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Abstract

This paper examines the extent to which children enter into occupations that are different from their father's occupation, but require similar skills, which we call task following. We also consider the possibility that fathers are able to transfer task specific human capital either through investments or genetic endowments to their children. We show that there is indeed substantial task following, beyond occupational following and that task following is associated with a wage premium of around 5% over otherwise identical workers employed in a job with the same primary task. The wage premium is robust to controls for industry, occupation categories and occupation characteristics. The premium is largest for followers in non-routine cognitive jobs and college graduates.

Keyword: Intergenerational transmission, Task measures, Occupation choice
JEL Codes: J24; J31

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Introduction

There exists an extensive literature documenting the prevalence of intergenerational occupational following. That is children have a greater-than-chance likelihood of working in the same occupation as their father, particularly among sons (Blau and Duncan, 1967; Rogoff, 1953).

Subsequent work has focused on occupational following within a specific occupation and found that occupation following is common and that there is a wage premium associated with it. Indeed this phenomenon has been found in truly a wide variety of professions including agriculture, proprietors, doctors, surgeons, politicians, public sector workers, race car drivers, lawyers and other professional occupations (Laband and Lentz, 1983; Lentz and Labond, 1989; Lentz and Labond, 1990, Groothuis and Groothuis, 2007; Scoppa, 2009; Feinstein, 2010; Aina and Nicoletti, 2014).

While most of the work on this has focused on sons, women are increasingly more likely to work in their father's occupation, beyond what is predicted by the fact that women are now more likely to work in any male dominated occupation than in previous generations (Hellerstein and Morrill, 2011).

Laband and Lentz (1983) present an economic framework based on human capital acquisition to explain occupational following and its apparent wage premium. In their model children acquire more occupation specific human capital in their father's occupation due to differences in the marginal cost of acquiring occupation specific human capital. In addition to making them more likely to choose this occupation, the occupation specific human capital is unobserved by researchers, thus providing an explanation for the apparent wage premium associated with occupation followers. Similarly, children may inherit unobserved skills that make them better at their father's occupation than others.

Empirically, a number of papers have attempted to find evidence for the mechanism at work among occupational followers. Laband and Lentz (1992) find evidence of occupation specific human capital transfers among lawyers and that recipients of these transfers earn more than lawyers that do not receive such transfers. Lentz and Laband (1990) provide further evidence of transfers of human capital among entrepreneurs. While, Knoll et al (2013) offer evidence that occupational following is not due to genetic similarity, but rather is caused by upbringing.

Other work has focused on the possibility of nepotism or family networks as the source of occupational following. Lentz and Laband (1989) document a 14% increase in the likelihood of being accepted to medical school among the children of doctors that cannot be explained. Scoppa (2009) finds evidence that in Italy the children of public sector employees have a substantial advantage in gaining employment in public sector jobs themselves. Aina and Nicoletti (2014), also using Italian data, suggest that nepotism and networks are common across professions requiring a degree and some sort of licensing exam.

Finally, an alternative explanation is that children are occupation followers because of intergenerational correlation, either transferred or inherited, of preferences. If children have similar preferences over occupation characteristics then it would hardly be surprising to find they are more likely to be employed in the same occupations. There is some evidence that this might play a role. Altonji and Dunn (2000) show substantial correlation in wages and working hours within families that are primarily driven by correlations in preferences. Escriche (2007) demonstrates this on one dimension: the likelihood of children to work in gender mixed occupations based on the gender-mix of their parents' occupations. While Ham et al (2009) find that the intergenerational transmission of personality matters for occupation choice. Although, it is not entirely clear if personality reflects a difference in preferences or a difference in skill.

In this paper, we explore a similar type of skill transfer from fathers to children: task specific skills. In particular, there is the possibility that in addition to general human capital and occupation specific human capital, fathers can also transfer task-specific human capital to their children. By task specific human capital, we mean skills that are important for the father's occupation, but might also have a return in other occupations that require similar skills. For example, the child of an engineer might receive some human capital that is also relevant to being a computer programmer. We document that children are more likely to be employed in an occupation where the primary task is the same as that of their father, even when the children are not in the same occupation as the father. Further, we find that task following is associated with a wage premium, again independent of occupational following. That is to say, individuals employed in the same task as their father, earn more than otherwise observationally equivalent workers employed in that same task.

Empirically, we examine whether children enter into occupations where the dominant task, defined as the primary task of the occupation in the Dictionary of Occupational Titles (DOT), is the same as the dominant task in their father's occupation and are not in the same occupation as their father, where occupation is defined by the occ1990dd code. We call these individuals who are not working in the same occupation, but employed in an occupation with the same dominant task as task followers. Thus, while occupational followers are also working in the same task as their fathers, they are generally excluded from what we call task followers.

Our work is closely related to a pair of recent papers written by Okumura and Usui. In the first (Okumura and Usui, 2014), they look at the social skills of parents and the social skills of their children using the National Longitudinal Survey of Youth 1979 (NLSY79). To proxy for parents' social skills, which are not measured, they use the skills needed in the father's occupation. They find a large transmission of social skills from parents to their children and substantial returns to children from their parents' social skills. That is they see better social skills in the children of fathers who are employed in an occupation that requires higher social skills. This implies that on at least one dimension fathers are able to transfer a skill associated with their occupation.

The second paper (Okumura and Usui, 2015) develops a model where fathers can invest in a multidimensional set of skills for their children. Empirically, they use National Longitudinal Survey of Youth (NLSY) 1979 data to investigate the intergenerational transmission of occupational skills and racial disparities in their transmission. To do this they calculate the correlation (cosine of the angle) between the vector of skills required in the father's occupation to the vector of skills required by the son's occupation. They find a greater than random intergenerational skill correlation and that the correlation is greater for whites than for blacks. Implying that task following is common, but more so for whites. White sons also earn a significant wage premium from working in occupations requiring similar skills, while black sons face a wage penalty. Further, the degree of skill correlation between fathers and sons is larger for highly educated whites, but not for blacks. They conclude this intergenerational skill transmission explains a significant portion of the black-white wage gap.

There are a few notable differences in their approach to ours. Most significantly, while they compute the correlation across a breadth of specific skills and individual tasks performed in a current job, we follow the approach taken in Autor, Levy and Murnane (2003) and Autor and Acemoglu (2010), and group these skills/tasks into 6 more general groups. DOT has about 40 task components and ONET has about 400, this generalization enables us first have a consistent measure throughout the data period. Moreover as one can imagine many of these individual tasks are highly correlated and require the same type of transferable skills. Working with these groups also enables us to derive intuition on how task following has been affected by structural changes in the labor market and is more directly comparable to other literature using task measures. Among these tasks in our analysis we further focus only on the primary task of a job along with its importance share in some settings. Their approach captures correlation in skills outside of the primary task, while our approach allows us to see the returns to following based on the task. We also distinguish between task followers and occupational followers. Given the previous literature on occupational following, task following (and its premium) could be just a byproduct of occupational followers also being task followers. Another notable difference is that we include women in our analyses as well.

We contribute to the understanding of intergenerational occupation transmission in the following ways. First, there does exist substantial task following that is distinct from occupational followers. Second, there exists a 5% wage premium associated with task following. This premium is independent of the premium associated with occupation followers. For comparison, the premium associated with occupational following is estimated to be 5-7%. We find, contrary to Okumara and Usui (2016), no difference in the task or occupational following premium by race. Third, for college educated women there exists a wage premium associated with task and occupation following, but not so for non-college graduates. For men the premium for task following is confined to college graduates, while the premium from occupational following is the same for both groups.

Our results have implications for intergenerational income persistence as well as gender wage differences. First, if the return to transmitting task specific human capital is restricted to certain occupations or skills, then, fathers employed in those occupations have the potential to transfer more human capital to their children. This could amplify intergenerational income persistence. Second, if daughters are unlikely to benefit from certain task specific human capital transfers, then the nature of human capital investment in daughters will be different than investment in sons for fathers employed in those occupations. This could feed greater gender wage differentials, although this might be countered by increased investment in general human capital for daughters.

The paper is organized as follows: the following section describes the theoretical framework, section 3 describes the date, section 4 the methodology, section 5 presents our main results, section 6 provides discussion of the implications and section 7 concludes.

Data

For this analysis we use the core cohort of the General Social Survey (GSS) data from 1972-2010. This is a nationally representative cross-sectional sample. We restrict our sample to individuals between the ages of 18-65, with a valid census occupational code (occ70, occ80), no missing information and who are employed by someone other than themselves or the military.[1] This leaves us with 19051 observations over 28 cohorts from 1972-2010.

Occupational codes are not recorded consistently across each wave of the survey. Between 1972 and 1987, the occupations are coded according to both the 1970 census codes. Between 1988 and 2010, however, jobs are exclusively identified using the 1980 census codes to capture the new and emerging occupations.

We mapped these occupational codes so as to be able to study the full extent of the occupation data panel available to us. Specifically, we used the crosswalks provided by David Dorn (2009) and Autor and Dorn (2013), giving 3-digit occupation codes—or 1990dd—that can serve as a link between occupation codes of 1970, 1990, and 2000 census. We first use their crosswalk linking 1970 and 1990dd and then the crosswalk linking 2000 and 1990dd, so that all occupations in our sample will be measured by 1990dd codes in a consistent fashion.[2]

After successfully converting the occupational codes to 1990dd, we merge in characteristics of jobs using skills and task measures embedded in each job. The

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[1] Employed is defined as having a working status is "Working full time", "Working part-time", and "With a job, but not at work because of temp illness, vacation and strikes". We do not consider individuals whose working status are "Unemployed or laid off", "Retired", "In School", and "Keeping house". We also excluded individuals who are 1) current armed-forces, 2) former armed forces with no valid occupational codes, 3) self-employed.

[2] These occupational codes were downloaded from David Dorn's website http://www.cemfi.es /~dorn/data.htm on on Sep.24, 2015. In GSS data, occupational codes are not recorded consistently across each wave of the survey. Between 1972 and 1987, the occupations are coded according to both the 1970 census codes. Between 1988 and 2010, however, jobs are exclusively identified using the 1980 census codes to capture the new and emerging occupations. In the mapping of occ1970 to occ1990dd, two occupations that could not be directly mapped. One of them is occupation "280" from occ1970 "sales and salesmen clerk" (884 respondents in the sample). We assign occ1990dd code 274 to this occupation, guided by the occupation definitions contained in Meyer and Osborne (2005) and in Dorn (2009). Another occupation with occ70 coded as 590 in GSS data, containing 165 observations in fathers' data and 191 observations in individuals' data. Since the code cannot be found in census 1970 codes, (https://usa.ipums.org/usa/volii/97occup.shtml), it is left un-coded in occ1990dd. All the occ80 codes are matched to occ1990dd expect for current and former arm-forces. Details of the procedure are available upon request.

measures were developed by a series of studies on skills of jobs by Autor, Levy and Murnane (2003), Autor, Katz and Kearney (2006) and Acemoglu and Autor (2011), making effort to define the "task content" for different occupations. Where a task is a unit of work activity that can produce either goods or service or both, and workers are regarded as allocating their skills on different tasks required on different jobs.[3]

Occupations are then categorized based on the composition of tasks[4]. For our purposes we will use six categories defining the task associated with a job: non-routine cognitive, analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, non-routine manual physical and non-routine manual interpersonal.[5]

Methodology

In order to document the nature of task following we will first provide a descriptive look at the dominant task in an individual's occupation conditional on only their father's occupations' dominant task. In these tabulations we will try to capture if individuals are disproportionally more likely to be in occupations where they perform the same main tasks as their father. Our main test of this is whether the likelihood an individual is in task *i* conditional on their father being in task *i* is higher than the likelihood an individual is in task *i* conditional on their father being in a task other than task *i*. We do this for all individuals and for the subsample that does not include individuals that are in the same occupation as their father (at a three digit occupation code).

[3] The Department of Labor's Dictionary of Occupational Titles (DOT) is originally used by Autor, Levy and Murnane (2003) to impute to workers the task measures associated with their occupations, and then it is also verified and merged with Occupational Information Network (O* Net), Census and CPS occupational categories.

[4] There are 4 occupations have no task measurements in Autors' data, and they are: 1) occ1990dd=227, occ80=227: "Air traffic Controllers and Airfield Operations Specialists". 2) Occ1990dd=303, occ1980=303: "First-Line Supervisors/Managers of Office and Administrative Support". 3) Occ1990dd=503, occ1980=503: "First-Line Supervisors/Managers of Mechanics, Installers, and Repairers". 4) Occ1990dd=803, occ1980=803:"Supervisors, Transportation and Material Moving Workers". Given that these occupations accounts for a small proportion in sample (less than 100 observations), we do not include these observations in the analysis.

[5] See definitions for particular skills in the Appendix B

Then we will estimate log wage equations in a Mincerian setting to capture the wage returns to task following. In these equations in addition to standard controls we will specifically control for whether the individuals are in the same task or the same occupation as their fathers. For all of our wage regressions, we define task-followers as individuals that are in the same task, but different occupations (defined at a three digit level).

The following is the baseline log wage equation we estimate:

$$\log(realwage) = \alpha' X + \beta_1(sametask) + \beta_2(sameoccupation) + \varepsilon$$

where real wage is calculated in 1982 dollars and X is a vector of individual level controls for respondents' highest years of schooling, age, age-squared, marital status, race, gender, union-status, number of children, and their fathers' highest years of schooling, mothers' highest years of schooling, cohort indicators as well as dummy controls for occupation groups and industries for the specific (at three digit level) occupation they are employed in. We also include gender controls and gender interactions with the task and occupation following dummies in the baseline model. We sometimes estimate this basic model separately by gender to allow for more flexible slope estimates. We might expect the returns to task following to be different by education status or across general occupational groups. In order to allow differential returns by education, in an extension to the basic model, we include an indicator for being a college graduate and following one's father's task. To allow for differential returns by the earnings potential of the task we estimate quantile wage regressions. Finally, we interact task following with the dominant task to determine if the returns to task following differ by task.

Main Results

Our main results are organized as follows. First we present the evidence that task following is a real phenomenon and is distinct from occupational following. Next we present the basic results on the wage premium associated with task following and finally we explore how this varies by the interaction of education and gender.

Task Followers

To describe the nature and degree of task following, we first calculate the matrix of child task and father task combinations, including those who work in the same occupation as their father. The results are presented in table 1.

[Table 1]

Each cell represents the fraction of all children with that own task/father task combination. For example, the first cell (upper left) shows that in 2.5 percent of all observations the child is in a non-routine, cognitive analytical task and has a father that was also in a non-routine cognitive analytical task. The diagonal of table 1 is the fraction of all offspring that are task followers by each dominant task. The total row reports the fraction of fathers that are employed in each dominant task, while the total column reports the fraction of children by their dominant task. This serves to highlight the differences across generations in the share of jobs with each dominant task, partly due to changes in overall job composition in the economy and partly due to the inclusion of women. While only 4.5% of fathers are employed in a routine cognitive task, 16.5% of the offspring are employed in an occupation with that dominant task. Non-routine manual physical tasks, on the hand, make up 37.1% of the father's task, while only 16.1% of the children. These changes in composition muddy the degree of task following among children. For example, while the fraction of children whose father was employed in a non-routine manual physical task, that follow their father is just 20.8% (7.7/37.1), among the children that are employed in a non-routine manual physical task, nearly 50% (7.7/16.1) are task followers.

[Table 2]

In table 2 we report the fraction of offspring in each task conditional on the dominant task in their father's occupation (each cell in table 1 divided by the total row). The diagonal of table 2 is the fraction of children that are task followers (including occupational followers) by each task. The next to last column reports the fraction of offspring in each task, conditional on not being a task follower. The last column reports the results of a t-test that the diagonal is the same as the next to last column.

The most pronounced task following is in the non-routine cognitive analytical task, where the fraction of offspring, conditional on that also being the father's task, is nearly twice as large as the unconditional fraction (26% vs. 13.5%). For each task, the dominant task of the father is either the most common or second most common outcome. Further the likelihood an offspring enters a given task, conditional on their father being in that task, is higher than the likelihood an individual enters that task conditional on the father not being in that task and this difference is statistically significant for every task.

Of course, this could just be a reflection of the fact that occupation followers are also employed in the same task as their fathers. To demonstrate that task following exists and is distinct from occupation following, we report the same calculation as in table 2 excluding the occupation followers.

[Table 3]

Again, task following is common and the likelihood an offspring enters a task conditional on their father being in that task is higher than the likelihood an offspring enters that task conditional on their father not being employed in that task. This difference is statistically significant for all tasks except routine cognitive.

Since we are interested in task followers as distinct from occupation followers, for all of the remaining analyses we will not count an occupational follower as a task follower, but will instead include a separate occupational follower dummy.

Wage Premium

The results from the wage regression are presented in Table 4. In specification I we report the correlation between wages and following, while specification II includes standard individual controls. Specification III adds industry controls and occupation group controls and is the baseline model we will use in the analyses to follow. Finally, specification IV includes detailed occupation controls.

[Table 4]

When there are no controls for occupations (specifications 1 and 2), there is a statistically significant 5-6% wage premium associated with task followers. Occupation followers earn a statistically significant 9-10% wage premium, when standard individual characteristics are included.

When controlling for occupation groups and industry groups (specification 3), there is a 5% wage premium for task followers, while the premium associated with occupation followers is reduced to 4%. Finally, when detailed occupational controls are added in addition to occupation group controls and industry controls, the wage premium remains at 4.5% for task followers and 4% for occupational followers. This suggests that task followers, even when working in occupations that are similar by group and by detailed job requirements, earn a wage premium over those that are not task followers.

Okumura and Usui find a similar task premium, however, they find this only for whites. To compare our findings to their results, we do the same analysis as in table 4, only grouping by race and gender (they only consider men).

[Table 5]

While there does seem to be a negative relationship between wages and both task and occupation following in blacks (specification I), this disappears when occupation and industry controls are included. Looking just at white men and black men in our baseline model (specification 3), the point estimates on task following are almost identical (5.2% vs. 5.4%). The estimate for black men is more imprecisely identified and is not statistically significant. Occupational following follows a similar pattern. Thus, we discern no differences in task and occupational following by race among men. For black women, however, there is a large statistically significant negative effect associated with occupational followers. There is no such relationship among white women.

To explore the source of the task and the occupational follower premium we next run the wage regression with interaction terms between an individuals' education status and task/occupation following.

[Table 6]

For all three samples (pooled, men and women) the coefficient on task following is insignificant, but a large, positive, statistically significant coefficient is found on the interaction between task following and college graduates. Interestingly the occupation following premium for men is largely unaffected and the interaction between occupation followers and college graduates is close to zero and statistically insignificant. However, for women the occupation premium coefficient is very small, but the interaction term is large (25%) and significant at the 5% level when controlling for occupations.

These results imply that task following is associated with higher wages primarily for college graduates and that is true across gender. This could be partly because of changes in the rewards to specific tasks overtime. If the market return to skills that are not associated with college graduates has decreased, then the investments that the fathers with those skills made in their children are less valuable in the future.

Discussion

Factors that Determine Task Following

The fact that the wage premium differs across gender and schooling is suggestive that task and occupation following might also vary along these dimensions. To test for differences, we perform a logit analysis on the likelihood of being an occupation follower and an analysis on the likelihood of being a task follower.

[Table 7]

Table 7 reports the coefficients on gender, race and schooling from the logit analysis. For both occupation and task following, women are much less likely to be followers. Education is also associated with being less likely to be a follower. This could be a function of the higher education attainments of children. However, the interaction between gender and schooling is positive and significant. That is to say that highly educated women are much more likely to be task and occupation followers than highly educated men, controlling for the fact that women in general are less likely to be followers.

Consistent with the results in Okumura and Usui, African Americans are less likely to be occupational followers. However, when only looking at task followers, the effect is small and statistically insignificant.

Time Trend

Given the change in the composition of occupations and the dominant task associated with each occupation over time, we perform our baseline analysis with interaction terms between task followers and post 1990 and occupation followers and post 1990. The results of this are presented in table 8.

[Table 8]

For men there is little to suggest that the premium associated with task and occupation following is different. However, for women the premium for occupation following is large in the post 1990s period, while indistinct from zero previously. This is likely driven by the increased integration of women in previously male dominated jobs.

Quantile Regression

We might also be interested in which parts of the wage distribution do the effects of task and occupation following appear to be most salient. To do this we perform a quantile regression on earnings. The results are in table 9.

[Table 9]

The most striking result is that while occupation following appears to be larger in the middle to upper end of the distribution, the premium with task following is largest at the bottom of the distribution.

Wage Premium by Task

Given the results suggestive of differences by education and gender, we perform our baseline analysis with interaction terms between being a task follower and the dominant task. Thus, the interaction term is the difference between task followers in that task and task followers employed in a routine manual job.

[Table 10]

The only interaction term that is statistically significant is for followers in a non-routine, cognitive, analytical task. This difference could be driven by changes in the rewards to this task overtime. That is, the fathers in these tasks made similar task specific investments as other fathers, but now the reward from those is larger due to market changes.

Conclusion

In this paper we document that there is a substantial amount of what we refer to as task following; that is children who enter into occupations that use similar skills as their father's occupation, but are not the same occupation. We find that task following is lower among women and the higher educated, however it is relatively higher for more educated women.

Further, in line with previous work on occupational following, task following is associated with higher wages. The magnitude of the premium is of a similar magnitude as occupation following when controlling for occupation groups. This premium appears to be much larger for college graduates. We find no differences in the task premium associated with race.

This provides additional evidence that fathers are able to transmit task related skills to their children and this has benefits in the labor market. While not a direct test of the nepotism hypothesis for occupational following, this seems to be an unlikely source of the task following premium. While, fathers may be able to provide opportunities within an occupation, this seems much less likely to be true across occupations. Although, if fathers networks span occupations within a task grouping, then nepotism could still be an explanation.

Appendix

Following Autor and Acemoglu (2010), the tasks and skills in the work activities are defined as follows:

Non-routine cognitive: Analytical
Analyzing data/information
Thinking creatively
Interpreting information for others

Examples of jobs with intensive non-routine cognitive analytical tasks: actuaries, physicists and astronomers, economists, market researcher and survey researcher

Non-routine cognitive: Interpersonal
Establishing and maintaining personal relationships
Guiding, directing and motivating subordinates
Coaching/Developing others
Examples of jobs with intensive non-routine cognitive interpersonal tasks: clergy and religious workers, athletes, sports instructors, and officials

Routine cognitive
Importance of repeating the same task
Importance of being exact or accurate
Structured v. Unstructured work (reverse)

Examples of jobs with intensive routine cognitive tasks: telephone operators, transportation ticket and reservation agents, and cashiers

Routine manual
Pace determined by speed of equipment
Controlling machines and processes
Spend time making repetitive motions

Examples of jobs with intensive routine manual tasks: machine operators, winding and twisting textile/apparel operatives, crane, derrick, winch and hoist operators

Non-routine manual physical
Operating vehicles, mechanized devices, or equipment
Spend time using hands to handle, control or feel objects, tools, or controls
Manual dexterity
Spatial orientation

Examples of jobs with intensive non-routine manual physical tasks: airplane pilots and navigators, excavating and loading machine operators, millwrights, taxi drivers and chauffeurs

Non-routine manual interpersonal
Performing for or working directly with the public
Provide consultation and advice to others

Examples of jobs with intensive non-routine manual interpersonal tasks: psychologists, managers of food-serving and lodging establishments, actors, directors and producers

We further utilized Autor and Dorn's aggregation to group all occupations to the 1-digit level as follows:
management/professional/technical/financial/sales/public security,
administraive support and retail sales,
low-skill service,
precision production and craft, *machine operators, assemblers and inspectors*
transportation/construction/mechanics-/mining/agricultural.

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Tables

Table 1: Intergenerational Task Transition, and Distribution of Tasks for Fathers and Offsprings

Offspring's O*Net tasks	Fathers' O*Net tasks: Non-routine Cognitive Analytical Tasks	Non-routine Cognitive Interpersonal	Routine Cognitive Tasks	Routine Manual Tasks	Non-routine Manual Physical Tasks	Non-routine Manual Interpersonal	Total
Non-routine Cognitive Analytical Tasks	2.5	3.2	0.8	2.0	3.6	1.6	13.5
Non-routine Cognitive Interpersonal Tasks	2.5	5.6	1.0	3.5	6.4	1.9	20.8
Routine Cognitive Tasks	1.4	3.4	0.9	3.4	6.3	1.2	16.5
Routine Manual Tasks	0.7	2.2	0.5	4.7	7.6	0.6	16.3
Non-routine Manual Physical Tasks	0.8	2.3	0.5	3.9	7.7	0.9	16.1
Non-routine Manual Interpersonal Tasks	1.8	3.9	0.9	3.0	5.6	1.7	16.9
Total	9.6	20.6	4.5	20.5	37.1	7.8	100.0

Notes: All statistics are calculated using sampling weights.

Table 2: Intergenerational Task Transition, Share Conditional on Father's Task

Offspring's O*Net tasks	Fathers' O*Net tasks: Non-routine Cognitive Analytical Tasks	Non-routine Cognitive Interpersonal Tasks	Routine Cognitive Tasks	Routine Manual Tasks	Non-routine Manual Physical Tasks	Non-routine Manual Interpersonal Tasks	Father not in the same task	|t|-statistics
Non-routine Cognitive Analytical Tasks	26.0	15.6	16.7	10.0	10.0	19.3	12.4	14.53
Non-routine Cognitive Interpersonal Tasks	25.3	27.2	21.9	17.1	17.1	23.5	19.0	10.3
Routine Cognitive Tasks	14.4	16.3	19.4	16.8	16.8	15.8	16.4	2.11
Routine Manual Tasks	7.4	10.6	10.8	22.9	20.4	7.7	14.6	11.46
Non-routine Manual Physical Tasks	8.3	11.3	11.5	18.5	20.8	11.6	13.3	12.38
Non-routine Manual Interpersonal Tasks	18.6	19.0	19.7	14.8	14.9	22.2	16.4	5.2

Note: All statistics are calculated using sampling weights.

Table 3: Task Transition for Non-Occupation Followers

Offspring's O*Net tasks	Fathers' O*Net tasks: Non-routine Cognitive Analytical Tasks	Non-routine Cognitive Interpersonal Tasks	Routine Cognitive Tasks	Routine Manual Tasks	Non-routine Manual Physical Tasks	Non-routine Manual Interpersonal Tasks	Father not in the same task	|*t*|-*statistics*
Non-routine Cognitive Analytical Tasks	23.07	16.86	17.11	10.31	10.33	20.03	12.95	*10.48*
Non-routine Cognitive Interpersonal Tasks	26.33	21.31	22.51	17.66	17.71	24.32	19.65	*2.02*
Routine Cognitive Tasks	14.98	17.58	17.25	17.34	17.39	16.35	17.09	*0.11*
Routine Manual Tasks	7.74	11.5	11.11	20.27	21.15	7.96	15.23	*6.74*
Non-routine Manual Physical Tasks	8.59	12.25	11.84	19.16	17.97	11.99	13.91	*6.61*
Non-routine Manual Interpersonal Tasks	19.3	20.5	20.18	15.26	15.45	19.35	17.13	*1.93*

Note: All statistics are calculated using sampling weights.

Table 4: Father Follower Premium Coefficients, GSS 1972-2010

		I	II	III	IV
All	Task Followers	0.063**	0.056**	0.049**	0.045**
		(0.017)	(0.015)	(0.014)	(0.014)
	Occupation Followers	0.184**	0.108**	0.054+	0.073*
		(0.035)	(0.031)	(0.031)	(0.003)
Female	Task Followers	0.050+	0.065**	0.041+	0.040+
		(0.027)	(0.024)	(0.024)	(0.023)
	Occupation Followers	0.217**	0.144*	0.056	0.085
		(0.081)	(0.065)	(0.068)	(0.066)
Male	Task Follower	0.035+	0.045*	0.057**	0.052**
		(0.021)	(0.018)	(0.018)	(0.018)
	Occupation Follower	0.007	0.089*	0.052	0.069+
		(0.039)	(0.035)	(0.036)	(0.036)
Industry Group Controls		NO	NO	YES	YES
Occupation Group Controls		NO	NO	YES	YES
Additional Occupational Controls		NO	NO	NO	YES

Notes: (1) The coefficients are estimated by robust OLS regression on individuals' real yearly wages. (2) Basic, Standard and Expanded models all include individual characteristics (i.e. years of education, working experience, working experience squared, marital status, the number of children, union membership, race, gender and weekly working hours), parents' education, year and region dummies. (3) Additional Occupational Controls include O*NET occupational quality indices for environment, hazards, physical and strength requirements and OPTD measures of occupational education and training requirements, as well as mean tenure years in each occupation created using CPS supplements. (4) Robust standard errors in parentheses. **, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 5: Father Follower Premium Coefficients by Race, GSS 1972-2010

		I	II	III	IV
White All	Task Followers	0.064	0.049	0.04	0.039
		(0.018)**	(0.016)**	(0.015)**	(0.015)*
	Occupation Followers	0.213	0.121	0.06	0.079
		(0.036)**	(0.032)**	(0.032)+	(0.033)*
White Female	Task Followers	0.041	0.048	0.022	0.028
		(0.03)	(0.026)	(0.026)	(0.026)
	Occupation Followers	0.225	0.137	0.043	0.08
		(0.086)**	(0.068)*	(0.069)	(0.067)
White Male	Task Follower	-0.025	0.042	0.052	0.048
		(0.022)	(0.019)*	(0.019)**	(0.019)*
	Occupation Follower	0.045	0.106	0.065	0.078
		(0.040)	(0.036)**	(0.037)+	(0.038)*
Black All	Task Followers	-0.019	0.07	0.082	0.042
		(0.049)	(0.053)	(0.052)	(0.051)
	Occupation Followers	-0.069	0.009	0.017	-0.016
		(0.121)	(0.145)	(0.139)	(0.144)
Black Female	Task Followers	-0.053	0.1	0.111	0.052
		(0.071)	(0.082)	(0.078)	(0.072)
	Occupation Followers	-0.175	-0.186	-0.295	-0.413
		(0.111)	(0.182)	(0.155)+	(0.165)*
Black Male	Task Follower	-0.108	0.032	0.054	0.044
		(0.067)	(0.071)	(0.073)	(0.075)
	Occupation Follower	-0.208	0.056	0.061	0.084
		(0.142)	(0.192)	(0.187)	(0.197)
Industry Group Controls		NO	NO	YES	YES
Occupation Group Controls		NO	NO	YES	YES
Additional Occupational Controls		NO	NO	NO	YES

Notes: (1) The coefficients are estimated by robust OLS regression on individuals' real yearly wages. (2) Basic, Standard and Expanded models all include individual characteristics (i.e. years of education, working experience, working experience squared, marital status, the number of children, union membership, race, gender and weekly working hours), parents' education, year and region dummies. (3) Additional Occupational Controls include O*NET occupational quality indices for environment, hazards, physical and strength requirements and OPTD measures of occupational education and training requirements, as well as mean tenure years in each occupation created using CPS supplements. (4) Robust standard errors in parentheses. **, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 6: Wage Premium of Task-Followers and Occupation Followers, Role of Education

	All	Female	Male
Father Task Followers	0.029	-0.009	0.025
	(0.018)	(0.03)	(0.021)
Father Occupation Followers	0.067	-0.106	0.059
	(0.041)	(0.08)	(0.046)
College Graduates or Higher	0.087**	0.008	0.111**
	(0.023)	(0.032)	(0.03)
Father Task Followers* College Graduates	0.081**	0.122**	0.104*
	(0.031)	(0.047)	(0.039)
Father Occupation Followers* College Graduates	0.085	0.391**	-0.02
	(0.061)	(0.135)	(0.066)
Observations	12882	5999	6883
R-squared	0.35	0.34	0.37

Notes: (1) The dependent variable is individuals' real yearly wages. (2) Control variables are the same as in the main model defined in Table 5. (3) Robust standard errors in parentheses. (4) **, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 7: Probability of Being Father Follower, Logit Model Estimates

	Occupation Followers			Task Followers		
	Coeff.	Odds Ratio	M.E.	Coeff.	Odds Ratio	M.E.
Female	-2.828	0.059	-0.091	-2.249	0.105	-0.328
	(0.524)**	(0.031)**	(0.016)**	(0.271)**	(0.029)**	(0.039)**
Years of Schooling	-0.065	0.937	-0.002	-0.107	0.899	-0.016
	(0.018)**	(0.017)**	(0.0006)**	(0.011)**	(0.009)**	(0.002)**
Female*Years of Schooling	0.114	0.039	0.004	0.125	1.133	0.018
	(0.036)**	(0.040)**	(0.001)**	(0.019)**	(0.022)**	(0.003)**
Black	-0.522	0.594	-0.014	-0.055	0.946	-0.008
	(0.184)**	(0.109)**	(0.004)**	(0.080)	(0.076)	(0.011)
Other Race	0.137	1.147	0.005	0.056	1.057	0.008
	(0.195)	(0.223)	(0.007)	(0.111)	(0.118)	(0.017)
Observations		13438			13438	

Notes: (1) The estimations are made based on the Logit model. (2) Robust standard errors in parentheses. (3) The base-line group is white males. (4)Control variables are the same as in the "basic" specifications defined in Table 5. (5)**, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 8: Wage Premium for Father Followers over Time

	All	Female	Male
Father Task Followers	0.048*	0.032	0.047+
	(0.022)	(0.037)	(0.026)
Father Occupational Followers	0.02	-0.08	0.039
	(0.043)	(0.095)	(0.049)
Father Task Followers*After the 1990s	-0.003	0.015	0.005
	(0.028)	(0.047)	(0.036)
Father Occupational Followers*After the 1990s	0.055	0.246+	0.025
	(0.061)	(0.132)	(0.069)
Observations	12882	5999	6883
R-squared	0.37	0.33	0.36

Notes: (1) The dependent variable is individuals' real yearly wages. (2) Control variables are the same as in the baseline model defined in Table 4. (3) Robust standard errors in parentheses. (4) **, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 9: Qauntile Wage Regressions

	10%	25%	50%	75%	90%
Father Task Followers	0.105**	0.043*	0.034*	0.037*	0.004
	(0.028)	(0.018)	(0.014)	(0.015)	(0.019)
Father Occupation Followers	-0.003	0.024	0.085**	0.083**	0.042*
	(0.075)	(0.039)	(0.025)	(0.030)	(0.018)
Female	-0.363**	-0.318**	-0.298**	-0.279**	-0.329**
	(0.025)	(0.015)	(0.012)	(0.010)	(0.013)
Female *Father Task Followers	-0.068	0.001	-0.016	-0.043+	0.028
	(0.055)	(0.036)	(0.024)	(0.022)	(0.025)
Female *Father Occupation Followers	-0.051	-0.067	-0.081*	-0.049	0.004
	(0.21)	(0.048)	(0.039)	(0.073)	(0.105)
Observations	12882	12882	12882	12882	12882

Notes: (1) The dependent variable is individuals' real yearly wages. (2) Control variables are the same as in the baseline model defined in Table 4. (3) Robust standard errors in parentheses. (4) **, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.

Table 10: Wage Premium of Task Followers in Different Tasks

	All	Female	Male
Father Task Followers	0.006	-0.025	0.022
	(0.035)	(0.057)	(0.044)
Father Task Followers*Non-routine Cognitive Analytical Tasks	0.124*	0.127	0.13*
	(0.051)	(0.092)	(0.062)
Father Task Followers*Non-routine Cognitive Interpersonal Tasks	0.081+	0.108	0.077
	(0.045)	(0.07)	(0.059)
Father Task Followers*Routine Cognitive Tasks	-0.054	0.016	-0.243
	(0.07)	(0.085)	(0.165)
Father Task Followers*Non-routine Manual PhysicalTasks	-0.021	0.003	-0.041
	(0.046)	(0.104)	(0.054)
Father Task Followers*Non-routine Manual Interpersonal Tasks	0.083	0.122	0.06
	(0.061)	(0.087)	(0.088)
Non-routine Cognitive Analytical Tasks	0.302**	0.234**	0.366**
	(0.034)	(0.054)	(0.045)
Non-routine Cognitive Interpersonal Tasks	0.202**	0.155**	0.201**
	(0.032)	(0.053)	(0.040)
Routine Cognitive Tasks	0.171**	0.132*	0.186**
	(0.034)	(0.052)	(0.050)
Non-routine Manual Physical Tasks	0.11**	0.12+	0.112**
	(0.029)	(0.068)	(0.033)
Non-routine Manual Interpersonal Tasks	0.157**	0.092+	0.186**
	(0.032)	(0.048)	(0.047)
Father Occupation Followers	0.055+	0.059	0.057
	(0.033)	(0.073)	(0.037)
Observations	12882	5999	6883
R-squared	0.36	0.31	0.34

Notes: (1) The dependent variable is individuals' real yearly wages. (2) The base-line group is father task-followers in routine manual tasks. (3) Control variables are the same as in baseline model defined in Table 4. (4) Robust standard errors in parentheses. (5) **, *, + denote statistical significance at the 0.01, 0.05 and 0.1 levels, respectively.