Extended Data Table 12. Impact of Childcare Deserts on Tenure Promotion: Controlling for Postdoc Plans or Postdoc Commitments Upon Graduation

Postdoc Definition: Obs. Length After Graduation	Postdoc Plan			Postdoc Commitment		
	≥ 7 Yrs (1)	≥ 7 Yrs (2)	≥ 9 Yrs (3)	≥ 7 Yrs (4)	≥ 7 Yrs (5)	≥ 9 Yrs (6)
Female	-0.030 (0.018)	-0.036 (0.030)	-0.037 (0.031)	-0.030 (0.018)	-0.036 (0.026)	-0.038 (0.027)
Desert	0.013 (0.021)	0.025 (0.037)	0.029 (0.040)	0.014 (0.021)	0.022 (0.033)	0.025 (0.036)
Female X Desert	-0.050** (0.021)	-0.060* (0.035)	-0.066* (0.038)	-0.051** (0.021)	-0.061* (0.031)	-0.068* (0.035)
Postdoc	-0.055*** (0.014)	-0.052 (0.032)	-0.043 (0.035)	-0.042** (0.016)	-0.046 (0.030)	-0.037 (0.034)
Female X Postdoc		0.014 (0.044)	0.014 (0.047)		0.016 (0.038)	0.018 (0.040)
Desert X Postdoc		-0.026 (0.047)	-0.035 (0.050)		-0.019 (0.040)	-0.030 (0.044)
Female X Desert X Postdoc		0.022 (0.052)	0.028 (0.056)		0.026 (0.044)	0.033 (0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	4826	4826	4408	4819	4819	4401
Adj. R-Sq	0.20	0.20	0.19	0.20	0.20	0.19

Notes: In sciences and engineering, many PhD recipients take postdoctoral positions prior to starting tenure track positions, which will lead to a delay of start in tenure clock. In some fields⁶⁸, the rates of taking postdoc positions differ by gender. This set of analyses therefore examines the robustness of the results accounting for post-doc status upon graduation.

In Columns 1 to 3, postdoc equals one if an individual reports planning to take a postdoc position (either seeking or having committed to such a position), and zero otherwise. In Columns 4 to 6, postdoc equals one if an individual reports having committed to a postdoc position, and zero otherwise. Tenure outcome is measured at least seven years after graduation in Columns 1, 2, 3, and 4. As a robustness and considering typical postdoc lengths (i.e., 2 years), we extend the observation window for tenure to nine years in Columns 3 and 6. Columns 1 and 4 include only the main effect of postdoc, while other columns include both the main effect of postdoc and its interactions with gender and childcare deserts.

The results in this table indicate that the impact of childcare desert on tenure gender gap is consistent with and without the controls of postdoc. The results are again consistent if we extend the observation window by two years (typical post doc periods). In Column 5 and 6, we can see that postdoc has a positive, yet small and statistically non-significant moderating effects on the differential impact of childcare deserts (0.026 and 0.033, p-value>0.1). In other words, seeking a post doc position, which extends the pre-tenure time, may reduce the impact of childcare desert on tenure gender gap, but the scale of the effect is small and statistically nonsignificant.

The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

***, p< 0.01. **, p< 0.05, *, p< 0.1.

Extended Data Table 13. Impact of Childcare Desert on Tenure Promotion: Controlling for Institution Fixed Effects and Institution Tenure Stoppage Policy

Sample:	Without Postdoc Plans Upon Graduation (1)	Without Postdoc Commitments Upon Graduation (2)
Female	-0.028 (0.102)	-0.046 (0.085)
Desert	-0.060 (0.062)	-0.022 (0.053)
Female X Desert	-0.083* (0.044)	-0.100** (0.040)
Tenure Stoppage Policy		
Female Only	0.024 (0.160)	0.197 (0.125)
Gender Neutral	-0.004 (0.089)	0.084 (0.069)
Female X Tenure Stoppage Policy		
Female X Female Only	0.091 (0.119)	-0.018 (0.096)
Female X Gender Neutral	0.027 (0.096)	0.055 (0.081)
Controls	Yes	Yes
No. of Obs	861	988
Adj. R-Sq	0.17	0.17

Notes: This set of analyses examines the robustness of the results accounting for institution fixed effects and institution-specific tenure stoppage policy. Many research-intensive universities have adopted tenure clock stopping policies over recent decades. These policies allow tenure-track faculty to pause their tenure clock for one year following childbirth or adoption. Universities have implemented two types of policies at different times: (1) female-only policies, which apply exclusively to female faculty, and (2) gender-neutral policies, which apply to both male and female faculty. Recent literature has found gendered effects of tenure stoppage policies among 1,392 researchers who were hired as assistant professors in the top 50 US economics departments between 1980 to 2005¹⁸. We further collected data on tenure stoppage policies of these institutions until 2024. See Extended Data Table 14 for the list of universities, types of tenure clock stoppage policies they have adopted and the timing. Column 1 includes researchers without postdoc plans upon graduation, and Column 2 includes researchers without postdoc commitment upon graduation.

The results are consistent after controlling for institution-specific, time-variant tenure stoppage policy, as well as institution fixed effects. We would like to note since our sample starts in 1997, for most institutions, the majority of the observation years (87%) are during the period where they have moved to the gender-neutral tenure stoppage policy. Female-only policy only represents 6% of the observations. And no tenure stoppage policy represents 7% of the observations. We do not find a statistically significant effect on female-only nor gender-neutral policy themselves likely due to lack of variation (most institutions have adopted gender neutral policies).

The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and institution fixed effects. Standard errors are clustered at the institution level.

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

Extended Data Table 14. Tenure Clock Stoppage Policy By Institution 1980 to 2024

University	Female Only Policy	Gender Neutral Policy
Arizona State University	2003	2007
Boston College		1993
Boston University		2010
Carnegie Mellon University	1992	2002
Columbia University	1995	1997
Cornell University	2003	2004
Duke University		2003
Georgetown University		1999
Georgia Institute of Technology		2009
Harvard University		2001
Indiana University		2021
Johns Hopkins University		2000
Massachusetts Institute of Technology		2001
Michigan State University		1996
New York University	1999	2004
North Carolina State University–Raleigh		2002
Northwestern University		1981
Ohio State University		1996
Pennsylvania State University–University Park	1990	2017
Princeton	1970	1991
Purdue University–West Lafayette		1991
Rice University		1993
Rutgers University–Newark and New Brunswick		1992
Stanford University	1971	2002
Texas A&M University–College Station		2003
University of Arizona		1990
University of California Davis	1988	1997
University of California San Diego	1988	1997
University of California Santa Barbara	1988	1997
University of California–Berkeley	1988	1997
University of California–Irvine	1988	1997
University of California–Los Angeles	1988	1997
University of Chicago	1996	2009
University of Florida		2004
University of Illinois at Urbana-Champaign		1999
University of Iowa		1993
University of Maryland–College Park		1996
University of Michigan–Ann Arbor		1990
University of Minnesota–Twin Cities		1992
University of North Carolina–Chapel Hill		2004
University of Pennsylvania		1997
University of Rochester		1993
University of Southern California		1993
University of Texas–Austin	1997	2015
University of Virginia	1987	2000
University of Washington		2005
University of Wisconsin–Madison		1994
Vanderbilt University		2003
Washington University in St. Louis		1999
Yale University	2003 [†]	2008

Notes: The list is based on Antecol et al. (2018), which studies how tenure clock stoppage policies affect tenure outcome among 1,392 researchers who were hired as assistant professors in the top 50 US economics departments between 1980 to 2005¹⁸. We collected data from 2005 to 2024 and updated the table. Data are collected from current and archived University faculty handbooks. [†] Unable to retrieve archival data prior to 2003 from either public access or direct inquiry.

Extended Data Table 15. Impact of Childcare Desert on Tenure Promotion: Controlling for Percentages of Democratic Votes by Election Year By County

	(1)	(2)
Female	-0.103 (0.074)	-0.100 (0.073)
Desert	0.018 (0.019)	0.018 (0.019)
Female X Desert	-0.054** (0.021)	-0.054** (0.021)
% of Democratic Votes	-0.127 (0.094)	-0.123 (0.093)
Female X % of Democratic Votes	0.120 (0.119)	0.121 (0.122)
Controls	Yes	Yes
No. of Obs	5117	5117
Adj. R-Sq	0.21	0.21

Notes: This set of analyses examines the robustness of the results accounting for the percentage of democratic votes at the county level by election year. Data on percentages of democratic votes are obtained from Presidential Elections in US Counties (1868-2020)⁶⁹. The percentage of democratic votes in Column 1 is calculated as the ratio of number of votes won by the Democratic presidential nominee divided by the total number of Democratic and Republican votes cast in a given county in the most recent presidential election. The percentage of democratic votes in Column 2 is calculated as the ratio of number of votes won by the Democratic presidential nominee divided by the total number of votes cast in a given county in the most recent presidential election. The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

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

Extended Data Table 16. Impact of Childcare Desert on Tenure Promotion: Controlling for Facility Density and Capacity Concentration Level

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.032*	-0.032*	-0.032*	-0.046*	-0.032*	-0.044
	(0.017)	(0.017)	(0.017)	(0.025)	(0.017)	(0.028)
Desert	-0.012	-0.012	0.009	0.018	0.018	0.015
	(0.020)	(0.020)	(0.018)	(0.022)	(0.022)	(0.023)
Female X Desert	-0.052**	-0.052**	-0.052**	-0.045**	-0.053**	-0.047**
	(0.021)	(0.021)	(0.021)	(0.023)	(0.021)	(0.025)
Center Density	-0.003	-0.002			-0.003	-0.002
	(0.002)	(0.003)			(0.002)	(0.003)
Female X Center Density		-0.000				-0.001
		(0.004)				(0.004)
HHI			0.015	0.005	0.017	0.006
			(0.018)	(0.021)	(0.018)	(0.021)
Female X HHI				0.022		0.023
				(0.033)		(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	5125	5125	5125	5125	5125	5125
Adj. R-Sq	0.21	0.21	0.21	0.21	0.21	0.21

Notes: This set of analyses examines the robustness of the results accounting for childcare capacity concentration, childcare facility density, and childcare facility density by type (school-based versus service-based centers), as well as their interactions with gender. Childcare capacity concentration is measured using the Herfindahl-Hirschman Index (HHI) at the census tract level. Childcare center density is measured as the number of childcare facilities (primary SIC code: 8351) divided by the land area at the census tract level.

The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. The outcome variable is tenure promotion. Standard errors are clustered at the state level.

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

Extended Data Table 17. Impact of Childcare Desert on Tenure Promotion: Controlling For County Level Median or 75th Percentile Center-Based Childcare Price

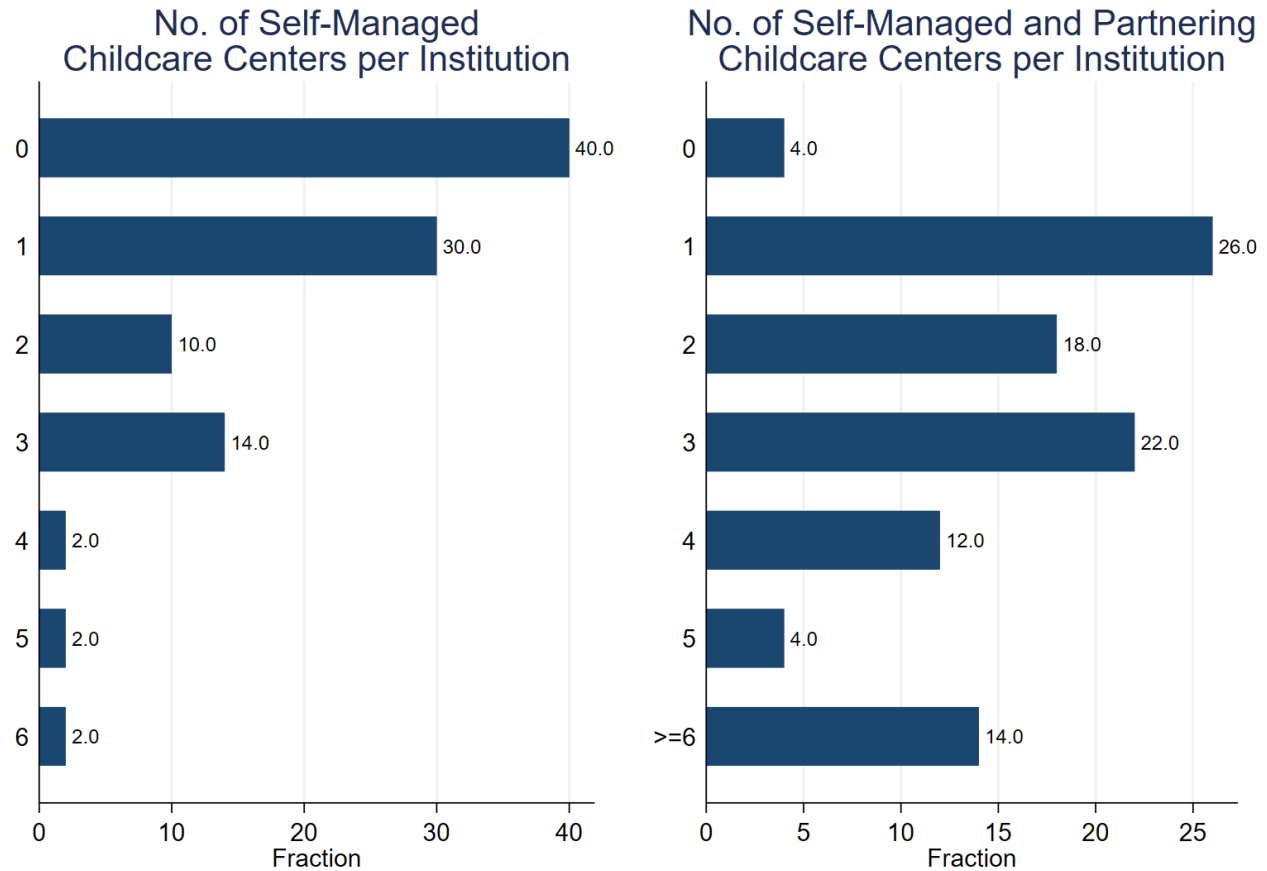
	(1)	(2)	(3)
Female	-0.020 (0.029)	0.034 (0.259)	0.003 (0.256)
Desert	-0.019 (0.033)	-0.021 (0.032)	-0.022 (0.032)
Female X Desert	-0.048 (0.045)	-0.048 (0.046)	-0.048 (0.045)
Median Price		-0.106 (0.108)	
Female X Median Price		-0.010 (0.050)	
75th Percentile Price			-0.140 (0.096)
Female X 75th Percentile Price			-0.004 (0.047)
Controls	Yes	Yes	Yes
No. of Obs	2393	2393	2393
Adj. R-Sq	0.21	0.21	0.21

Notes: This set of analyses examines the robustness of the results accounting for median and 75th percentile center-based childcare prices at county level. Childcare price data are obtained from the US Department of Labor, Women’s Bureau National Database of Childcare Prices, available at the county level from 2008 to 2018. Data are collected through market rate surveys (MRS) conducted by states either annually or biennially, and more recently, every three years. These surveys collect prices of regulated childcare centers, typically located in commercial buildings and serve multiple groups or classrooms of similarly aged children. Note significant amounts of data are missing due to inconsistent reporting or low response rates. Only 16-17% price data are directly reported, and rest are imputed (different age group, weekly pricing conversion, statewide to county-level, 50th/75th percentile, and in between years imputations). 32% price data are still missing even after imputation.

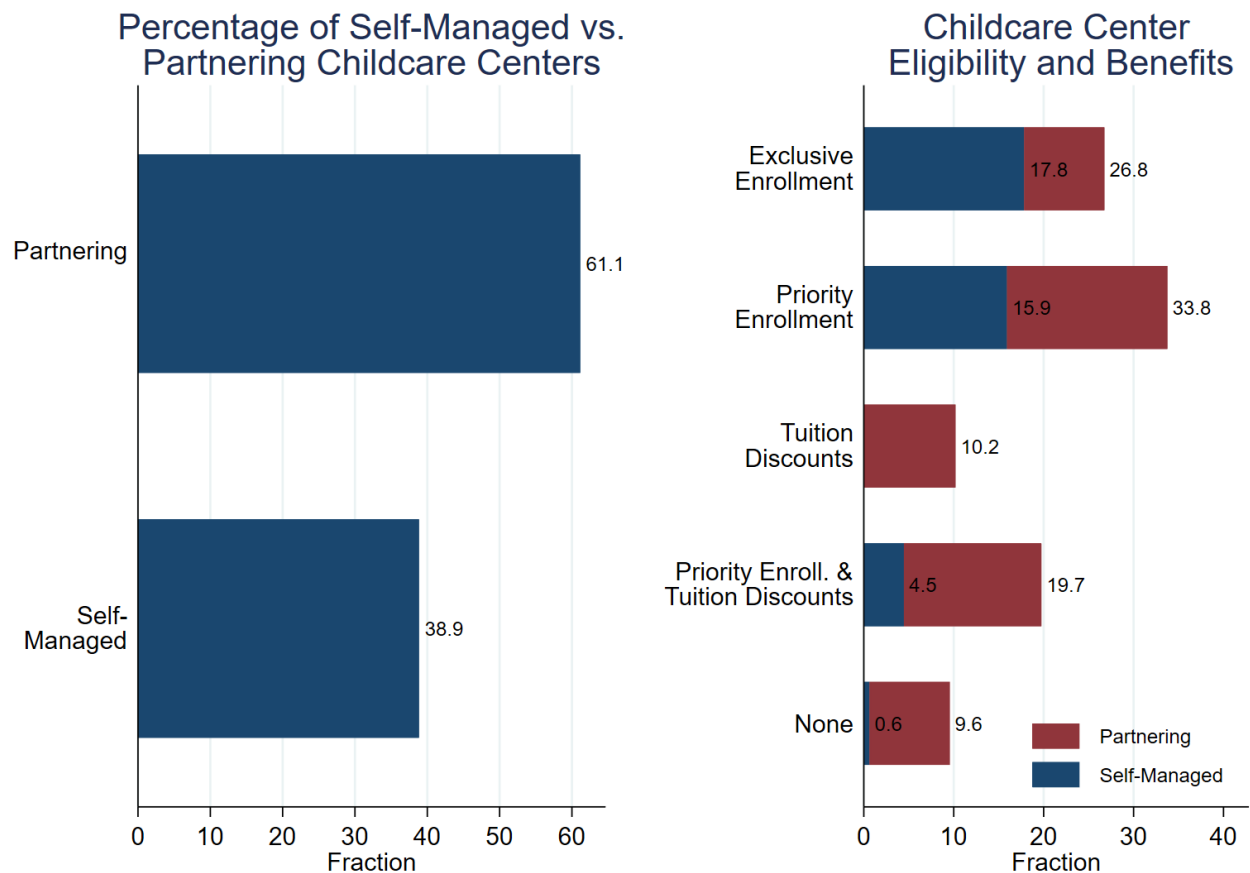
Column 1 replicates the results from the main analysis on the sample where county level price data are available. Column 2 includes median price of center-based full-time weekly care and its interaction with gender as additional controls. Column 3 includes 75th percentile price and its interaction with gender as additional controls.

The model is the OLS regression. The outcome variable is tenure promotion. The controls include individual, employer and regional characteristics listed in Table 1, PhD graduation year dummies, first SDR response year dummies, and state fixed effects. Standard errors are clustered at the state level.

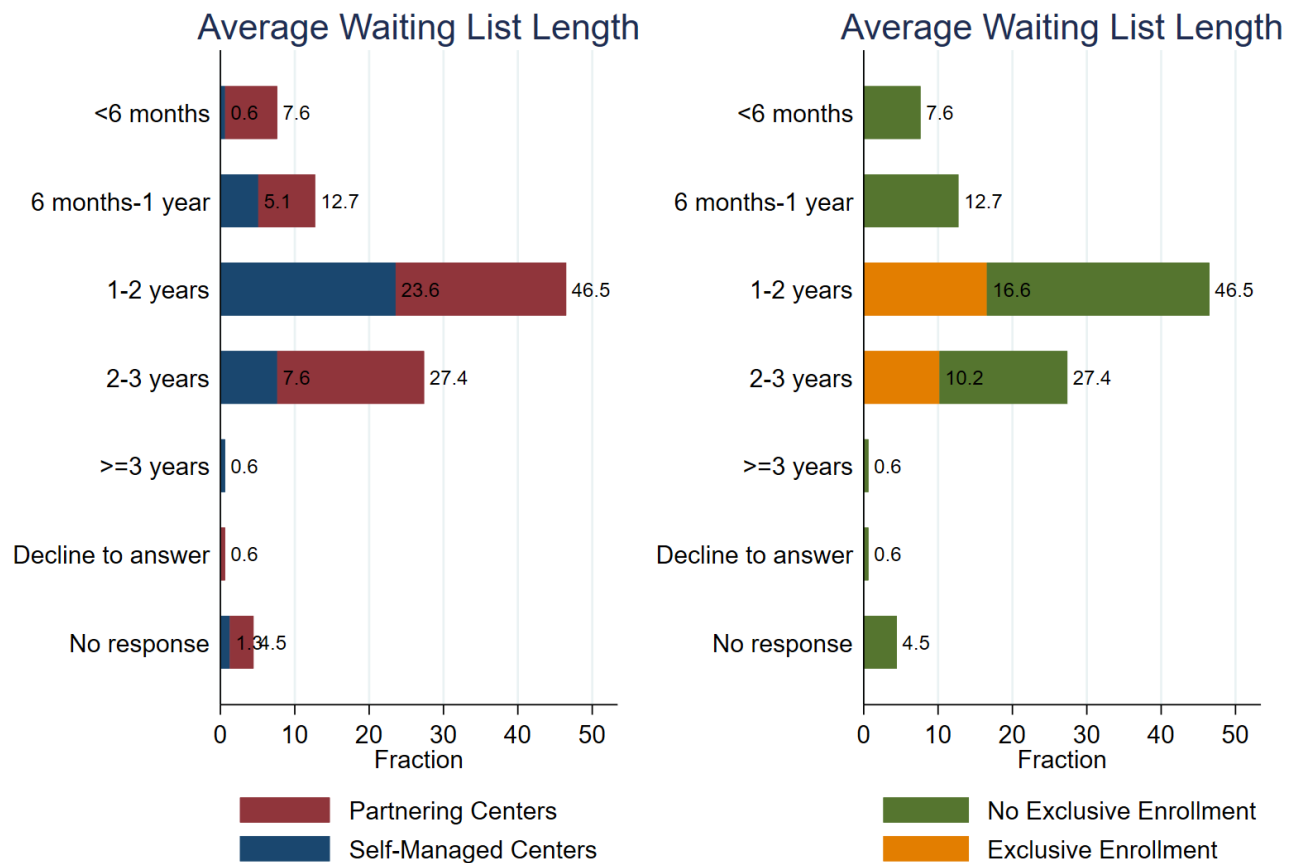
***, $p < 0.01$. **, $p < 0.05$, *, $p < 0.1$.



Extended Data Figure 7. Histograms of the Number of Childcare Centers at Top 50 US Research Institutions Ranked by R&D Expenditures | The figure displays histograms showing the number of childcare centers at the top 50 U.S. institutions, ranked by Research & Development Expenditures. The list of institutions are obtained from the National Science Foundation [webpage](#). The most recent list (i.e., 2022) is used. Percentages are shown next to the bars. The figure on the left shows the histogram of self-managed childcare centers per institution. These centers are typically managed by universities' human resources departments. The figure on the right shows the histogram of self-managed and partnering childcare centers per institution. Partnering centers are those managed by either independent childcare providers or childcare chains. These centers may provide university affiliates (i.e., faculty, staff, students) childcare benefits such as priority enrollment and tuition discounts. Data are obtained in summer 2024.



Extended Data Figure 8. Childcare Centers by Type—Self-Managed versus Partnering—and by Enrollment Eligibility and Benefits Provided at Top 50 US Research Institutions | Figure on the left displays the percentages of childcare centers managed by the institution itself (38.9%) and by partnering providers (61.1%). Sample is all childcare centers at top 50 US research institutions ranked by R&D expenditures in 2022. N=157 centers. The figure on the right displays the percentages of centers offering exclusive enrollment (26.8%), priority enrollment (33.8%), tuition discounts (10.2%), and priority enrollment and tuition discounts (19.7%) to university affiliates including faculty, staff, and students. **Exclusive enrollment** means only university affiliates (faculty, staff, and students) are eligible to enroll their children in the center. **Priority enrollment** means enrollment is open to the community; however, university affiliates receive waiting list priority (or dedicated space) for enrollment. **Tuition discounts** means enrollment is open to the community; however, university affiliates receive tuition discounts for their enrolled children. Typical discount levels are 5%, 10%, and 15% off. Tuition discounts may be offered simultaneously with priority enrollment. Data are obtained in summer 2024.



Extended Data Figure 9. Average Waiting List Length by Childcare Center Types and Enrollment Eligibility | The figure on the left displays center-level average waiting list lengths for self managed and partnering childcare centers at top 50 US research institutions. N = 157 centers. Percentages are displayed next to the bars. Majority of centers (46.5%) have an average waiting list length of 1 (incl.) to 2 years, followed by 26.3% of centers with an average waiting length of 2 (incl.) to 3 years, and 12.6% of centers with an average waiting length of 6 months (incl.) to 1 year. One center has a waiting list of more than 3 years. Moreover, 4.5% of centers did not respond to the inquiry, and one center declined to respond. Taking the middle point of each category as the representative value (e.g., 18 months as the average for the 1 to 2 years range) and taking 42 months as the representative value for the > 3 years range, we obtain an average waiting length of 20.6 months across all centers (SD = 7.4 months). We do not observe a statistically significant difference between self-managed versus partnering centers. The figure on the right displays center-level average waiting list lengths for centers with and without exclusive enrollment policy. Centers with exclusive enrollment for university affiliates have a longer average waiting list length, 22.6 months versus 19.8 months, as compared to centers without exclusive enrollment policies (p-value<0.05). Waiting list length data are obtained through center webpage searches (12%), email inquiries (22%) and phone (66%) inquiries in summer 2024.

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