Online Appendix for ”Earnings Dynamics, Changing Job Skills, and STEM Careers”

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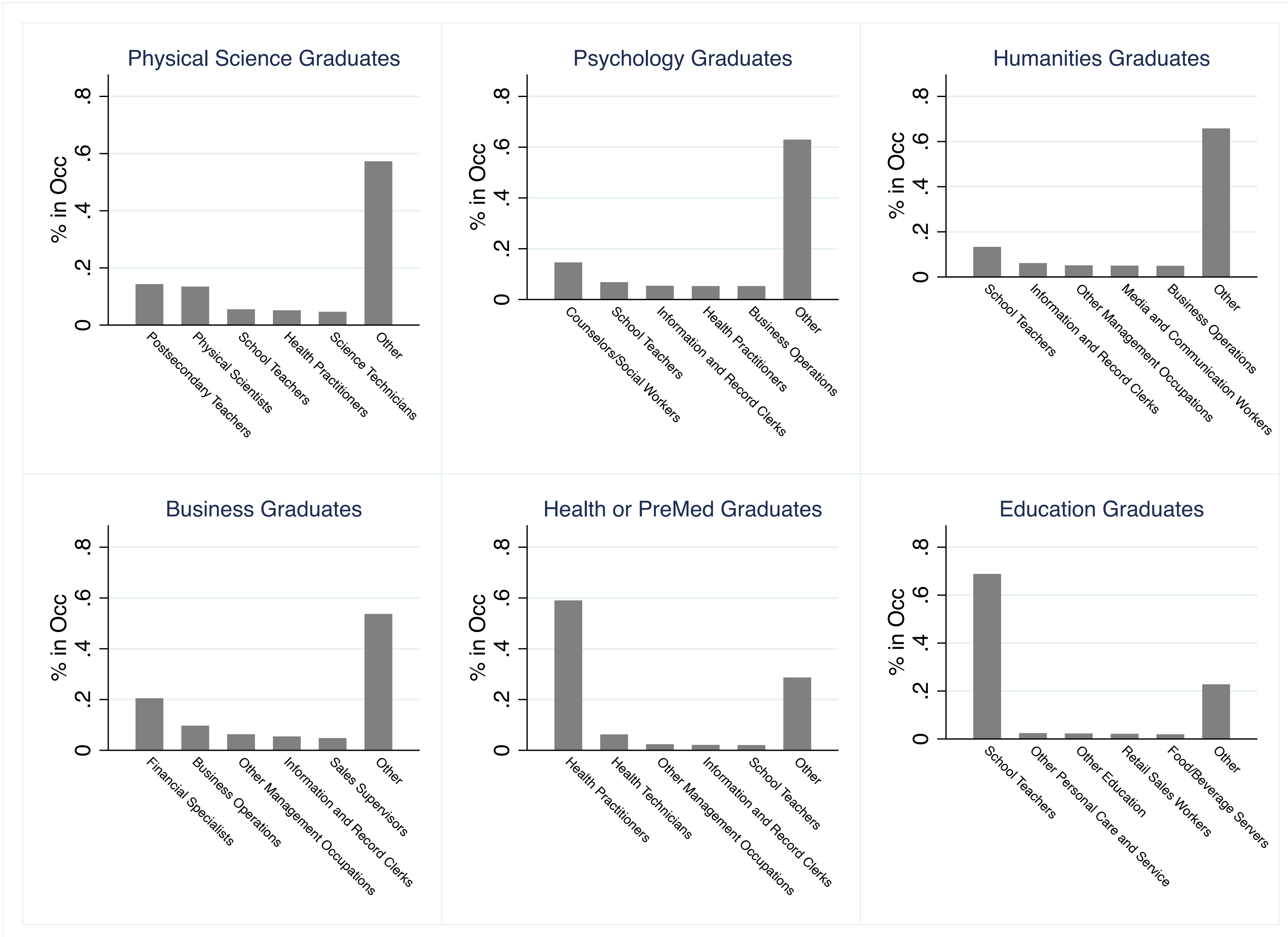
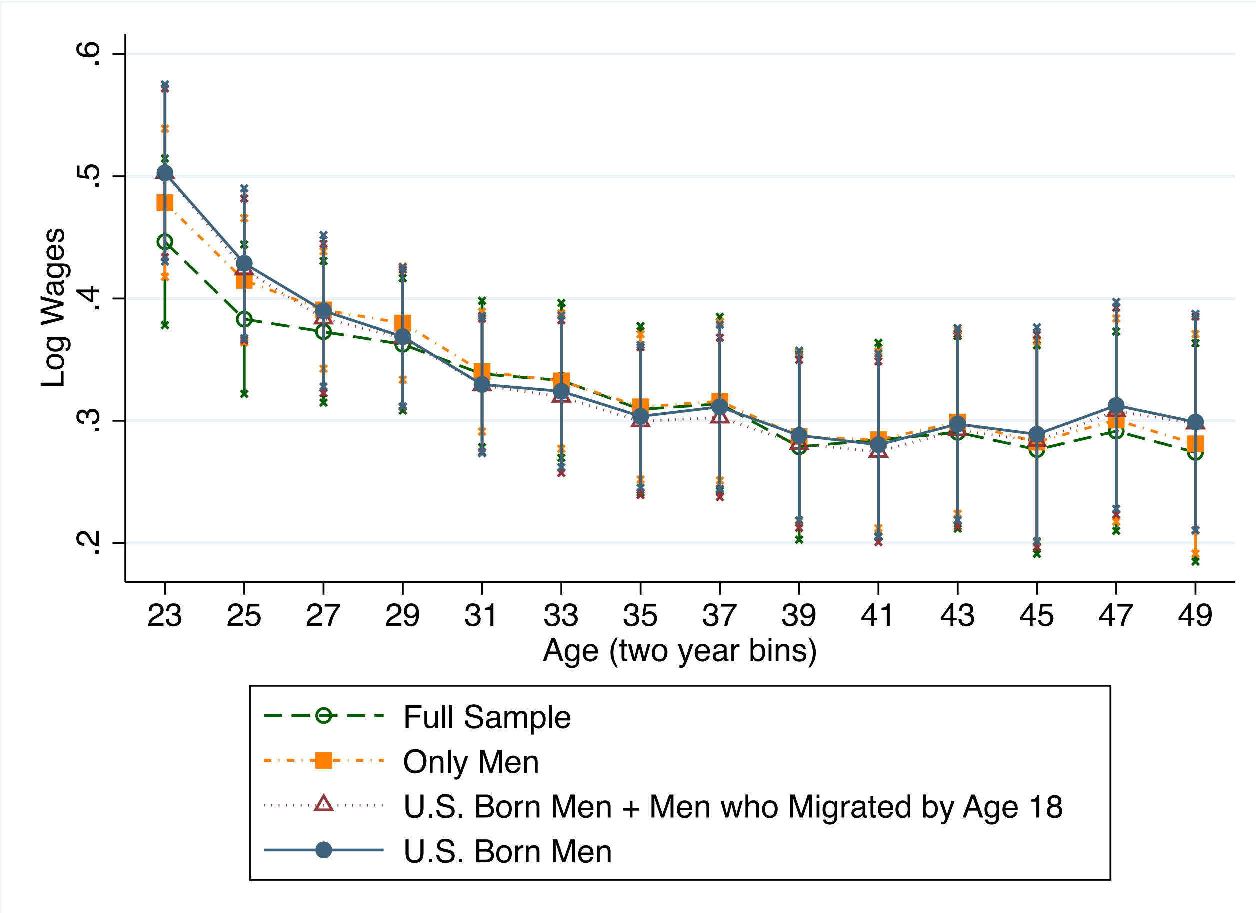
Appendix A: Additional Figures and Tables

Figure A1: Early Career Occupations of College Graduates, by Major



Notes: Each panel shows frequency distributions of the 5 most common occupations held by full-time working college graduates age 23-26 in the 2009-2017 waves of the American Community Survey who majored in the indicated subject. Occupations are defined here as 3-digit Standard Occupation Classification (SOC) codes. The "Other" category comprises all 3 digit SOC codes other than the top 5. Physical Science majors include Chemistry and Physics. Humanities includes English, History, Foreign Languages, Fine Arts and General Liberal Arts.

Figure A2: Declining Wage Returns for Engineering/CS Majors (Different Samples)



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (8) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and indicators for majoring in computer science or engineering. The sample always includes college graduates ages 23-50 in the 2009-2017 American Community Survey, with other restrictions varying according to the legend. The full sample also includes women. The left-out category is all other majors. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

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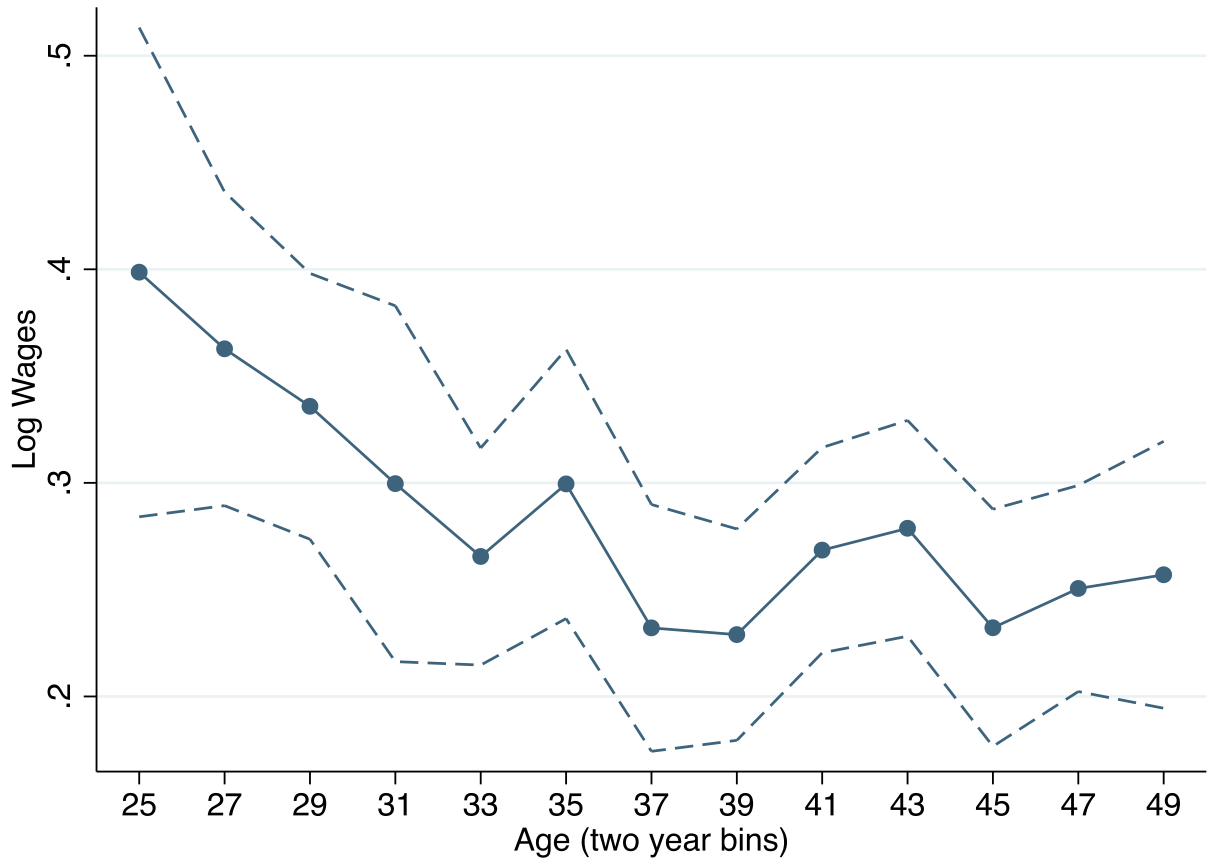
Figure A3: Declining Wage Returns for Engineering/CS Majors (National Survey of College Graduates)



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (8) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and indicators for a college major in engineering or computer science. The sample is all four-year college graduates ages 25-50 in the 1993-2017 National Survey of College Graduates. The left-out category is all other majors. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

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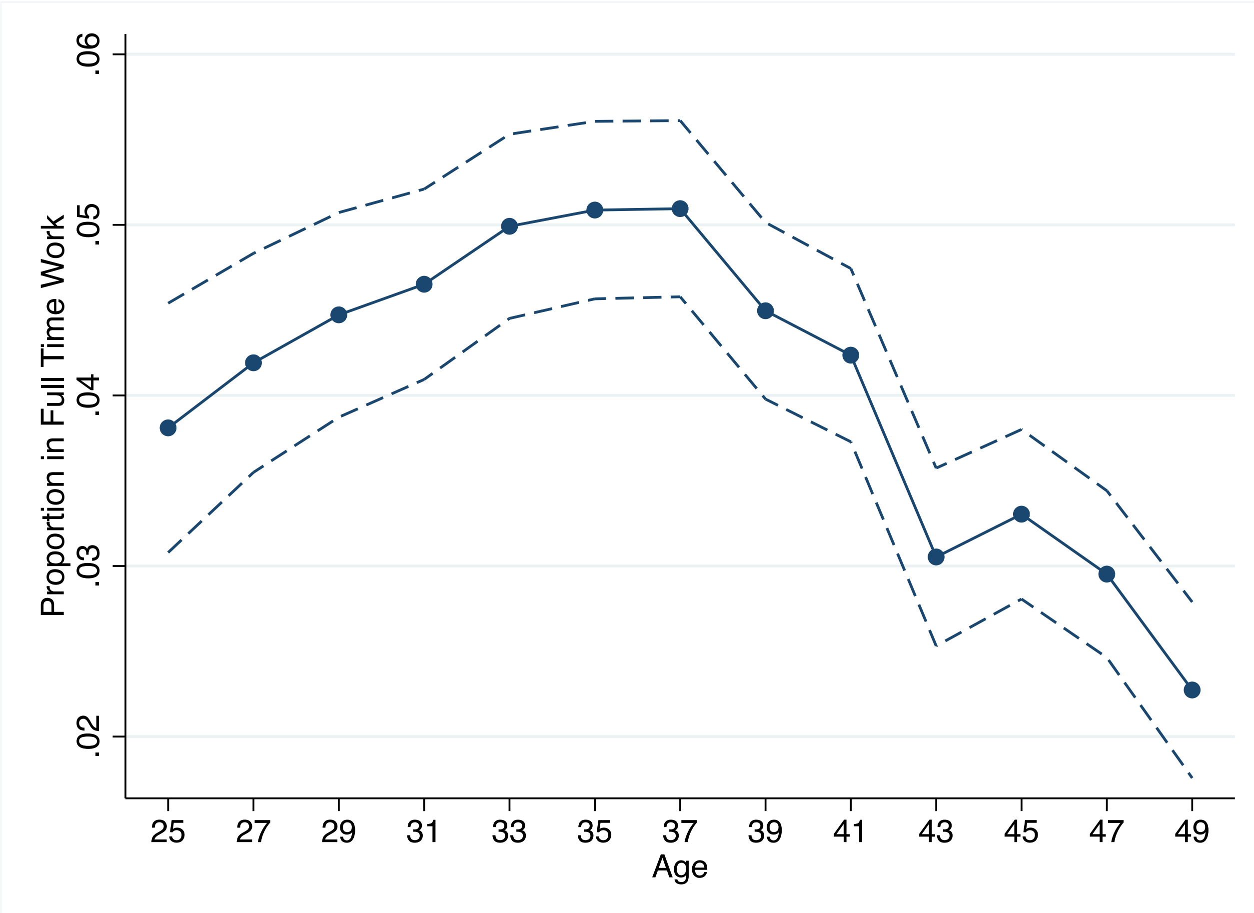
Figure A4: Differential Rates of Selection into Full-Time Work for Engineering/CS Majors



Notes: The figure plots coefficients and 95 percent confidence intervals from a regression of an indicator for full-time work on interactions between two-year age bins and indicators for majoring in computer science or engineering. The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey. The left-out category is all other majors. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education.

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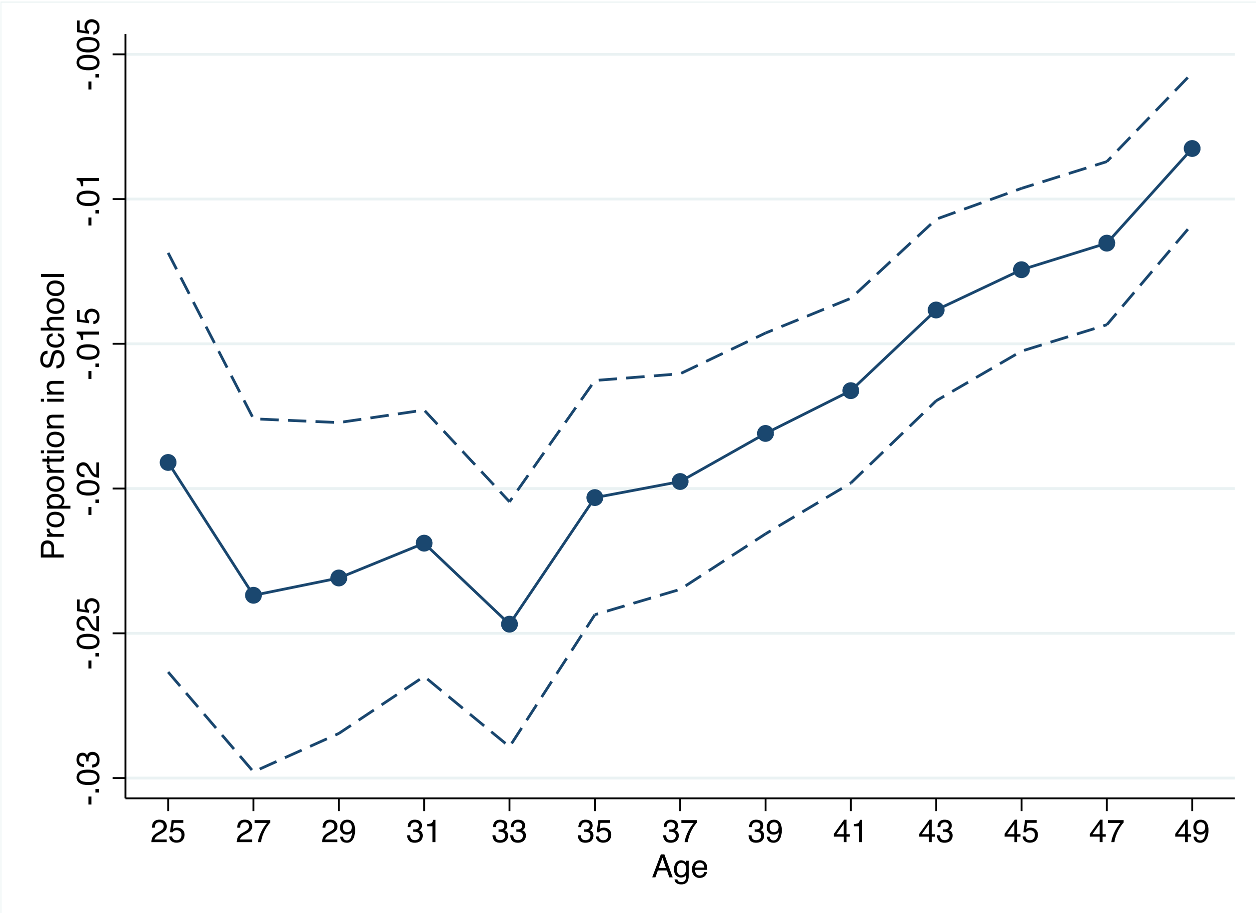
Figure A5: Differential Rates of Selection into Graduate School Enrollment for Engineering/CS Majors



Notes: The figure plots coefficients and 95 percent confidence intervals from a regression of an indicator for current enrollment in school on interactions between two-year age bins and indicators for majoring in computer science or engineering. The left-out category is all other majors. The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education.

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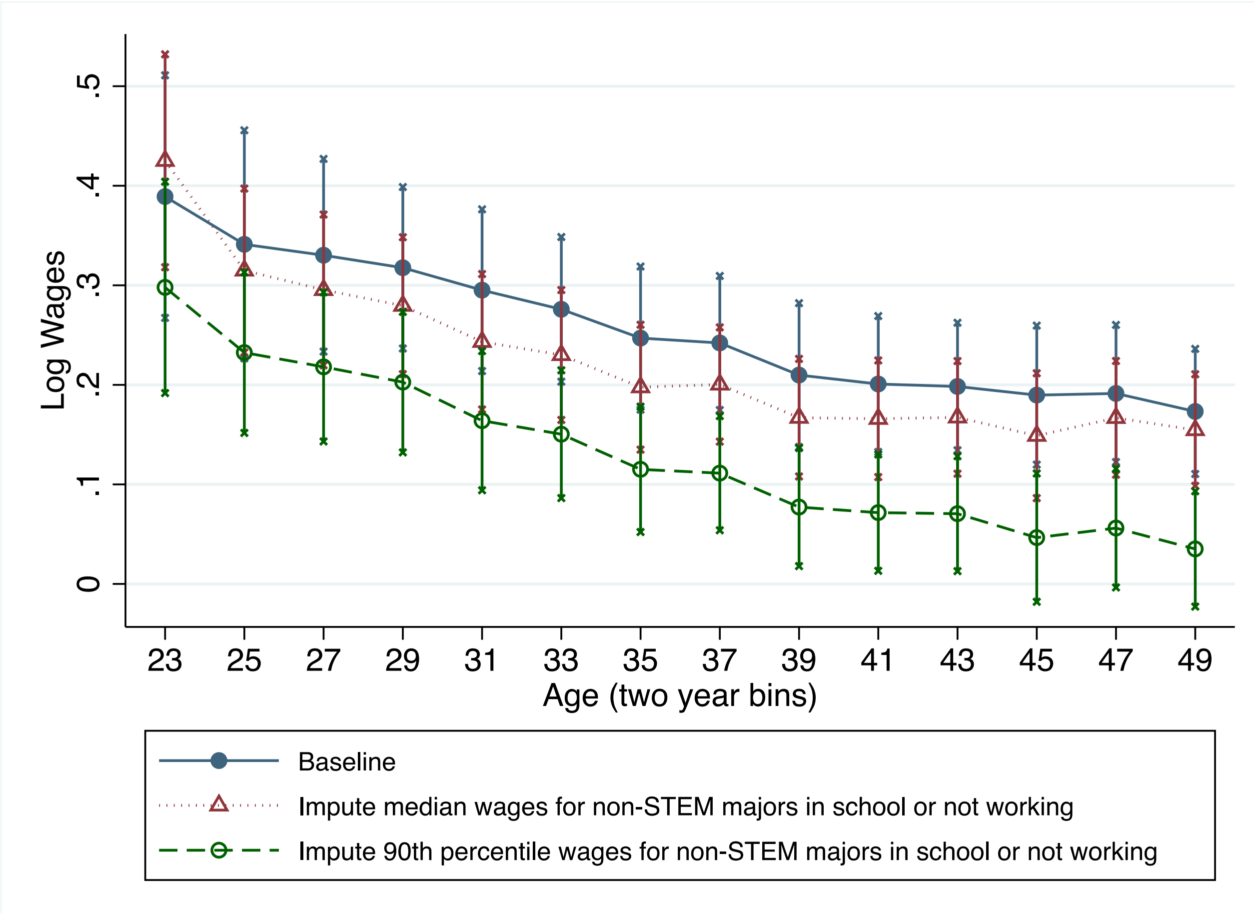
Figure A6: Declining Wage Returns for Engineering/CS Majors (Alternative Assumptions for Missing Earners)



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (8) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and indicators for college major. The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey, excluding education majors. For the unemployed, part-time workers and those who are currently enrolled in school, we impute missing wages by major, age and other demographics under different assumptions as indicated in the legend. See the text for details on the imputation procedure. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

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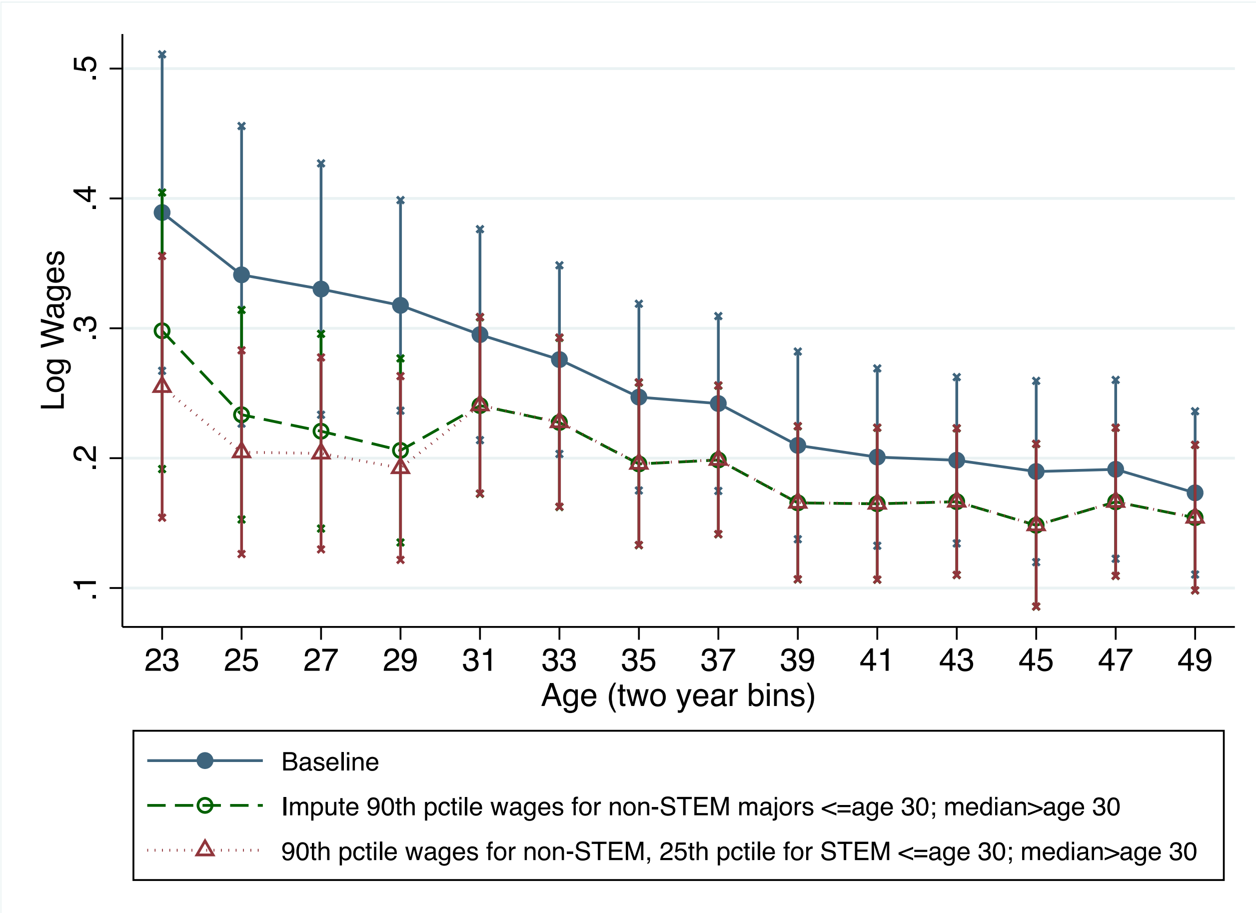
Figure A7: Declining Wage Returns for Engineering/CS Majors (Alternative Assumptions for Missing Earners)



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate of equation (8) in the paper, a regression of log annual wage and salary income on interactions between two-year age bins and indicators for college major. The sample is all four-year college graduates ages 23-50 in the 2009-2017 American Community Survey, excluding education majors. For the unemployed, part-time workers and those who are currently enrolled in school, we impute missing wages by major, age and other demographics under different assumptions as indicated in the legend. See the text for details on the imputation procedure. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

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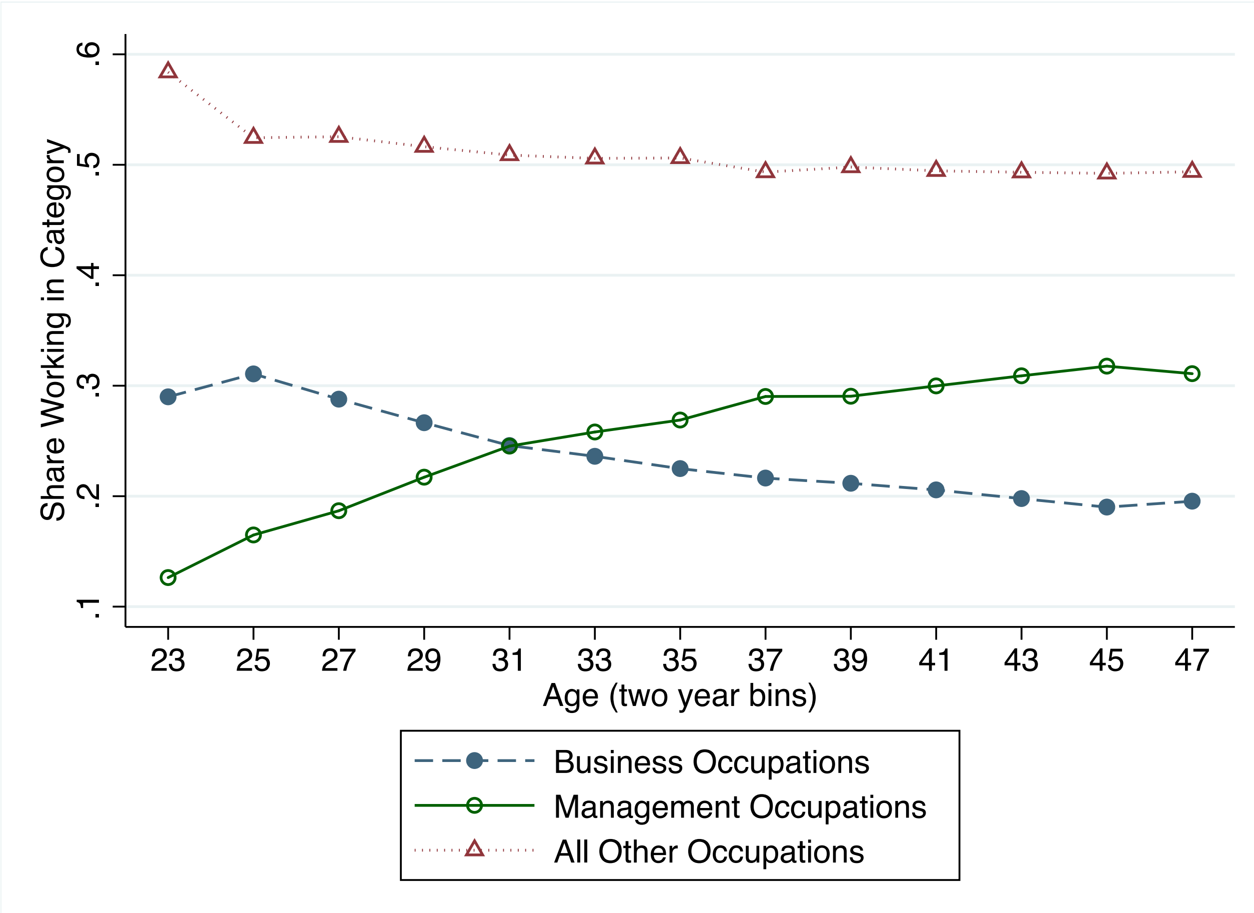
Figure A8: Occupational Sorting by Age for Business Majors



Notes: The figure plots coefficients from three separate regressions of indicators for working in the labeled occupation category on two-year age bins plus controls for sex-by-age indicators, year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. The sample is all full-time working four-year college graduates ages 23-50 in the 2009-2017 American Community Survey, who also majored in Business. Business occupations are 2-digit Standard Occupational Classification (SOC) code 13. Management is 2-digit SOC code 11. See the text for details.

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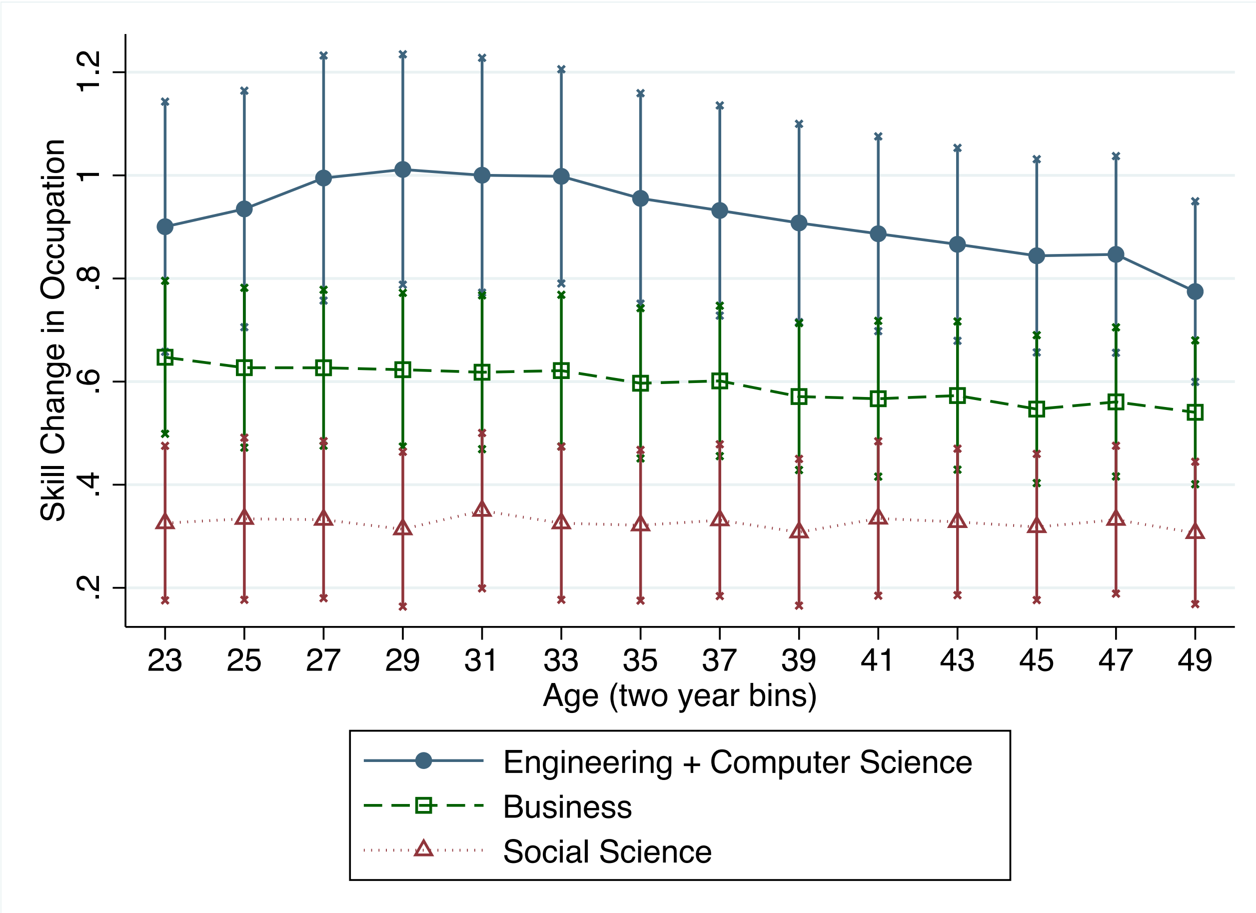
Figure A9: College Graduates Majoring in Fast-Changing Careers Exit them Over Time



Notes: The figure plots coefficients and 95 percent confidence intervals from an estimate similar to equation (8) in the paper, but with the skill change measure Δ_j of the 6-digit Standard Occupation Classification (SOC) code in each respondent's occupation regressed on interactions between two-year age bins and indicators for college major. The standard deviation of Δ_j is 1.01. The skill change measure is constructed using 2007-2019 online job vacancy data from Burning Glass Technologies. See the text for details. The sample is all full-time working four-year college graduates ages 23-50 in the 2009-2017 American Community Survey. The regression also includes controls for sex-by-age indicators, age and year fixed effects, race and ethnicity, citizenship, veteran status and an indicator for having any graduate school education. Standard errors are clustered at the major-by-age level.

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Table A1: Skill Requirements by Occupation Category in 2007

Panel A	Social (1)	Cognitive (2)	Character (3)	Creative (4)	Writing (5)	Manage (6)	Finance (7)
Management	0.606	0.421	0.453	0.077	0.172	0.382	0.402
STEM	0.540	0.536	0.345	0.063	0.208	0.170	0.167
Business	0.651	0.551	0.463	0.100	0.182	0.258	0.475
Social-Science/Service	0.362	0.356	0.220	0.062	0.158	0.147	0.081
Art/Design/Media	0.585	0.397	0.502	0.256	0.465	0.138	0.160
Health	0.331	0.238	0.190	0.021	0.063	0.136	0.053
Sales/Admin	0.626	0.321	0.423	0.073	0.127	0.180	0.222
Total	0.566	0.458	0.386	0.077	0.177	0.213	0.269

Panel B	Business Systems	Customer Service	Office Software	Technical Support	Data Analysis	Specialized Software	ML/AI
Management	0.243	0.315	0.033	0.115	0.057	0.209	0.006
STEM	0.260	0.207	0.207	0.328	0.092	0.593	0.043
Business	0.272	0.340	0.043	0.123	0.083	0.260	0.006
Social-Science/Service	0.045	0.134	0.012	0.053	0.023	0.094	0.004
Art/Design/Media	0.125	0.195	0.057	0.153	0.029	0.396	0.010
Health	0.022	0.392	0.005	0.037	0.026	0.048	0.003
Sales/Admin	0.193	0.763	0.035	0.126	0.040	0.156	0.012
Total	0.218	0.354	0.088	0.177	0.067	0.320	0.018

Notes: Each cell in this table presents the share of postings in an occupation category that requires at least one skill in the categories indicated in each column. The occupations are grouped based on 2010 Standard Occupation Classification (SOC) codes. Data come from online job vacancies collected by Burning Glass Technologies in 2007. See the Data Appendix for detailed descriptions of how each skill category is constructed.

Table A2: Skill Requirements by Occupation Category in 2019

Panel A	Social (1)	Cognitive (2)	Character (3)	Creative (4)	Writing (5)	Manage (6)	Finance (7)
Management	0.733	0.528	0.591	0.119	0.223	0.440	0.462
STEM	0.668	0.641	0.450	0.112	0.254	0.203	0.181
Business	0.764	0.645	0.617	0.158	0.250	0.290	0.453
Social-Science/Service	0.520	0.364	0.350	0.097	0.207	0.204	0.072
Art/Design/Media	0.740	0.502	0.656	0.415	0.519	0.155	0.170
Health	0.481	0.346	0.333	0.029	0.086	0.187	0.058
Sales/Admin	0.778	0.463	0.630	0.113	0.196	0.231	0.276
Total	0.680	0.543	0.513	0.122	0.227	0.254	0.268

Panel B	Business Systems	Customer Service	Office Software	Technical Support	Data Analysis	Specialized Software	ML/AI
Management	0.287	0.362	0.050	0.088	0.092	0.270	0.021
STEM	0.289	0.219	0.298	0.310	0.187	0.694	0.207
Business	0.346	0.380	0.072	0.091	0.132	0.376	0.033
Social-Science/Service	0.039	0.176	0.012	0.033	0.054	0.110	0.015
Art/Design/Media	0.135	0.206	0.060	0.107	0.060	0.519	0.027
Health	0.032	0.544	0.005	0.028	0.049	0.060	0.007
Sales/Admin	0.269	0.735	0.065	0.077	0.068	0.277	0.018
Total	0.244	0.370	0.120	0.139	0.116	0.386	0.074

Notes: Each cell in this table presents the share of postings in an occupation category that requires at least one skill in the categories indicated in each column. The occupations are grouped based on 2010 Standard Occupation Classification (SOC) codes. Data come from online job vacancies collected by Burning Glass Technologies in 2019. See the Data Appendix for detailed descriptions of how each skill category is constructed.

Table A3: Occupations in Order of Skill Change

Occupation Title	SOC Code	Rate of Skill Change
Computer Occupations	151	4.80
Advertising, Marketing and Sales Managers	112	4.04
Sales Representatives, Services	413	3.92
Operations Specialties Managers	113	3.91
Life, Physical, and Social Science Technicians	194	3.91
Electrical and Electronic Equipment Mechanics, Installers, and Repairers	492	3.83
Engineers	172	3.77
Financial Specialists	132	3.75
Business Operations Specialists	131	3.67
Supervisors of Installation, Maintenance, and Repair Workers	491	3.63
Supervisors of Sales Workers	411	3.55
Life Scientists	191	3.54
Mathematical Science Occupations	152	3.51
Top Executives	111	3.49
Media and Communication Workers	273	3.47
Supervisors of Office and Administrative Support Workers	431	3.45
Secretaries and Administrative Assistants	436	3.43
Physical Scientists	192	3.42
Art and Design Workers	271	3.39
Other Management Occupations	119	3.25
Sales Representatives, Wholesale and Manufacturing	414	3.25
Other Sales and Related Workers	419	3.20
Supervisors of Production Workers	511	3.17
Social Scientists and Related Workers	193	3.14
Other Healthcare Practitioners and Technical Occupations	299	3.14
Other Installation, Maintenance, and Repair Occupations	499	3.13
Architects, Surveyors, and Cartographers	171	3.07
Drafters, Engineering Technicians, and Mapping Technicians	173	3.05
Other Healthcare Support Occupations	319	3.03
Supervisors of Transportation and Material Moving Workers	531	2.94
Retail Sales Workers	412	2.90
Legal Support Workers	232	2.86
Material Recording, Scheduling, Dispatching, and Distributing Workers	435	2.79
Financial Clerks	433	2.79
Other Office and Administrative Support Workers	439	2.77
Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	493	2.75
Information and Record Clerks	434	2.74
Supervisors of Building and Grounds Cleaning and Maintenance Workers	371	2.73
Counselors and Social Workers	211	2.69
Media and Communication Equipment Workers	274	2.69
Supervisors of Food Preparation and Serving Workers	351	2.64
Animal Care and Service Workers	392	2.61
Other Production Occupations	519	2.53
Lawyers, Judges, and Related Workers	231	2.53
Health Technologists and Technicians	292	2.49
Nursing, Psychiatric, and Home Health Aides	311	2.45
Entertainers and Performers, Sports and Related Workers	272	2.44
Construction Trades Workers	472	2.37
Other Education, Training, and Library Occupations	259	2.37
Health Diagnosing and Treating Practitioners	291	2.33
Law Enforcement Workers	333	2.29
Occupational Therapy and Physical Therapist Assistants and Aides	312	2.25
Other Protective Service Workers	339	2.25
Assemblers and Fabricators	512	2.17
Other Construction and Related Workers	474	2.17
Metal Workers and Plastic Workers	514	2.15
Postsecondary Teachers	251	2.05
Other Personal Care and Service Workers	399	1.95
Textile, Apparel, and Furnishings Workers	516	1.86
Other Transportation Workers	536	1.82
Grounds Maintenance Workers	373	1.79
Other Teachers and Instructors	253	1.78
Food and Beverage Serving Workers	353	1.77
Material Moving Workers	537	1.75
Entertainment Attendants and Related Workers	393	1.75
Baggage Porters, Bellhops, and Concierges	396	1.73
Food Processing Workers	513	1.72
Preschool, Primary, Secondary, and Special Education School Teachers	252	1.64
Building Cleaning and Pest Control Workers	372	1.59
Personal Appearance Workers	395	1.40
Cooks and Food Preparation Workers	352	1.38
Other Food Preparation and Serving Related Workers	359	1.37
Motor Vehicle Operators	533	1.27

Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of skill change between 2007 and 2019 for each 3-digit Standard Occupational Classification (SOC) code. The average value of the skill change measure is 3.01 - see the text for details.

Table A4a: Occupations in Order of Skill Change

Occupation Title	SOC Code	Rate of Skill Change
Web Developers	151134	6.29
Sales Engineers	419031	5.71
Sales Representatives, Services, All Other	413099	5.42
Database Administrators	151141	5.42
Computer Network Architects	151143	5.16
Network and Computer Systems Administrators	151142	5.15
Software Developers, Applications	151132	5.00
Telecommunications Equipment Installers and Repairers, Except Line Installers	492022	4.94
Purchasing Managers	113061	4.88
Software Developers, Systems Software	151133	4.83
Statisticians	152041	4.80
Information Security Analysts	151122	4.79
Market Research Analysts and Marketing Specialists	131161	4.78
Computer and Information Systems Managers	113021	4.66
Computer Network Support Specialists	151152	4.63
Veterinarians	291131	4.58
Marketing Managers	112021	4.56
Computer Occupations, All Other	151199	4.54
Computer and Information Research Scientists	151111	4.50
Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	414011	4.45
Computer Programmers	151131	4.44
Tax Preparers	132082	4.43
Graphic Designers	271024	4.43
Commercial and Industrial Designers	271021	4.38
Computer Systems Analysts	151121	4.37
Chemical Engineers	172041	4.32
Biological Scientists, All Other	191029	4.32
Logisticians	131081	4.31
Computer Hardware Engineers	172061	4.21
Financial Analysts	132051	4.15
First-Line Supervisors of Non-Retail Sales Workers	411012	4.13
Technical Writers	273042	4.12
Industrial Engineers	172112	4.11
Executive Secretaries and Executive Administrative Assistants	436011	4.09
Electrical Engineers	172071	4.08
Industrial Production Managers	113051	4.08
Tax Examiners and Collectors, and Revenue Agents	132081	4.07
Instructional Coordinators	259031	4.07
Computer User Support Specialists	151151	4.01
Financial Specialists, All Other	132099	4.00
Public Relations Specialists	273031	3.97
Architectural and Engineering Managers	119041	3.96
Natural Sciences Managers	119121	3.95
Environmental Engineers	172081	3.90
Financial Managers	113031	3.88
Life, Physical, and Social Science Technicians, All Other	194099	3.83
Purchasing Agents, Except Wholesale, Retail, and Farm Products	131023	3.82
Business Operations Specialists, All Other	131199	3.80
Production, Planning, and Expediting Clerks	435061	3.80
Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	172111	3.79
Mechanical Engineers	172141	3.78
Training and Development Managers	113131	3.78
Human Resources Managers	113121	3.76
Administrative Services Managers	113011	3.76
Management Analysts	131111	3.75
Sales Managers	112022	3.75
Accountants and Auditors	132011	3.72
Construction Managers	119021	3.70
Electronics Engineers, Except Computer	172072	3.68
Personal Financial Advisors	132052	3.67
Sales and Related Workers, All Other	419099	3.67
Public Relations and Fundraising Managers	112031	3.65
Helpers–Production Workers	519198	3.64
Compensation and Benefits Managers	113111	3.63
First-Line Supervisors of Mechanics, Installers, and Repairers	491011	3.63
Fundraisers	131131	3.58
Interior Designers	271025	3.58
Electrical and Electronics Engineering Technicians	173023	3.56
Dental Hygienists	292021	3.56
Transportation, Storage, and Distribution Managers	113071	3.55
Insurance Sales Agents	413021	3.55
General and Operations Managers	111021	3.54
Medical Equipment Repairers	499062	3.54
Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	436014	3.53
Chemists	192031	3.52
Managers, All Other	119199	3.51
Engineers, All Other	172199	3.50
First-Line Supervisors of Retail Sales Workers	411011	3.50
Procurement Clerks	433061	3.49
Medical Scientists, Except Epidemiologists	191042	3.48
Civil Engineers	172051	3.47
First-Line Supervisors of Office and Administrative Support Workers	431011	3.45
Compliance Officers	131041	3.44
Payroll and Timekeeping Clerks	433051	3.44
Credit Analysts	132041	3.38
Medical Records and Health Information Technicians	292071	3.37
Operations Research Analysts	152031	3.37
Loan Officers	132072	3.34
Medical Assistants	319092	3.34
Training and Development Specialists	131151	3.33
Producers and Directors	272012	3.33
Telecommunications Line Installers and Repairers	499052	3.32
Writers and Authors	273043	3.31
Maintenance and Repair Workers, General	499071	3.30
Health Diagnosing and Treating Practitioners, All Other	291199	3.29
Property, Real Estate, and Community Association Managers	119141	3.27
Cost Estimators	131051	3.27
Human Resources Specialists	131071	3.26
Securities, Commodities, and Financial Services Sales Agents	413031	3.25
Demonstrators and Product Promoters	419011	3.25

Table continues on next page.

Table A4b: Occupations in Order of Skill Change

Occupation Title	SOC Code	Rate of Skill Change
Counselors, All Other	211019	3.25
Architects, Except Landscape and Naval	171011	3.24
Occupational Health and Safety Specialists	299011	3.23
Designers, All Other	271029	3.22
Billing and Posting Clerks	433021	3.22
Bookkeeping, Accounting, and Auditing Clerks	433031	3.21
Phlebotomists	319097	3.21
First-Line Supervisors of Production and Operating Workers	511011	3.17
Dental Assistants	319091	3.16
Counter and Rental Clerks	412021	3.16
Vocational Education Teachers, Postsecondary	251194	3.14
Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	414012	3.14
Compensation, Benefits, and Job Analysis Specialists	131141	3.13
Electro-Mechanical Technicians	173024	3.12
Social and Human Service Assistants	211093	3.10
Cargo and Freight Agents	435011	3.10
Loan Interviewers and Clerks	434131	3.09
Editors	273041	3.09
Retail Salespersons	412031	3.07
Meeting, Convention, and Event Planners	131121	3.06
Engineering Technicians, Except Drafters, All Other	173029	3.05
Electricians	472111	3.02
Human Resources Assistants, Except Payroll and Timekeeping	434161	3.01
Medical and Health Services Managers	119111	3.00
Operating Engineers and Other Construction Equipment Operators	472073	3.00
First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators	531031	2.99
Automotive Service Technicians and Mechanics	493023	2.98
Private Detectives and Investigators	339021	2.97
Insurance Underwriters	132053	2.94
Construction Laborers	472061	2.93
Drafters, All Other	173019	2.92
Social and Community Service Managers	119151	2.92
Merchandise Displayers and Window Trimmers	271026	2.90
First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	531021	2.89
Weighers, Measurers, Checkers, and Samplers, Recordkeeping	435111	2.88
Interpreters and Translators	273091	2.88
Credit Counselors	132071	2.87
Installation, Maintenance, and Repair Workers, All Other	499099	2.87
Healthcare Social Workers	211022	2.87
First-Line Supervisors of Construction Trades and Extraction Workers	471011	2.86
Customer Service Representatives	434051	2.85
Food Service Managers	119051	2.85
Paralegals and Legal Assistants	232011	2.85
Medical Secretaries	436013	2.84
Protective Service Workers, All Other	339099	2.83
Telemarketers	419041	2.83
Office Clerks, General	439061	2.83
Social Workers, All Other	211029	2.82
Lodging Managers	119081	2.81
Actuaries	152011	2.81
Health Educators	211091	2.81
Insurance Claims and Policy Processing Clerks	439041	2.81
Automotive Body and Related Repairers	493021	2.79
Chief Executives	111011	2.79
Detectives and Criminal Investigators	333021	2.78
Police, Fire, and Ambulance Dispatchers	435031	2.78
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	499021	2.76
Shipping, Receiving, and Traffic Clerks	435071	2.76
Inspectors, Testers, Sorters, Samplers, and Weighers	519061	2.74
Office and Administrative Support Workers, All Other	439199	2.72
Receptionists and Information Clerks	434171	2.72
First-Line Supervisors of Food Preparation and Serving Workers	351012	2.72
Industrial Engineering Technicians	173026	2.72
Educational, Guidance, School, and Vocational Counselors	211012	2.71
Nonfarm Animal Caretakers	392021	2.71
Dietitians and Nutritionists	291031	2.71
Claims Adjusters, Examiners, and Investigators	131031	2.70
Medical and Clinical Laboratory Technicians	292012	2.69
First-Line Supervisors of Housekeeping and Janitorial Workers	371011	2.67
Education Administrators, Postsecondary	119033	2.65
Audio and Video Equipment Technicians	274011	2.64
Helpers–Installation, Maintenance, and Repair Workers	499098	2.63
Child, Family, and School Social Workers	211021	2.61
Industrial Machinery Mechanics	499041	2.60
Real Estate Sales Agents	419022	2.60
Respiratory Therapists	291126	2.59
Orderlies	311015	2.58
Mobile Heavy Equipment Mechanics, Except Engines	493042	2.56
Computer-Controlled Machine Tool Operators, Metal and Plastic	514011	2.56
File Clerks	434071	2.56
Librarians	254021	2.54
Lawyers	231011	2.54
Stock Clerks and Order Fillers	435081	2.52
Radiologic Technologists	292034	2.52
Bill and Account Collectors	433011	2.51
Pharmacy Technicians	292052	2.51
Nurse Practitioners	291171	2.51
Medical and Clinical Laboratory Technologists	292011	2.50
Mail Clerks and Mail Machine Operators, Except Postal Service	439051	2.49
Mechanical Drafters	173013	2.48
Parts Salespersons	412022	2.48
Home Health Aides	311011	2.47
Butchers and Meat Cutters	513021	2.45
Data Entry Keyers	439021	2.44
Nursing Assistants	311014	2.44
Interviewers, Except Eligibility and Loan	434111	2.42
Bus and Truck Mechanics and Diesel Engine Specialists	493031	2.42
Registered Nurses	291141	2.40
Clinical, Counseling, and School Psychologists	193031	2.39
Chefs and Head Cooks	351011	2.37

Table continues on next page.

Table A4c: Occupations in Order of Skill Change

Occupation Title	SOC Code	Rate of Skill Change
Physical Therapists	291123	2.33
Physician Assistants	291071	2.33
Occupational Therapists	291122	2.33
Tire Repairers and Changers	493093	2.32
Health Technologists and Technicians, All Other	292099	2.30
Surgical Technologists	292055	2.30
Occupational Therapy Aides	312012	2.28
Psychiatric Technicians	292053	2.27
Medical Equipment Preparers	319093	2.27
Production Workers, All Other	519199	2.25
Aircraft Mechanics and Service Technicians	493011	2.25
Physical Therapist Assistants	312021	2.24
Machinists	514041	2.22
Speech-Language Pathologists	291127	2.22
Coaches and Scouts	272022	2.22
Personal Care Aides	399021	2.20
Cardiovascular Technologists and Technicians	292031	2.20
Residential Advisors	399041	2.20
Photographers	274021	2.19
Occupational Therapy Assistants	312011	2.18
Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	512011	2.17
Education Administrators, Elementary and Secondary School	119032	2.14
Marriage and Family Therapists	211013	2.13
Cooks, Short Order	352015	2.13
Mental Health Counselors	211014	2.13
Reporters and Correspondents	273022	2.12
Licensed Practical and Licensed Vocational Nurses	292061	2.12
Magnetic Resonance Imaging Technologists	292035	2.11
Dispatchers, Except Police, Fire, and Ambulance	435032	2.11
Construction and Building Inspectors	474011	2.10
Combined Food Preparation and Serving Workers, Including Fast Food	353021	2.09
Pharmacists	291051	2.08
Security Guards	339032	2.08
Diagnostic Medical Sonographers	292032	2.06
Police and Sheriff's Patrol Officers	333051	2.06
Cashiers	412011	2.05
Tellers	433071	2.03
Massage Therapists	319011	2.03
Special Education Teachers, Middle School	252053	2.02
Hotel, Motel, and Resort Desk Clerks	434081	1.96
Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	514031	1.95
Light Truck or Delivery Services Drivers	533033	1.95
Emergency Medical Technicians and Paramedics	292041	1.92
Health Specialties Teachers, Postsecondary	251071	1.92
Carpenters	472031	1.88
Fitness Trainers and Aerobics Instructors	399031	1.87
Locker Room, Coatroom, and Dressing Room Attendants	393093	1.87
Concierges	396012	1.87
Recreation Workers	399032	1.84
Plumbers, Pipefitters, and Steamfitters	472152	1.84
Team Assemblers	512092	1.83
Teachers and Instructors, All Other	253099	1.82
Couriers and Messengers	435021	1.81
Postsecondary Teachers, All Other	251199	1.80
Food Servers, Nonrestaurant	353041	1.77
Preschool Teachers, Except Special Education	252011	1.77
Laborers and Freight, Stock, and Material Movers, Hand	537062	1.74
Maids and Housekeeping Cleaners	372012	1.74
Driver/Sales Workers	533031	1.73
Teacher Assistants	259041	1.72
Special Education Teachers, All Other	252059	1.70
Family and General Practitioners	291062	1.70
Industrial Truck and Tractor Operators	537051	1.70
Psychiatrists	291066	1.68
Laundry and Dry-Cleaning Workers	516011	1.67
Pest Control Workers	372021	1.66
Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	353022	1.66
Physicians and Surgeons, All Other	291069	1.63
Food Preparation Workers	352021	1.62
Self-Enrichment Education Teachers	253021	1.62
Dentists, General	291021	1.61
Parking Lot Attendants	536021	1.60
Welders, Cutters, Solderers, and Brazers	514121	1.60
Landscaping and Groundskeeping Workers	373011	1.57
Internists, General	291063	1.56
Amusement and Recreation Attendants	393091	1.56
Cleaners of Vehicles and Equipment	537061	1.55
Obstetricians and Gynecologists	291064	1.54
Surgeons	291067	1.52
Clergy	212011	1.51
Packers and Packagers, Hand	537064	1.50
Secondary School Teachers, Except Special and Career/Technical Education	252031	1.48
Childcare Workers	399011	1.47
Bartenders	353011	1.46
Janitors and Cleaners, Except Maids and Housekeeping Cleaners	372011	1.46
Elementary School Teachers, Except Special Education	252021	1.43
Middle School Teachers, Except Special and Career/Technical Education	252022	1.41
Waiters and Waitresses	353031	1.39
Dining Room and Cafeteria Attendants and Bartender Helpers	359011	1.38
Taxi Drivers and Chauffeurs	533041	1.38
Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	359031	1.37
Dishwashers	359021	1.37
Hairdressers, Hairstylists, and Cosmetologists	395012	1.32
Painters, Construction and Maintenance	472141	1.31
Bakers	513011	1.30
Cooks, Restaurant	352014	1.24
Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers	339092	1.23
Heavy and Tractor-Trailer Truck Drivers	533032	1.12
Bus Drivers, Transit and Intercity	533021	1.03

Notes: This table uses online job vacancy data from Burning Glass Technologies (BG) to calculate the rate of skill change between 2007 and 2019 for each 6-digit Standard Occupational Classification (SOC) code. The average value of the skill change measure is 3.01 - see the text for details on the construction of the skill change measure.

Table A5: Life-Cycle Earnings by Degree Category

	Engineer/CS.	*Business*	*Life/Phys Sciences*	*Social Sciences*
Age	Income	Income	Income	Income
23	41,937	34,068	24,328	29,625
24	48,693	38,546	28,948	34,421
25	56,028	46,076	37,148	43,348
26	59,004	49,160	41,541	47,396
27	62,949	53,236	46,222	51,651
28	67,178	56,378	50,495	56,204
29	71,776	59,416	54,754	59,169
30	74,116	63,764	60,017	64,498
31	77,875	66,711	67,179	69,989
32	81,777	70,237	71,812	73,780
33	85,859	72,526	78,940	78,775
34	88,756	75,089	83,857	80,910
35	94,049	81,170	89,130	86,385
36	97,421	83,425	97,501	91,237
37	100,522	85,544	99,661	97,585
38	102,415	86,189	102,754	97,456
39	104,584	89,813	105,773	98,178
40	105,691	88,297	109,135	99,640
41	108,231	92,766	111,009	104,065
42	107,733	90,774	109,340	104,350
43	112,259	93,390	114,818	105,600
44	113,354	94,934	113,408	107,592
45	114,134	96,831	117,122	110,558
46	114,658	97,610	122,176	109,329
47	115,074	96,237	121,765	109,557
48	115,472	97,741	120,839	109,157
49	114,577	96,950	121,381	109,822
50	115,896	96,823	119,021	108,742

Notes: This table presents population-weighted average annual wage and salary income by major and age, using the 2009-2017 American Community Survey Integrated Public Use Microdata Series (IPUMS, Ruggles et al 2017). The sample is restricted to respondents with at least a college degree who were employed at the time of the survey and worked at least 40 weeks during the year. Earnings are in constant 2016 dollars. Life and Physical Science majors are Biology, Chemistry, Physics and similar subjects. Social Science majors are Economics, Political Science, Sociology and similar subjects.

Table A6: Ability Sorting into STEM Majors in the NLSY

Outcome is AFQT score (standardized)	(1)	(2)	(3)
STEM Major	0.120***	0.111**	
	(0.030)	(0.041)	
NLSY 97 Wave	0.033	0.030	0.027
	(0.035)	(0.036)	(0.036)
STEM Major * NLSY 97 Wave		0.022	
		(0.060)	
CS/Engineering Major * NLSY 97 Wave			0.045
			(0.074)
CS/Engineering Major			0.070
			(0.048)
Observations	3084	3084	3084
R^2	0.236	0.236	0.234

Notes: Each column reports results from a regression of an indicator for graduate school attendance on the Armed Forces Qualifying Test (AFQT) score, indicators for college major, an indicator for whether the respondent is in the National Longitudinal Survey of Youth (NLSY) 1997 survey wave, and other variables as shown. The regression also includes controls for race and sex-by-age. The sample pools the 1979 and 1997 NLSY waves together and is restricted to respondents with at least a college degree. STEM majors are defined as computer science, engineering, physics, chemistry and biology. We normalize scores across NLSY waves using the crosswalk developed by Altonji, Bharadwaj and Lange (2012). The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A7: Labor Market Returns to STEM Majors in the NLSY

Outcome is Log Hourly Wages (2016 $)	(1)	(2)	(3)	(4)	(5)	(6)
Applied Science Major	0.203***	0.197***	0.085**	0.058*	0.033	0.043
	(0.028)	(0.027)	(0.028)	(0.025)	(0.031)	(0.030)
Pure Science Major	-0.007	-0.029	-0.077	-0.070	-0.067	0.033
	(0.044)	(0.042)	(0.041)	(0.036)	(0.043)	(0.048)
Cognitive Skills (AFQT, Standardized)		0.132***	0.122***	0.097***	0.097***	0.058***
		(0.014)	(0.014)	(0.012)	(0.012)	(0.014)
Social Skills (Standardized)		0.015	0.018*	0.014	0.014	0.004
		(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Noncognitive Skills (Standardized)		0.069***	0.067***	0.053***	0.053***	0.043***
		(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
STEM Occupation			0.260***	0.146***	0.119***	
			(0.020)	(0.019)	(0.022)	
Applied Science * STEM Occupation					0.075	
					(0.040)	
Pure Science * STEM Occupation					0.009	
					(0.073)	
Demographics and Age/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	No
Occupation by Industry FE	No	No	No	No	No	Yes
Observations	19358	19358	19358	19358	19358	19358
R^2	0.265	0.287	0.298	0.401	0.401	0.614

Notes: Each column reports results from a regression of real log hourly wages on indicators for college major, occupation and/or industry (in columns 3 through 5), individual skills, indicator variables for sex-by-age, race and years of completed education, year fixed effects, and additional controls as indicated. The data source is the National Longitudinal Survey of Youth (NLSY) 1979 and 1997, and the sample is restricted to respondents with at least a college degree. The waves are pooled and an indicator for sample wave is included in the regression. Science, Technology, Engineering and Mathematics (STEM) occupations are defined using the 2010 Census Bureau classification. Pure Science majors include biology, chemistry, physics, mathematics and statistics, while Applied Science includes engineering and computer science. Cognitive skills are measured by each respondent's score on the Armed Forces Qualifying Test (AFQT). We normalize scores across NLSY waves using the crosswalk developed by Altonji, Bharadwaj and Lange (2012). Social and noncognitive skill definitions are taken from Deming (2017). All skill measures are normalized to have a mean of zero and a standard deviation of one. Person-year is the unit of observation, and all standard errors are clustered at the person level. The sample is restricted to ages 23-34 to maximize comparability across survey waves. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Appendix B: Model

B.1 A Model of Career Choice with 2 Careers and 2 Periods

Assume there are two careers $j \in \{1, 2\}$ that an individual can choose to work in. Each career pays an exogenous wage w_j, which is time-invariant. Each career also has an exogenous rate of skill change $\Delta_j \in (0, 1)$, which represents the proportion of skills that become obsolete each period. Individuals are exogenously endowed an 2-dimensional vector of human capital $\overrightarrow{H} = (H_1, H_2)$[1] each dimension of which is equivalent to the labor units an individual can provide in each career j during the first period. We interpret H_j as reflecting the level of competence in the skills required in career j. Finally, individuals are also endowed with ability a, which governs how quickly a worker learns on the job (OTJ).

Individuals make a discrete choice that maximizes the net present value of their earnings over two periods. Specifically, we have

$$\max_{j^1, j^2} w_{j^1} H_{j^1} + w_{j^2}(H_{j^2} + a)(1 - \Delta_{j^2})$$

where j^t represents an individual's career choice in period t. Because career choice in period 1 is does not impact earnings potential in period 2, we can rewrite this problem as

$$\max_{j^1, j^2} w_{j^1} H_{j^1} + w_{j^2}(H_{j^2} + a)(1 - \Delta_{j^2}) = \max_{j^1} w_{j^1} H_{j^1} + \max_{j^2} w_{j^2}(H_{j^2} + a)(1 - \Delta_{j^2}).$$

Optimal career choice, then, amounts to a simple decision rule: choose the career that provides the highest earnings in each period. Formally, if we letj^{1*} and j^{2*} represent the optimal career choice

[1] See Section B.3 for an extension with endogenous human capital.

in period 1 and 2, then the career "demand" functions are

$$j^{1*} = \begin{cases} 1 & \text{if } H_1 w_1 > H_2 w_2 \\ 2 & \text{if } H_1 w_1 \leq H_2 w_2 \end{cases},$$

$$j^{2*} = \begin{cases} 1 & \text{if } w_1(H_1 + a)(1 - \Delta_1) > w_2(H_2 + a)(1 - \Delta_2) \\ 2 & \text{if } w_1(H_1 + a)(1 - \Delta_1) \leq w_2(H_2 + a)(1 - \Delta_2) \end{cases}.$$

The intuition behind this model's predictions comes from differentiating the period 2 earnings equation by Δ_j and a. This gives us the following:

$$\frac{dw_{j^2}(H_{j^2} + a)(1 - \Delta_{j^2})}{d\Delta_j} = -w_{j^2}(H_{j^2} + a) < 0,$$
$$\frac{d^2 w_{j^2}(H_{j^2} + a)(1 - \Delta_{j^2})}{d\Delta_j da} = -w_{j^2} < 0.$$

In order, these equations can be translated as follows: (1) earnings decline in the rate of skill change in the second period and (2) the rate of this decline has a larger magnitude for higher ability workers. This downward pressure on earnings will tend to drive workers out of high Δ_j careers over time, especially if they are high ability.

The earnings ratio between the two careers in the second period determines optimal career choice and is the key object required to prove the predictions above. The earnings ratio is

$$\frac{w_1(H_1 + a)(1 - \Delta_1)}{w_2(H_2 + a)(1 - \Delta_2)}.$$

Below are proofs of the two predictions (see Figure MA1 for a graphical representation):

Proposition 1 *The relative return to working in a fast-changing career diminishes over time.*

Proof. To see this, take the derivative of the second period earnings ratio with respect to the ratio of skill change between careers. This gives

$$\frac{d\frac{w_1(H_1+a)(1-\Delta_1)}{w_2(H_2+a)(1-\Delta_2)}}{d\frac{\Delta_1}{\Delta_2}} = -\frac{d\frac{w_1(H_1+a)(1-\Delta_1)}{w_2(H_2+a)(1-\Delta_2)}}{d\frac{(1-\Delta_1)}{(1-\Delta_2)}} = -\frac{w_1(H_1+a)}{w_2(H_2+a)} < 0.$$

This means that, regardless of initial human capital, the earnings of working in an career 1 relative to an alternative 2 in period 2 goes down as the rate of skill change increases in career 1 relative to 2. This implies declining returns over time because the period 1 earnings gap is unrelated to $\frac{\Delta_1}{\Delta_2}$. ■

Proposition 2 *Let $\Delta_2 < \Delta_1$. Workers will tend to switch out of career 1 (the fast-changing career) to 2 (the slow-changing career) if $\frac{w_1(1-\Delta_1)}{w_2(1-\Delta_2)} < 1$. Furthermore, those who switch will be positively selected on ability.*

Proof. To see this, differentiate the second period career-specific human capital ratio with respect to a. This yields

$$\frac{d\frac{w_1(H_1+a)(1-\Delta_1)}{w_2(H_2+a)(1-\Delta_2)}}{da} = \frac{w_1(1-\Delta_1)(H_2-H_1)}{w_2(1-\Delta_2)(H_2+a)^2},$$

which shows that if $H_1 > H_2$, then ability monotonically reduces the earnings ratio, but if $H_2 > H_1$, then ability monotonically increases the ratio. Additionally,

$$\lim_{a->\infty} \frac{w_1(H_1+a)(1-\Delta_1)}{w_2(H_2+a)(1-\Delta_2)} = \frac{w_1(1-\Delta_1)}{w_2(1-\Delta_2)} < 1.$$

this means that $\frac{w_1 H_1}{w_2 H_2} \leq 1$ implies $\frac{w_1(H_1+a)(1-\Delta_1)}{w_2(H_2+a)(1-\Delta_2)} \leq 1$, so workers employed in career 2 (the slow-changing career) during period 1 remain in that career in period 2. Alternatively, if $\frac{w_1 H_1}{w_2 H_2} > 1$, then it is still possible that $\mathbf{\frac{w_1(H_1+a)(1-\Delta_1)}{w_2(H_2+a)(1-\Delta_2)} \leq 1}$ as long as $H_1 > H_2$ and a is sufficiently large. This means that some workers in career 1 (the fast-changing career) in period 1 switch to career 2 in period 2, and these "switchers" will have high ability. ■

B.2 Extension to N Careers and T Periods

Now assume there are n careers $j \in \{1, 2, 3, ..., n\}$ that an individual can choose to work in. Like in the two career case, each career pays an exogenous time-invariant wage w_j, and has an exogenous rate of skill change $\Delta_j \in (0, 1)$. Individuals are endowed an n-dimensional vector of human capital $\overrightarrow{H_j} = (H_1, H_2, ..., H_n)$ each dimension of which is equivalent to the labor units an individual can provide in each career j during the first period. Like before, H_j is interpreted as reflecting the level of competence in the skills required by career j and individuals are endowed with ability a, which governs the rate of OTJ learning.

Individuals make a discrete choice that maximizes the net present value of their earnings over T periods. Specifically, we have

$$\max_{\overrightarrow{j}} \sum_{t=1}^{T} w_{j^t}(H_{j^t} + (t-1)a)(1 - \Delta_{j^t})^{t-1}$$

where $\overrightarrow{j} = (j^1, j^2, ..., j^T)$ represents an individual's career choice in each of T periods. Because career choice in period $t - 1$ is does not impact earnings potential in period t, we can rewrite this problem as

$$\max_{\overrightarrow{j}} \sum_{t=1}^{T} w_{j^t}(H_{j^t} + (t-1)a)(1 - \Delta_{j^t})^{t-1} = \sum_{t=1}^{T} \max_{j^t} w_{j^t}(H_{j^t} + (t-1)a)(1 - \Delta_{j^t})^{t-1}.$$

To simplify notation, we define $W_j(H_j, \Delta_j, a, t) \equiv w_{j^t}(H_{j^t} + (t-1)a)(1 - \Delta_{j^t})^{t-1}$. Optimal career choice, then, amounts to a simple decision rule: choose the career that provides the best total earnings in each period. Formally, j^* is the optimal occupation in period t if $W_{j^*}(H_{j^*}, \Delta_{j^*}, a, t) > W_i(H_i, \Delta_i, a, t)$ for all $i \neq j^*$.

The intuition behind the predictions this model makes comes from differentiating the period t

earnings equation by Δ_j and a. This gives us the following:

$$\frac{dW_j(H_j,\Delta_j,a,t)}{d\Delta_j} = -(t-1)w_{j^t}(H_{j^t}+(t-1)a)(1-\Delta_{j^t})^{t-2} < 0$$
$$\frac{d^2W_j(H_j,\Delta_j,a,t)}{d\Delta_j da} = -(t-1)^2 w_{j^t}(1-\Delta_{j^t})^{t-2} < 0.$$

In order, these equations can be translated as follows: (1) earnings decline in the rate of skill change at all time periods after the first period and (2) the rate of this decline is higher in magnitude for higher ability workers. This downward pressure on earnings will tend to drive workers out of high Δ_j careers over time, especially if they are high ability.

The earnings ratio between two careers j and i determines the optimal choice of career and is the key object required to prove the predictions above. Symbolically, the earnings ratio is

$$\frac{W_j(H_j,\Delta_j,a,t)}{W_i(H_i,\Delta_i,a,t)} = \frac{w_{j^t}(H_{j^t}+(t-1)a)(1-\Delta_{j^t})^{t-1}}{w_{i^t}(H_{i^t}+(t-1)a)(1-\Delta_{i^t})^{t-1}} \equiv R_{ji}(H_j,H_i,\Delta_j,\Delta_i,a,t).$$

Below are proofs of the two predictions:

Proposition 3 *The relative return to working in a fast-changing career diminishes over time.*

Proof. To see this, take the derivative of the second period earnings ratio with respect to the ratio of skill change between careers. This gives

$$\frac{dR_{ji}(H_j,H_i,\Delta_j,\Delta_i,a,t)}{d\frac{\Delta_j}{\Delta_i}} = -\frac{dR_{ji}(H_j,H_i,\Delta_j,\Delta_i,a,t)}{d\frac{(1-\Delta_j)}{(1-\Delta_i)}} = -(t-1)\frac{w_{j^t}(H_{j^t}+a)}{w_{i^t}(H_{i^t}+a)} < 0.$$

This means that, regardless of initial human capital, the earnings of working in an career j relative to an alternative i in period t goes down as the rate of skill change increases in j relative to i. This implies declining returns over time because the period 1 earnings gap is unrelated to $\frac{\Delta_j}{\Delta_i}$. ■

Proposition 4 *Let $\Delta_i < \Delta_j$. Workers will tend to switch out of career j (the fast-changing career) to i (the slow-changing career) if $\frac{w_j(1-\Delta_j)^{t-1}}{w_i(1-\Delta_i)^{t-1}} < 1$. Furthermore, those who switch will be positively selected on ability.*

Proof. Let $\Delta_i < \Delta_j$. To see the result, differentiate the second period career-specific human capital ratio with respect to a. This yields

$$\frac{dR_{ji}(H_j, H_i, \Delta_j, \Delta_i, a, t)}{da} = \frac{w_j(t-1)(1-\Delta_j)^{t-1}(H_i - H_j)}{w_i(1-\Delta_i)^{t-1}(H_i + (t-1)a)^2},$$

which shows that if $H_j > H_i$, then ability monotonically reduces the earnings ratio, but if $H_i > H_j$, then ability monotonically increases the ratio. Additionally,

$$\lim_{a->\infty} \frac{dR_{ji}(H_j, H_i, \Delta_j, \Delta_i, a, t)}{da} = \lim_{a->\infty} \frac{w_j(H_j + (t-1)a)(1-\Delta_j)^{t-1}}{w_i(H_i + (t-1)a)(1-\Delta_i)^{t-1}} = \frac{w_j(1-\Delta_j)^{t-1}}{w_i(1-\Delta_i)^{t-1}}.$$

this means that if $\frac{w_j(H_{jt-1}+(t-2)a)(1-\Delta_{jt-1})^{t-2}}{w_i(H_{it-1}+(t-2)a)(1-\Delta_{it-1})^{t-2}} \leq 1$ then $\frac{w_j(H_{jt}+(t-1)a)(1-\Delta_{jt})^{t-1}}{w_i(H_{it}+(t-1)a)(1-\Delta_{it})^{t-1}} \leq 1$, so workers employed in career i (the slow-changing career) during period $t-1$ remain in that career in period t. Alternatively, if $\frac{w_j(H_{jt-1}+(t-2)a)(1-\Delta_{jt-1})^{t-2}}{w_i(H_{it-1}+(t-2)a)(1-\Delta_{it-1})^{t-2}} > 1$, then it is still possible that $\frac{w_j(H_{jt}+(t-1)a)(1-\Delta_{jt})^{t-1}}{w_i(H_{it}+(t-1)a)(1-\Delta_{it})^{t-1}} \leq 1$ if $H_j > H_i$ and a is large. This means that some workers that work in career j (the fast-changing career) in $t-1$ move to career i in period t, and that these workers will tend to have high ability. ■

B.3 Career Selection with Endogenous Human Capital

In the previous versions of the model, we have taken human capital to be exogenous. To show that the predictions we explore in the paper are unaffected by endogenizing human capital, we show that it is optimal for some workers to choose human capital bundles consistent with each of the three possible career types in a two period model: (1) working only in a fast-changing career, (2) working only in a slow-changing career, and (3) switching from a fast to a slow-changing career. See Figure MA2 for a graphical representation of these predictions with endogenous human capital.

Individuals face a decision to invest in some combination of human capital $\overrightarrow{H} = (H_1, H_2)$ across two occupations. Like in proposition 2, let $\Delta_1 > \Delta_2$. Also, we assume an inherent tradeoff between investing in the two types of capital, which leads them to face a concave production possibilities frontier in initial skills. We also introduce a parameter u that represents an individual's preference for fast-changing, technology-intensive education. Finally, we assume that it is easier to learn the skills required for career 1, the technology-intensive career, if one has higher a and higher u. And, if either a or u are 0, then it is infinitely costly to invest in any H_1.

We formalize these assumptions into the following conditions: $H_1(H_2) = F(H_2, a, u)$, $\frac{dF}{dH_2} < 0$, $\frac{d^2F}{d(H_2)^2} < 0$, $\frac{dF}{da} > 0$, $\frac{d^2F}{dH_2da} < 0 \frac{dF}{du} > 0$, $\frac{d^2F}{dH_2du} < 0$, $H_1(0) = H_1^{max} = a * u$, $F^{-1}(a, u, 0) = H_2^{max} = 1$, and $F(H_2, a, 0) = F(H_2, 0, u) = 0$.

We know from proposition 2 that, if workers switch careers at all, they will only switch from career 1 to career 2 regardless of the human capital bundle they choose. This leaves us with three cases: (1) a worker chooses career 1 during both periods, (2) a worker chooses career 2 during both periods, or (3) a worker chooses career 1 initially and moves to career 2 for the second period. Thus, we have the following optimization problems for each case:

$$\text{Case 1 (Career 1): } \max_{H_1} w_1 H_1 + w_1(H_1 + a)(1 - \Delta_1),$$

$$\text{Case 2 (Career 2): } \max_{H_2} w_2 H_2 + w_2(H_2 + a)(1 - \Delta_2),$$

$$\text{Case 3 (Switch) } \max_{H_2} w_1 H_1(H_2) + w_2(H_2 + a)(1 - \Delta_2).$$

The optimal solutions for cases 1 and 2 are $(H_1^{max}, 0)$ and $(0, H_2^{max})$, respectively. This is clear because when a worker commits to specializing, there is always positive return to investing in the skills required for the career she will work in. Case 3, however, does not necessarily result in specialization. The first order condition for case 3 is

$$w_1 \frac{dF(H_2, a, u)}{dH_2} + w_2(1 - \Delta_2) = 0.$$

Because the second order conditions are satisfied by assumption (i.e. $w_1 \frac{d^2F}{d(H_2)^2} < 0$), the implicit function theorem implies that an optimal choice $H_2^*(w_1, w_2, \Delta_2, a, u)$ and, therefore, $H_1^*(w_1, w_2, \Delta_2, a, u)$ exists[2].

[2]Note that full specialization is not guaranteed for switchers. This implies a prediction that we did not test in this paper: those who switch from high to low Δ careers should have more balanced human capital profiles.

Plugging this optimal human capital pair into the first order condition and differentiating gives the following intuitive comparative statics:

$$\frac{dH_2^*}{da} = -w_1 \frac{\frac{d^2F}{dH_2 da}}{\frac{d^2F}{d(H_2)^2}} < 0 \implies \frac{dH_1^*}{da} > 0,$$
$$\frac{dH_2^*}{du} = -w_1 \frac{\frac{d^2F}{dH_2 du}}{\frac{d^2F}{d(H_2)^2}} < 0 \implies \frac{dH_1^*}{du} > 0,$$
$$\frac{dH_2^*}{d\Delta_2} = \frac{w_2}{w_1 \frac{d^2F}{d(H_2)^2}} < 0 \implies \frac{dH_1^*}{d\Delta_2} > 0,$$
$$\frac{dH_2^*}{dw_1} = \frac{-\frac{dF(H_2,a,u)}{dH_2}}{w_1 \frac{d^2F}{d(H_2)^2}} < 0 \implies \frac{dH_1^*}{dw_1} > 0,$$
$$\frac{dH_2^*}{dw_2} = \frac{-(1-\Delta_2)}{w_1 \frac{d^2F}{d(H_2)^2}} > 0 \implies \frac{dH_1^*}{dw_1} < 0.$$

Given the solution to these three suboptimization problems, the final step is for individuals to maximize their lifetime earnings given optimal human capital choices for each case. Each worker's optimization problem is the following:

$$\max_{(j^1,j^2)} \{w_1 H_1^{max} + w_1(H_1^{max}+a)(1-\Delta_1), w_2 H_2^{max} + w_2(H_2^{max}+a)(1-\Delta_2), w_1 H_1^* + w_2(H_2^*+a)(1-\Delta_2)\},$$

which, because $H_1 \in (0, a*u)$ and $H_2 \in (0,1)$, can be reduced further to

$$\max_{(j^1,j^2)} \{w(a*u) + w_1(a*u+a)(1-\Delta_1), w_2 + w_2(1+a)(1-\Delta_2), w_1 H_1^* + w_2(H_2^*+a)(1-\Delta_2)\}.$$

To show that endogenous human capital is consistent with our previous predictions, it suffices to demonstrate that all three career paths can be optimal for some set of parameters $P = \{w_1, w_2, \Delta_1, \Delta_2\}$ an individual as long as she has the appropriate (a, u) type, which we demonstrate by comparing earnings in each case by type. (a graphical representation of the type selection into careers demonstrated below is given in Figure MA3):

Proposition 5 *For any set P there exists u^*such that $(j^1, j^2) = (1, 1)$ is the optimal career choice.*

Proof. If we compare lifetime earnings in $(1, 1)$ to the other two options we find that $(1, 1)$ is optimal iff

$$w_1 a * u + w_1(a * u + a)(1 - \Delta_1) > w_2 + w_2(1 + a)(1 - \Delta_2),$$

and

$$w_1 a * u + w_1(a * u + a)(1 - \Delta_1) > w_1 H_1^* + w_2(H_2^* + a)(1 - \Delta_2).$$

Because earnings increase in u under career choice $(1, 1)$ and they do not under career choice $(2, 2)$, there exists $u' > 0$ such that the first inequality holds. Because $w_1 a * u > w_1 H_1^*$ for all u, $w_1(a * u + a)(1 - \Delta_1)$ is increasing in u, and $w_2(H_2^* + a)(1 - \Delta_2)$ is decreasing in u, there exists $u'' > 0$ such that the second inequality holds. Let $u^* = max\{u', u''\}$. u^* can be set for any set P, which ends the proof. ■

Proposition 6 *For any set P there exists a^* such that $(j^1, j^2) = (2, 2)$ is the optimal career choice.*

Proof. If we compare lifetime earnings in $(2, 2)$ to the other two options we find that $(2, 2)$ is optimal iff

$$w_2 + w_2(1 + a)(1 - \Delta_2) > w_1 a * u + w_1(a * u + a)(1 - \Delta_1),$$

and

$$w_2 + w_2(1 + a)(1 - \Delta_2) > w_1 H_1^* + w_2(H_2^* + a)(1 - \Delta_2).$$

Because $\lim_{a \to 0} w_2 + w_2(1 + a)(1 - \Delta_2) = w_2 + w_2(1 - \Delta_2) > 0 = \lim_{a \to 0} w_1 a * u + w_1(a * u + a)(1 - \Delta_1)$, and both functions are continuous in a, there must exist at least one $a' > 0$ such that the first inequality holds. Because $w_2(1 + a)(1 - \Delta_2) > w_2(H_2^* + a)(1 - \Delta_2)$ for all a, $\lim_{a \to 0} w_1 H_1^* = 0$, $\lim_{a \to 0} w_2 = w_2$, there exists $a'' > 0$ such that the second inequality holds as well. Let $a^* = min\{a', a''\}$. a^* can be set for any set P, which ends the proof. ■

Proposition 7 *For any set P there exists a pair a' and u' such that $(j^1, j^2) = (1, 2)$ is the optimal career choice.*

Proof. If we compare lifetime earnings in $(1, 2)$ to the other two options we find that $(1, 2)$ is optimal iff

$$w_1 H_1^* + w_2(H_2^* + a)(1 - \Delta_2) > w_1 a * u + w_1(a * u + a)(1 - \Delta_1),$$

and

$$w_1 H_1^* + w_2(H_2^* + a)(1 - \Delta_2) > w_2 + w_2(1 + a)(1 - \Delta_2).$$

Because $\lim_{u \to 0} w_1 H_1^* + w_2(H_2^* + a)(1 - \Delta_2) = w_2(H_2^* + a)(1 - \Delta_2) > 0 = \lim_{u \to 0} w_1 a * u + w_1(a * u + a)(1 - \Delta_1)$, and both functions are continuous in u, there must exist at least one $u' > 0$ such that the first inequality holds. If we take the derivative of both sides of the second inequality with respect to a, we get the following

$$\text{LHS: } w_1 \frac{dH_1^*}{da} + w_2 \frac{dH_2^*}{da} + w_2(1 - \Delta_2),$$
$$\text{RHS: } w_2(1 - \Delta_2).$$

Though $\frac{dH_2^*}{da} < 0$, we know that $\lim_{a \to \infty} \frac{dH_2^*}{da} = 0$ because H_2^* is bounded below by zero. Thus, for high enough a, earnings in career $(1, 2)$ is increasing faster than earnings in career $(2, 2)$. This means that there exists a'' such that the second inequality holds. Thus, for any set P, we can select an individual with type (a', u') whose optimal career is $(1, 2)$. ■

Finally, with endogenous human capital, it is also easy to show that it is possible for ability selection into career 1 initially, which is what we find for STEM careers empirically. Furthermore, this will be more likely as w_1 increases.

Proposition 8 *Initial ability selection into career 1 is possible and it is more likely when w_1 is higher.*

Proof. Note that from Propositions 2 and 4, we know that those who switch from career 1 to 2 will be higher ability than those who remain in career 1, so it suffices to show that ability selection is possible for those who choose $(1,1)$ over $(2,2)$. If we look at the returns to choosing $(1,1)$ over $(2,2)$ we get

$$w_1 a * u + w_1(a * u + a)(1 - \Delta_1) - w_2 + w_2(1 + a)(1 - \Delta_2) \equiv R'_{12}.$$

If we differentiate this with respect to a we get

$$\frac{dR'_{12}}{da} = 2w_1 u + w_1(1 - \Delta_1) - w_2(1 - \Delta_2).$$

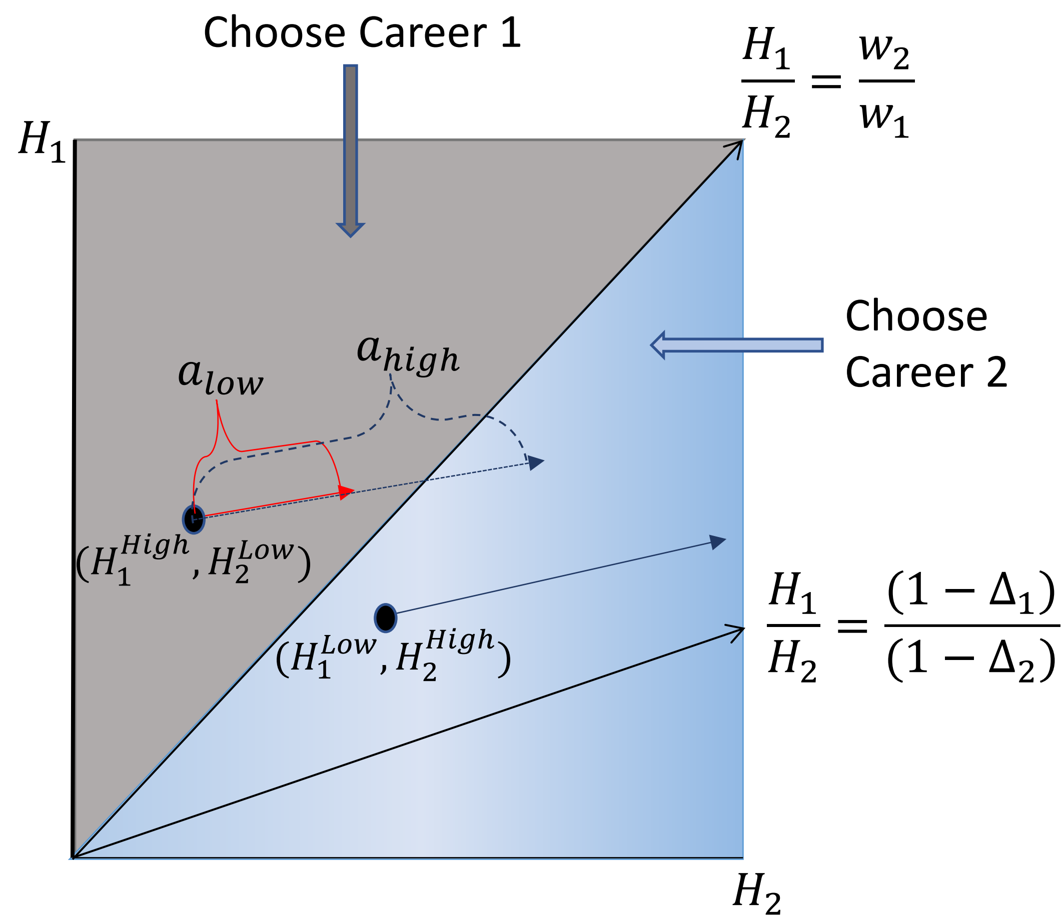
This term is ambiguous, meaning that it is possible that it is positive, which would drive ability selection into career 1. If we further differentiate this return with respect to w_1 we get

$$\frac{d^2 R'_{12}}{da dw_1} = 2u + (1 - \Delta_1) > 0.$$

This means that the marginal increase returns to selecting career $(1,1)$ by a increases in w_1 which implies that we should expect to see more ability selection into career 1 as the wage paid to career 1 increases. ■

B.4 Model Appendix Figures

Figure MA1: Career Selection with Exogenous Human Capital



Notes: This figure depicts the key aspects of our model. If an individual has a bundle of human capital above the line $H_1 = H_2 \frac{w_2}{w_1}$, such as (H_1^{High}, H_2^{Low}), then they choose to work in occupation 1. Otherwise, if an individual has a bundle of human capital below $H_1 = H_2 \frac{w_2}{w_1}$, such as (H_1^{Low}, H_2^{High}), then they choose to work in career 2. Finally, the vectors that point out of the human capital bundles represent how each bundle transforms between periods. The key feature is that the slope of the vector must be less than $\frac{w_2}{w_1}$ for those with relatively high H_1, and the length of the vectors increase in a, which induces ability selection out of career 1.

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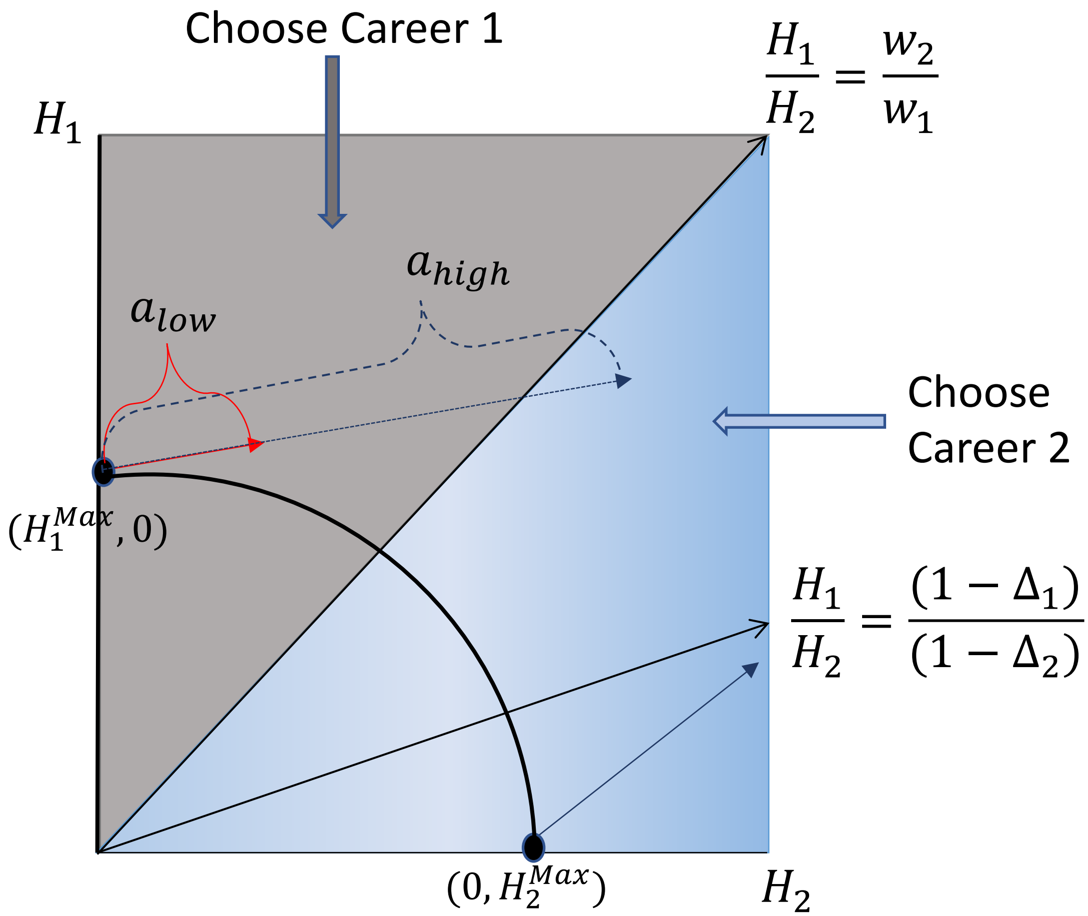
Figure MA2: Career Selection with Endogenous Human Capital



Notes: This figure depicts the key aspects of the model with endogenous human capital. Workers face a production possibilities frontier in human capital that is concave, which represents the tradeoff between investing in H_1 and H_2. In the figure we depict two types of worker: one type that specializes in H_1 and another type that specializes in H_2. The vectors that point out of the human capital bundles represent how each bundle transforms between periods. The key feature is that the slope of the vector must be less than $\frac{w_2}{w_1}$ for those with relatively high H_1, and the length of the vectors increase in a, which induces ability selection out of career 1.

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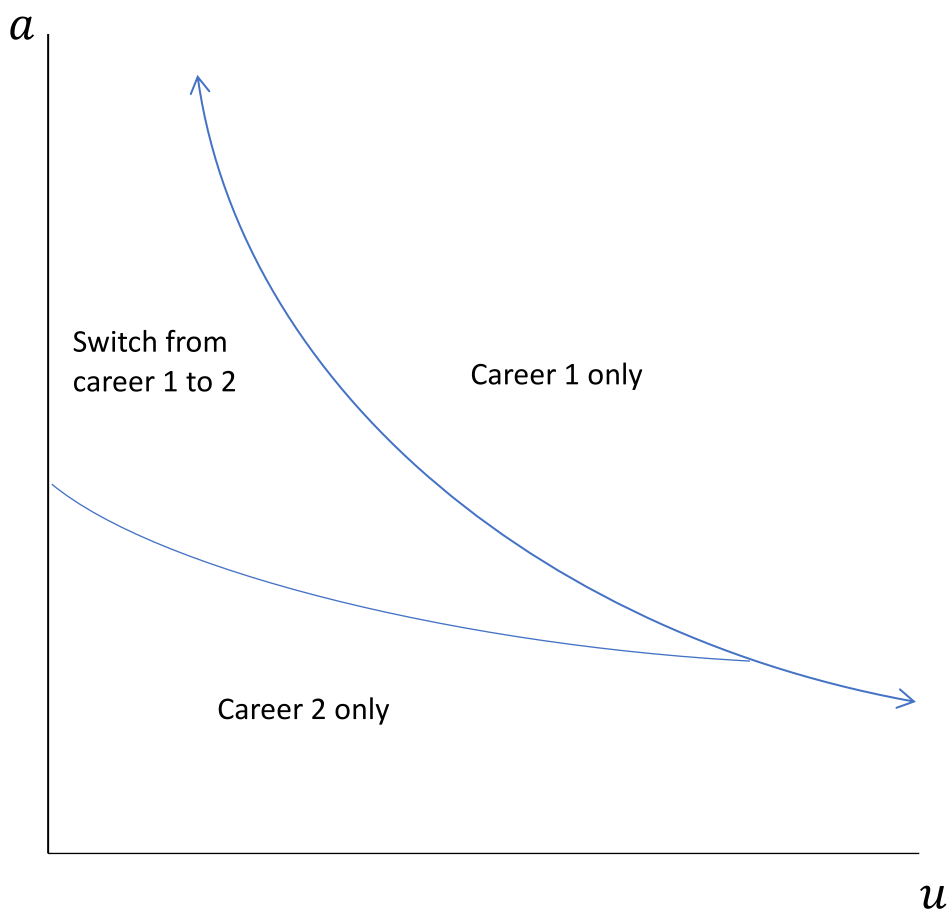
Figure MA3: Type Selection into Careers



Notes: This figure depicts type selection into different careers. Low ability workers with low taste for technology-intensive education tend to work in career 2 (the slow-changing careers) in both periods. High ability workers with a low taste for technology-intensive education tend to work in career 1 (the fast-changing career) initially, and switch into career 2. And, high ability workers with high taste for technology-intensive education tend to work in career 1 for both periods.

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Data Appendix

This paper uses data from Burning Glass Technologies (BG), an employment analytics and labor market information firm that scrapes job vacancy data from more than 40,000 online job boards and company websites. BG applies an algorithm to the raw scraped data that removes duplicate postings and parses the data into a number of fields, including job title and six digit Standard Occupational Classification (SOC) code, industry, firm, location, and education and work experience. BG also codes key words and phrases into a large number of unique skill requirements.

The BG database only covers job vacancies that are posted on the Internet. Rothwell (2014) compares the distribution of occupations in an extract of BG data to state vacancy surveys for select metropolitan areas for which data are available. He finds that computer, management, and business occupations are overrepresented relative to the state vacancy surveys, while health care support, transportation, maintenance, sales, and food service workers are underrepresented.

Carnevale et al. (2014) show that the occupation-industry composition of the BG data are similar to another database of online job vacancies, the Help-Wanted Online (HWOL) Index collected by the Conference Board. Carnevale et al. (2014) also compare a sample of job postings in the BG database to the actual text of the postings and find a high degree of accuracy for verifiable measures such as occupation and education and experience requirements. Additionally, BG has refined its algorithm over time to increase accuracy relative to the early extract studied by Carnevale et al. (2014).

Hershbein and Kahn (2018) and Deming and Kahn (2018) provide more detail on the representation of vacancies and occupations in BG data compared to other external sources such as JOLTS, OES and CPS. The bottom line is that while the BG data do have a higher share of technical, STEM jobs than other external sources, this relative representation has not changed over time. Similarly, the BG data underrepresent blue-collar and low-paid service jobs in fields such as food preparation and serving, production, and construction, although this has also not changed very much over time.

One of the most novel features of the BG data is the information available on job skills. BG use a parsing algorithm to identify key words and phrases and code them up as a set of skill requirements. BG regularly update the algorithm to pick up new skills, but then they apply the new algorithm to all years of data retrospectively. More than 93 percent of all job ads have at least one skill requirement, and the average number is 9. There are 13,544 unique skills in our analysis dataset.

We further refine the list of skills by creating a set of common categories that capture major features of the BG data. The table below lists the most common skill strings that we use to create our measures of skills in the paper. For the full list, please see the replication file

References

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Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1):S337–S369.

Hershbein, B. and Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review*, 108(7):1737–72.

Rothwell, J. (2014). Still searching: Job vacancies and stem skills. *Washington: Brookings Institution*.

Data Appendix Table 1: Common Skll Strings by Skill Category

Job Skills	Keywords and Phrases
Social	Communication, Collaboration, Negotiation, "Team", Persuasion, Listening, Presentation
Cognitive	Solving, Research, "Analy", Decision, Thinking, Math, "Statistic", Calculation
Character	Organizational Skills, Time Management, Detail-Oriented, Meeting Deadlines, Multi-Tasking, Energetic, Self-Starter, Initiative, Self-Motivation
Creativity	"Creativ"
Writing	Writing, Editing, Preparing Reports, Preparing Proposals
Management	Supervisory, Leadership, Mentoring, Staff Supervision/Development, Performance/Personnel Management
Finance	"Financ", Budgeting, Accounting, Cost
Business Systems	Systems Development/Integration/Architecture, Business Intelligence/Systems/Planning/Strategy, Six Sigma, KPIs
Customer Service	Customer, Sales, Patient, Client
Office Software	Microsoft Word/Excel/Outlook/PowerPoint/Office/Windows, Computer Literacy, Basic Internet Skills
Technical Support	Computer Installation/Repair/Maintenance/Troubleshooting, Web Development/Site Design, Software Installation, Help Desk Support
Data Analysis	Data Analysis/Analytics/Engineering/Modeling/Visualization/Mining/Science, Predictive Analytics/Models, Spreadsheets, Tableau
Specialized Software	Specific software that is tracked by BG and not otherwise categorized (e.g. SQL, Javascript, Adobe)
ML and AI	Artificial Intelligence, Machine Learning, Decision Trees, Apache Hadoop, Python, Bayesian Networks, Automation Tools, Neural Networks, Support Vector Machines (SVM), Decision Trees, Supervised Learning, TensorFlow, MapReduce, Splunk, Convolutional Neural Network (CNN), Cluster Analysis