Work and Grow Rich: The Dynamic Effects of Performance Pay Contracts

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Abstract

This paper studies the rise of performance pay contracts and their aggregate effects on the labor market. First, using the Panel Study of Income Dynamics and National Longitudinal Survey of Youth, I document three patterns: (i) the share of performance pay workers grew from 15% in 1970 to 50% by 2000, (ii) performance pay workers experience higher earnings levels and growth rates and work longer hours, and (iii) invest more in their on-the-job human capital. These differences persist even when comparing similar jobs in the same establishment using the National Compensation Survey. Second, I build a dynamic Roy model with heterogeneity in performance pay, time-varying probabilities of receiving performance pay, and human capital accumulation. The model is calibrated using simulated method of moments on the NLSY79. Third, I use my model to gauge the role of incentives, the contribution of performance pay to rising earnings inequality, and evaluate a recently proposed counterfactual 73% marginal tax rate.

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1. Introduction

The United States labor market has undergone a number of profound transformations over the past half-century with the rise of college attainment (Katz and Murphy, 1992) and information technology (Autor et al., 2003), decline in unions (Card, 1996; Card et al., 2004) and minimum wage laws (Lee, 1999), and changes in the returns to unobserved ability (Juhn et al., 1993). However, another major phenomenon has been taking place of the past forty years—a movement from fixed wage to performance pay contracts.[1] For example, whereas the share of the labor force with performance pay was only 15% in 1970, it was 50% by 2000 (see Figure 1). Identifying how the transition from fixed wage to performance pay schemes has influenced earnings dispersion, earnings growth, and job mobility comes at an especially important time as the labor market continues to undergo structural transformation, ranging from automation (Acemoglu and Restrepo, 2017) to freelancing (Katz and Krueger, 2016).

While it is now well-known that approximately half of the variation in lifetime earnings is explained by decisions individuals make before entering the labor market (Keane and Wolpin, 1997; Cunha et al., 2005; Huggett et al., 2011), that still means half of the variation that remains is explained by decisions on-the-job. This paper focuses on the rise of performance pay contracts as a new dimension of heterogeneity in the labor market and how it shapes the human capital and career motives of workers. Using a combination of public and restricted-access longitudinal micro-data, I structurally analyze the effect of performance pay contracts on the returns to human capital accumulation and labor supply, quantify its affects on aggregate labor market outcomes, and evaluate how these outcomes are shaped by marginal tax rates. The paper proceeds in three parts. The first uses a combination of the Panel Study of Income Dynamics (PSID, 1970-2014), National Longitudinal Survey of Youth (1985-2014), and National Compensation Survey (NCS, 2004-2016) to document three empirical regularities about performance pay workers in the labor market. Guided by these facts, the second devel-

[1] Of course, just like these other trends, such as the rise of college attainment and information technology, this shift towards performance pay is not exogenous. However, it is a large macro-wide force that will be the focus of this paper. The rise of performance pay could have occurred in part due to the rise of information technology, which may have made it easier for firms to track and observe individual output.

ops a dynamic search model with human capital accumulation (learning-by-doing), search, and contract heterogeneity. The third calibrates the model to the NLSY and uses it to structurally characterize the impact of incentives on labor supply and human capital decisions, and evaluate a counterfactual tax policy.

[INSERT FIGURE 1]

There are at least three challenges in measuring and identifying performance pay workers in the data. First, most household surveys do not ask about the provision of bonus and/or other variable pay components. Second, even among those that do, none (except the Survey of Consumer Finances) distinguishes between the contemporaneous receipt of performance pay within a year and the eligibility of it given that job. Third, even if eligibility could be measured, the presence of career concerns could produce similar human capital motives even in the absence of performance pay. Building on the seminal work of Lemieux et al. (2009), I classify workers as performance pay if they ever receive bonus, tip, or commission with the same employer (see the solid and dotted blue lines in Figure 1). I also use administrative data that directly measures performance pay status starting in 1994 to show that this measure is not too far off (see the red line in Figure 1). I also show robustness by restricting the sample in several exercises to manufacturing, trade, and business sectors where career concerns are less likely to persist.

The first part of the paper measures the incidence of performance pay contracts across space and time, quantifies differences in earnings and hours worked over time and the life cycle, and provides suggestive evidence that performance pay workers invest more in human capital. Using the PSID between 1970 and 2014, I show that the share of performance pay workers has grown from 15% of the labor force to 50%. The surge in performance pay contracts is not driven by composition effects relating to structural transformation. Combined with the NLSY, I show that differences between performance pay and fixed wage workers have not only grown over time, but also vary significantly over the life cycle. Exploiting job-to-job transitions as a partial solution to the presence of unobserved individual selection effects, performance pay workers earn (work) 10% (7%) more than their counterparts. These results are also robust to using new and under-utilized administrative data from the NCS, which allows me to compare similar jobs with different contracts within the same establishment.

Motivated by these results, I explore the life cycle profiles of earnings and hours worked. Hours worked among fixed wage workers plateaus around age 30, subsequently declining to levels observed when they initially entered the labor force; hours among performance pay workers, in contrast, plateau around age 40 and do not exhibit a similar decline. Earnings follows a similar pattern—growing over the life cycle for performance pay workers, but plateauing for fixed wage workers in their early 40s. These results have large implications for macroeconomic models of consumption and savings under complete (Deaton, 1991; Gourinchas and Parker, 2002) and incomplete (Aiyagari, 1994) markets. I also examine how these empirical patterns might be consistent with different models of human capital accumulation (e.g., Ben-Porath (1967) versus Imai and Keane (2004)).[2] In particular, I find that performance pay workers are willing to not only take reduced pay today in exchange for higher future earnings, but also work longer hours, which are capitalized into future earnings. Similar results hold for earnings growth.

The second part of the paper integrates these empirical regularities into a dynamic search and life cycle model with human capital accumulation. Building on a history of dynamic discrete choice models (Keane and Wolpin, 1997; Eckstein and Wolpin, 1999), I allow for not only the accumulation of physical assets, but also rich human capital dynamics by modeling earnings as a function of time-invariant industry-by-occupation differences, labor supply, cumulative hours worked, as well as specificity in the type of human capital (Kambourov and Manovskii, 2009a,b).[3] Individuals can implicitly sort into performance pay jobs by choosing their industry and occupation job, which varies in the probability of offering a performance pay contract over time. While individuals face a probability of being laid off each period, they also receive new offers and can sort into a new job. The model is calibrated to a panel of full-time workers from the NLSY79 using simulated method of moments (SMM).

The third part of the paper uses the structural model to understand the effects of these incentives on human capital accumulation, labor supply, and aggregate labor market outcomes. The model fits an array of labor market features with a minimum set of parameters that have

[2]Heckman et al. (2003) use variation in the earned income tax credit (EITC) to determine whether empirical evidence is more consistent with learning by doing versus on the job training; the two models have drastically different quantitative predictions since the only opportunity cost of human capital accumulation in an on the job learning model is leisure, whereas it is both the wage and leisure in the alternative setup. They conclude that the data is more consistent with learning by doing since wage growth declines with increases in short term tax rates (e.g., tax rates depressed labor supply, and thus learning). There is also a large psychology literature on the importance of learning-by-doing (Lemov et al., 2012; Duckworth et al., 2015). Differences in educational attainment are captured via the time-invariant unobserved heterogeneity term in my model, obviating concerns that omitted differences in education are driving the main results simply due to their correlation with performance pay.

[3]For example, Heckman and MacCurdy 1980 developed a life-cycle model to explain female labor supply, Eckstein and Wolpin 1989 developed a model of labor supply, wages, and fertility. More recent work has focused on the role of occupational choice over the long-run (Lee and Wolpin, 2006), effects of welfare policies on female labor supply (Blundell et al., 2016), parental investments and educational attainment (Keane and Wolpin, 2001), and savings and retirement (French and Jones, 2011).

typically been difficult to match, including the standard deviation of earnings and hours worked and job mobility rates. I subsequently implement three counterfactual exercises. First, to gauge the role of incentives and their dynamic effects, I solve two variants of the model: one without heterogeneity in performance pay and another without human capital accumulation. These two exercises allow me to explicitly disentangle the contribution of performance pay towards just higher income versus higher income and higher human capital. Second, to gauge the impact of performance pay on earnings inequality, I fix the probability an individual receives a performance pay contract to 1970 levels, allowing me to distinguish the static versus dynamic effects of performance pay (Lemieux et al., 2009). Third, to gauge the implications of this my model for policy evaluation, I simulate a counterfactual with a 73% marginal tax rate, which has been proposed by some prominent economists in the optimal tax literature (Diamond and Saez, 2011). My results show that higher marginal tax rates affect earnings by not only depressing hours worked (Prescott, 2004; Ohanian et al., 2008; Rogerson, 2006), but also the dynamic career incentives for work.

Despite a comprehensive microeconomic literature on optimal contracting within the firm starting with Holmstrom (1979) and Lazear (1986), there is surprisingly scarce evidence on the macroeconomic implications of performance pay. Building on Lemieux et al. (2009) who show that roughly 20% of the rise of earnings inequality can be explained by performance pay contracts, my paper focuses on the dynamic effects of performance pay on human capital accumulation, which generates further earnings dispersion. My focus on human capital also helps explain heterogeneity in the cyclical behavior of earnings and hours in performance pay and fixed wage jobs (Lemieux et al., 2014; Gittleman and Makridis, 2017). Closely connected with this paper is a literature in personnel economics, which shows that performance pay raises productivity (Paarsch and Shearer, 1999; Lazear, 2000a; Paarsch and Shearer, 2000; Shearer, 2004; Bandiera et al., 2005) and on-the-job learning (Shaw and Lazear, 2008).

This paper also contributes to two broader literatures in labor economics. The first is an empirical literature over the the driving sources of dispersion in the labor market, which has soared in the U.S. over the past four decades, more so than other OECD economies (Forster and Levy, 2014).[4] These changes are largely explained through changes in permanent income (Kopczuk et al., 2010). While a voluminous literature has emerged to explain these trends using models of skill-biased technical change (Acemoglu, 1998; Katz and Murphy, 1992; Acemoglu,

[4]Atkinson et al. (2011) show that a major fraction of wealth inequality is derived from earnings inequality.

2002; Autor et al., 2006, 2008), typically distinguishing between college and non-college workers and/or workers in non-routine or routine tasks (Autor et al., 1998, 2003; Autor and Dorn, 2013), these models fall short of explaining several key dimensions. For example, they cannot explain the changing nature of wage inequality (Lemieux, 2008; Card and DiNardo, 2002) or cross-country trends in inequality (Freeman and Katz, 1995).[5] Despite the large empirical literature on the effects of unions on the distribution of wages (Abowd and Card, 1989; Card, 1996) and rising inequality (Card et al., 2004; Champagne and Kurmann, 2013; Acikgoz and Kaymak, 2014), there has been much less attention directed towards the rise of performance pay.[6]

The second is a methodological literature over the solution and estimation of dynamic discrete-continuous programming models to explain labor market patterns. Starting with Rust (1987), a number of subsequent contributions emerged to understand the life cycle patterns of different workers in the labor market (Keane and Wolpin, 1997; Eckstein and Wolpin, 1999).[7] One important simplification in the majority of these models, however, is the treatment of human capital accumulation, which is typically modeled as the return to an additional year of experience in the labor market (with the exception of Imai and Keane (2004)). Extending these earlier approaches, this paper allows for continuous decisions in the investment of both human and physical capital. Doing so, however, raises the complexity of the state space given the span of cumulative hours worked over an individual's career. To deal with these complexities, I employ methods that have not been previously applied in economics, including the use of Gaussian Process Regressions (GPR) for interpolation and an adaptive grid (Scheidegger and Bilionis, 2017), which raise the accuracy and speed of the optimal policy rules.

This framework suggests an array of fruitful areas for further research. First, there has been a preponderance of new incentive mechanisms and non-wage amenities implemented across organizations (Oyer, 2008; Liu et al., 2017). They not only provide new opportunities to empirically quantify incentive effects on effort and productivity, but also structurally analyze their selection effects on the equilibrium search behavior of potential candidates. For example,

[5] A series of chapters in Freeman and Katz (1995) highlight this claim. Generally speaking, all developed economies experienced similar shifts in industrial composition (e.g., decline in manufacturing (Katz, 1994)), increases in the fraction of college graduates, and increases in information technology. See the Appendix for evidence on the latter.

[6] Lemieux et al. (2009) were among the first to point out the rise in performance pay jobs and Comin et al. (2009) speculates that it can help explain the rise in the sales volatility of publicly traded firms.

[7] While several recent contributions have involved estimating these models in general equilibrium (Lee and Wolpin, 2006), doing so is beyond the scope of the specific contribution in this paper, although it is the subject of ongoing companion work.

Oyer (2004) and Oyer and Schaefer (2005) show that the provision of stock options and equity compensation can help attract better workers. My results also underscore the ways in which organizational policies can help shape employee human capital accumulation over the long-run. If labor market distortions can be reduced, firms will face greater returns to create incentives that encourage skill accumulation among its employees, thereby raising aggregate productivity.[8]

Second, while the static factors that explain dispersion in performance pay were documented three decades ago by Lazear (1986), there is still ambiguity about the relative contributions of these different channels, as well as dynamic factors—what explains the cross-section of performance pay? For example, Lemieux et al. (2009) speculate that the rise of information technology made it easier to observe output, thereby raising the returns to performance pay. Similarly, motivated by Raith (2003) who develops a theoretical model where greater competition creates higher returns to stronger managerial incentives, the rise of globalization may have increased the returns to using performance pay. Finally, an alternative view that is based on the results in this paper is that the decline in marginal tax rates and unions created more employer-employee surplus for firms to bargain over, thereby raising the returns to stronger incentives. This paper provides a quantitative framework for analyzing these types of broader questions.[9]

2. Data and Reduced Form Analysis

2.1. Panel Data Samples

The ideal dataset for studying the incidence of performance pay would contain matched employee-employer records over individual-level outcomes, ranging from consumption to earnings, that allows me to distinguish between performance pay and fixed wage workers. Unfortunately,

[8]Incentives for accumulating human capital are crucial for understanding cross-country differences in not only economic growth rates (Manuelli and Seshadri, 2014; Jones, 2014), but also the level of inequality both across (Guvenen et al., 2014) and within (Huggett et al., 2011) societies. Human capital affects productivity by leading to new ideas among individuals (Romer, 1990; Jones, 2002) and shaping management practices among firms (Bloom et al., 2013).

[9]Given the increasing academic and political attention over inequality, together with taxation of the rich (forcefully advocated by Piketty et al., 2014), a new stream of theoretical models has emerged with endogenous human capital accumulation to study optimal taxation (Bohacek and Kapicka, 2008; Stantcheva, 2014; Badel and Huggett, 2014; Best and Kleven, 2013; Ales et al., 2014). Complementary to the literature on optimal taxation, my paper emphasizes that the underlying mechanism used to represent endogenous skill accumulation is a first-order ingredient behind optimal policy (see Badel and Huggett (2014) for a related point in response to Diamond and Saez (2011)).

the standard administrative datasets do not meet the appropriate criteria.[10] However, both the Panel Study of Income Dynamics (PSID, 1970-2014) and National Longitudinal Survey of Youth (NLSY, 1979-2014) contain longitudinal individual-level information with measurements of performance pay compensation.[11],[12] The PSID sample is restricted to able-bodied head of households between ages 25 and 65, producing waves of approximately 1,000-3,000 individuals per year (every other year from 1997 onwards); both the NLSY 79 and 97 cohort samples are restricted similarly (but none of the individuals are over 55 years old), producing a sample of approximately 6,000-8,000 individuals per year. All nominal variables deflated by the 2010 personal consumption expenditure index. Individuals working less than 500 hours per year or earning less than $5,000 per year are dropped.[13]

Given the limitations of both the PSID and NLSY, I introduce new restricted-access data from the National Compensation Survey (NCS) between 2004 and 2015.[14] Administered by the Bureau of Labor Statistics (BLS), survey economists from the BLS collect information

[10]For example, the neither the Longitudinal Employer-Household Dynamics (LEHD) nor Social Security Administration (SSA) contain information on bonus compensation and/or performance pay. Other public datasets, such as the Current Population Survey (CPS) or Survey of Income and Program Participation (SIPP) also do not.The private version of SIPP, however, does contain information on bonus income, which I am using in companion work to study the heterogeneous earnings patterns of performance pay and fixed wage workers following job displacement.

[11]An important drawback to these surveys is the presence of measurement error. Duncan and Fields (1985) document that the variance of measurement error among a set of 418 manufacturing workers in a validation study for the PSID was large (30%)—just as large as the variance of payroll earnings in 1981. The measurement error is mean reverting and, therefore, non-classical since workers with low (high) earnings tend to overstate (understate) their earnings. Gottschalk and Huynh (2010) implemented a similar comparison between the Survey of Income and Program Participation (SIPP) and Social Security Administration data, finding that it too was non-classical and mean reverting. (However, administrative data is not the gold standard—it too contains mean reverting "mismatch errors", which are documented in Kapteyn and Typma (2007), and can be just as damaging to estimation as labor survey data.) See Bound et al. (2001) for a thorough review of measurement error in labor economics applications and Chen et al. (2011) for a more recent and general survey.

[12]The NLSY offers two important advantages, relative to the PSID. The first advantage is that it contains less measurement error and complete employer profiles. One of the problems with the identification of performance pay in the PSID, for example, is that an individual might be observed in period t and $t+2$, but not $t+1$. Since the classification of performance pay is based on whether the individual receives performance compensation at least once with the same employer, the quality of the classification relies in part on the ability to properly identify employers. The second advantage is that it contains measurements of informal and formal training. In addition to capturing vocational training programs, NLSY also asks about the duration of training, the relevance, and other informal training from supervisors and/or coworkers. For example, one sample question is: *(Besides the schooling and training programs we've just talked about,) During the last 4 weeks while working at [name of employer()], did you receive any informal on-the-job training from your supervisor, your coworker(s) or both?*

[13]Although the results are very robust to the following assumption, I keep, for the reduced form exercises, individuals who are laid off during the year, but were working for part of it.

[14]Unfortunately, while the dataset began in 1994, the pre-2004 data is not available for various reasons, including comparability.

directly from employers on a representative set of jobs (typically between four and eight) across establishments throughout the United States. Establishments tend to reside in the NCS sample for 20 quarters, providing longitudinal variation for the same job-by-establishment. The NCS is unique among administrative datasets in that it is the only one containing information on the details of employment contracts for different jobs across establishments.[15] Jobs are also ranked by survey economists based on an established set of criteria, which allows me to compare observationally equivalent jobs—one with and one without performance pay—that are both in the same establishment. Performance pay jobs are defined according to Gittleman and Pierce (2013) as those that are either classified as incentive pay or receive non-production bonuses.

Appendix Section A1. provides detailed documentation of the cleaning and extraction of each dataset. Appendix Section A3.1. provides basic descriptive statistics for each dataset, highlighting the differences between performance pay and fixed wage workers. Of particular relevance are the new features of the NCS micro-data, including the dispersion in non-production bonus compensation across occupations, the intensive margin of performance pay across job levels, and earnings / hours premia across different partitions of the labor market.

2.2. Measuring Performance Pay in the Cross-section and over Time

Performance pay is a multi-dimensional term used to describe various types of compensation schemes, ranging from profit sharing to bonus payments.[16] These compensation schemes are designed to induce employees to work hard and effectively in the presence of moral hazard problems (Holmstrom, 1979). While the literature mostly focuses on moral hazard in the context of senior management (Edmans et al., 2012), performance pay for the average worker has received less attention. To facilitate an empirical analysis of labor market dynamics between

[15]Field economists identifiy workers in jobs as having time-based or incentive-based pay based on whether the worker's pay is based directly on actual production of the worker versus solely the number of hours worked. Time-based workers are those whose wages are based solely on an hourly rate or salary, whereas incentive workers are those whose wages are based at least partially on piece rates, commissions, or production bonuses. Performance pay is defined as either incentive-based pay or the receipt of non-production bonuses. https://www.bls.gov/opub/hom/pdf/homch8.pdf

[16]Of course, all jobs contain some extent of career concerns (Holmstrom, 1999), but this paper focuses on the role of explicit contractual incentives. There is evidence that career concerns exert their own effect on human capital formation; see, for example, Bonatti and Horner (2014). However, even independent of career concerns, explicit incentives play an important role (Gibbons and Murphy, 1992).

performance pay and fixed wage workers, it is vital to accurately classify these workers.

My main measure for performance pay follows Lemieux et al. (2009) by classifying employees as performance pay if they receive bonus, tip, or commission income at least once with the same employer, excluding workers who receive overtime.[17] In addition to extending the time series, I also leverage auxiliary information on the employee's contract, which is available in some years.[18] Starting in 1992, the PSID asks workers whether they also receive commission (on top of hourly and/or salary pay), which allows me to include those who report receiving commission (on top of either hourly or salary) and those who report "other" (e.g., bonus). Recognizing that some sectors infrequently provide performance pay, I exclude the education and public sectors, in addition to providing further robustness that contains only manufacturing, trade, and business sectors. To address the well-known measurement error in the PSID self-reported tenure measure, I use a combination of survey answers to measure whether or not an individual has switched employers and use a backwards imputation technique similar to Buchinsky et al. (2010) to correct tenure. These details are explained in the Appendix Section A1..

Since binary misclassification is a source of non-classical measurement error (Aigner, 1973; Bollinger, 1996), it is reasonable to question the accuracy of the constructed performance pay indicator. Using restricted-access data from the NCS between 2004 and 2014, I compare the incidence of performance pay between the two datasets to validate my baseline measure. The first row in Figure 2 plots the share of performance pay workers by two-digit industry and occupation. The two shares are very similar in every instance except protective, food preparation, and maintenance occupations, which defines performance pay workers differently in the NCS since they only track employer costs (excluding tips). The second row in Figure 2 plots the share of bonus compensation to wage income across the same classifications. While they match up in many cases, the PSID tends to underestimate bonus compensation significantly.

[17] There are clearly some occupations where performance pay exists, but is not in the form of bonus, tips, or commission. For example, promotions in academia provide strong incentive effects even if the bonus compensation is small or non-existent. Since there is no clean alternative based on available data, I show robustness excluding these sectors (focusing on manufacturing, trade, and business sectors). I also gauge the role that other incentive mechanisms, like promotions, might play in an organization by estimating models that relate the incidence of performance pay with job satisfaction, promotions, and other advancement opportunities. I find that performance pay workers have significantly higher job satisfaction and advancement opportunities, and are also much more likely to receive a promotion. In this sense, while there may be several instances where other forms of performance pay are used besides bonuses, tips, and commission, the baseline definition tends to capture most available incentive mechanisms.

[18] Specifically, the survey question reads as follows: "On your main job for [NAME OF EMPLOYER], are you (HEAD) salaried, paid by the hour, or what?"

Appendix Section A3. implements a similar validation with the NLSY.[19]

[INSERT FIGURE 2]

One concern with the documented rise of performance pay in Figure 1 from the introduction is that it is driven by composition. For example, in light of structural transformation and the transition towards services (Kongsamut et al., 2001; Ngai and Pissarides, 2007), it is possible that the spatial dispersion of performance pay is driven by mere composition effects. Figure 3 plots the share of performance pay across industries and occupations. While clearly some industries and occupations have experienced a larger increase in performance pay than others (e.g., business sector growing from 20% to 58%), the increase has been felt uniformly throughout the job distribution. I have also explored the role of information technology (measured through capital IT expenditures), but find that it does not explain variation in performance pay after controlling for variation in wage-setting institutions, such as unions and marginal tax rates.

[INSERT FIGURE 3]

2.3. Differences in Earnings and the Allocation of Time

A well-known fact from the personnel economics literature is that performance pay is used as both a sorting and incentive device among employers (Lazear, 1986). Many have documented the incentive effects of performance pay contracts on productivity (Lazear, 2000a; Friebel et al., forthcoming) and labor supply (Paarsch and Shearer, 1999, 2000; Shearer, 2004). Using a combination of the PSID (1970-2014) and NLSY (1984-2014), I begin by estimating conditional correlations of the returns to earning and working in performance pay jobs

$$y_{it} = \beta X_{it} + \gamma PP_{it} + \eta_i + \lambda_t + \epsilon_{it} \tag{1}$$

where y denotes logged annual earnings and hours worked, X denotes a vector of controlling covariates, PP denotes an indicator for performance pay status, and η and λ denote person and year fixed effects. Given that individuals sort into jobs based on their ability, which is

[19] Each of these datasets, however, provides a lower bound to the share of income coming from performance related pay—only their extensive margin measure of performance pay status is reasonable reliable. The Survey of Consumer Finances (SCF), for example, implies that roughly 20% of performance pay workers' income is from variable related pay, which is orders of magnitude higher than the shares implied from either the PSID or NLSY.

correlated with whether employers are offering a performance pay contract, Equation 1 identifies the conditional correlation of performance pay jobs based on job-to-job individual transitions.

Table 1 documents these results using the PSID (1970-2014) and NLSY (1985-2014). Columns 1 and 6 control for demographic characteristics, suggesting that performance pay workers earn (work) 13-16% (6-7%) more than their fixed wage worker counterparts. However, these results remain quite robust to controlling for occupation and/or person fixed effects (columns 2-3 and 7-8). These specifications exploit within-occupation and within-person variation to identify the returns of performance pay—comparing, for example, earnings for the same person at one point in time when they are in a fixed wage job with earnings when they have transitioned into a performance pay job. Columns 4-5 and 9-10 estimate the returns separately for college and non-college workers, showing that they are very similar between both groups. In this sense, performance pay is an incentive mechanism for both high and low skilled workers. Under the preferred specifications in columns 3 and 7, incentive effects explain roughly 46-50% (= 0.06/0.13 and = 0.11/0.22) of the variation in earnings and 50-78% (= 0.03/0.06 and = 0.055/0.07) of the variation in hours worked, which are in the range of Lazear (2000a).

[INSERT TABLE 1]

While these coefficients are identified off of variation within occupation and within person, it is still possible that there are other endogeneity problems. One important concern, for example, is that firms with better management and/or non-wage amenities are more likely to have performance pay. In Appendix Section A4.3., I use the NCS to address this concern in two ways. First, I compare differences in earnings and hours worked between performance pay and fixed wage jobs within the same establishment and of similar job levels (i.e., skill). By controlling for establishment and job level fixed effects, I remove variation that could otherwise be attributed to differences in managerial and/or other unobserved organizational practices that contribute to firm productivity (Bloom et al., 2013). Table 10 shows that the conditional correlations are almost identical to those obtained from the PSID and NLSY. Second, using variation in non-wage benefits to proxy for other typically unobserved amenities, I examine whether there are systematic differences in their conditional correlations in performance pay and fixed wage jobs—a variant of the coefficient comparison test (Pischke and Schwandt, 2015). These regressions suggest that non-wage amenities cannot account for the performance pay premium in earnings and hours worked.

Appendix Section A4.4. presents heterogeneous treatment effect estimates across college/non-college, male/female, and black/white dimensions (see Table 11). In contrast to Heywood and Parent (2012), I do not find evidence that performance pay has narrowed the black-white earnings gap, although I do find evidence that black performance pay workers allocate more time towards labor supply than their peers. I also do not find evidence that male performance pay workers earn more than their female counterparts, which points towards performance pay as a mechanism for reducing wage dispersion that is not driven by differences in skill.[20] I also find complementarity between education and performance pay; college degree performance pay workers earn 6% more than their counterparts, which is roughly a quarter of the direct association between earnings and performance pay.

Having documented these differences in the pooled sample, I now characterize the path of earnings and hours worked over the life cycle. Panel A of Figure 4 plots mean annual hours worked over the life cycle for performance pay and fixed wage workers. While both workers increase hours between ages 25 to 30, fixed wage workers plateau and subsequently reduce their allocation of time to the market back down to the same level they started out with at age 25. Performance pay workers, in contrast, keep raising their allocation of time to the market until their late 30s upon which hours plateaus for their careers. Panel B of Figure 4 tells a similar story for earnings. While there is incremental growth in annual earnings even for fixed wage workers, it is small and levels off around age 40, which is precisely the time when their hours worked begins declining. Performance pay workers, in contrast, exhibit a steady rise in annual earnings growth until the end of their life cycle. These differences also help explain the heterogeneity in the age profile for hours worked (Rupert and Zanella, 2015).

[INSERT FIGURE 4]

Appendix Section A4.1. examines several robustness exercise. First, I present analogous plots (see Figure 14) that residualize the contribution of various demographics (including education) to these profiles; the qualitative patterns are strengthened. Second, I plot both raw and residual hourly wages over the life cycle (see Figure 15), which again tell a similar story. Third, I show that these life cycle patterns are not unique to the specific time period (see Figure 16). Rather, the relative earnings and hours premia in performance pay jobs began widening in the

[20] As women began entering the sector for market services (Olivetti, 2006), and the technology for home production grew (Greenwood et al., 2005), the premium declined. These facts would be consistent with a model of adverse selection and performance pay introduced by Albanesi and Olivetti (2009).

1980s and grew up until the present.

2.4. Differences in Human Capital Investments

Information on earnings, hours worked, and their timing are informative for understanding the presence of implicit contracts (Ham and Reilly, 2002, 2013). In particular, if performance pay workers exhibit greater on the job learning, then their lagged hours worked should exhibit stronger, positive gradient with contemporaneous earnings. To test this hypothesis, I consider regressions of the form

$$w_{it} = \beta X_{it} + \gamma PP_{it} + \phi_1 l_{it} + \phi_2 l_{i,t-1} + \delta(PP_{it} \times l_{it}) + \rho w_{i,t-1} + \lambda_t + \epsilon_{it} \tag{2}$$

where w denotes logged earnings, X denotes a vector of individual covariates, PP denotes an indicator for performance pay status, l denotes logged hours worked, and λ denotes year fixed effects. The inclusion of lagged earnings in Equation 2 helps control for the persistence of earnings and unobserved shocks that are correlated with labor supply, but I also present results using person fixed effects given the potential endogeneity of controlling for lagged earnings.

Table 2 documents these results associated with Equation 2 under various specifications using both the NLSY and PSID.[21] In all cases, higher contemporaneous hours worked raises earnings. Two important insights emerge. First, while performance pay workers incur a large performance pay premium (recall the results from Table 1), controlling for lagged hours worked produces a negative performance pay gradient. The fact that it enters negatively when controlling for lagged hours worked is consistent with the interpretation that performance pay workers are willing to take a lower salary today to gain experience for tomorrow.[22]

Second, consistent with this interpretation is the fact that the interaction between performance pay and lagged hours worked is positive in every specification, ranging from 3-6%. In other words, working more today as a performance pay worker generates between 3-6% higher earnings tomorrow, relative to their fixed wage worker counterparts, consistent with the basic

[21] There are some differences in the implied correlations between these two datasets, but the main insights are common.

[22] If I instead use logged hourly wages as the outcome variable, the coefficient on lagged logged hours is 0.207 and the coefficient on the interaction between performance pay and lagged hours is 0.055. The coefficient of 0.207 is similar to the one estimated by Bell and Freeman (2000) who also use the NLSY over a shorter time span and recover coefficients in the range of 0.107 and 0.11. My estimate of 0.05 in column 2 using the NLSY is also very similar. Differences between columns 2 and 5 could be due to differences in the sampling frame of the PSID versus NLSY.

predictions from a model with human capital accumulation (Imai and Keane, 2004). In these models, individuals are willing to work below their marginal product since working conveys an additional benefit—namely learning, which is capitalized into future earnings. These results are robust both with and without the inclusion of person fixed effects, suggesting that unobserved heterogeneity and sorting is not biasing these estimates of learning by doing.

Interestingly, these returns are not trivial. Even under the fixed effects specification in columns 3 and 6, an additional 10% hours worked today is associated with nearly 3% higher earnings tomorrow. The fact that the return for performance pay workers is 3-6% higher, relative to fixed wage workers is best viewed in the context of the returns to schooling. Consider, for instance, the fact that the elasticity of an extra year of schooling is roughly 0.05-0.07 (Card, 2001). In this sense, going from 2000 to 2200 hours worked in a performance pay job tends to raise future earnings over three times as much an additional year of schooling.

[INSERT TABLE 2]

Appendix Section A5.1. examines several three additional pieces of supporting evidence pointing towards greater human capital accumulation in performance pay jobs. First, Figure 22 plots the distribution of worker value intensities from O*NET at the six-digit level between the two sets of jobs, showing that values typically thought to be correlated with learning, such as effort, leadership, persistence, and ambition, are significantly higher in performance pay jobs. Second, using a combination of NLSY data on informal training and subjective measures of organizational amenities from companion work (Makridis, 2016), Figures 23 and 24 show that workers in performance pay jobs are more likely to receive indirect on-the-job training and report higher levels of organizational practices, recognizing that performance pay is part of a broader portfolio of incentive mechanisms.[23] Third, while career concerns are always present to varying extents, I find that performance related pay is associated with higher hours worked and increasingly so over the life cycle, consistent with theoretical predictions from Gibbons and Murphy (1992). Fourth, using three-digit industry data on real gross output per worker, Figure 25 shows that increases in the growth rate of hours worked are significantly associated with increases in labor productivity for sectors with high shares of performance pay workers, but not for those sectors with low shares of performance pay workers.

[23] Using NLSY data on self-reported job satisfaction, I also find that workers in performance pay jobs have 3.5% higher job satisfaction, conditional on observables. In fact, the magnitude only declines to 3% when including person fixed effects, suggesting that most of the variation is not driven by person-specific heterogeneity.

3. Quantitative Framework

3.1. Preferences

Individuals enter the labor force at age 25 and retire at age 65. Each year, they face a probability of becoming unemployed, staying in employment, or switching jobs; these are discussed shortly. Conditional on switching jobs, individuals choose across one of nine different industry-by-occupation choices, denoted $j(j = 1, 2, ..., 9)$. While individuals cannot directly choose whether they have performance pay, they can indirectly influence their probability through their optimal sorting across jobs, which vary exogenously in their propensity of offering performance pay.

Conditional on the individual's discrete choice, d_{it}^{j}, over a sector-occupation pair $j(j \in \{1, 2, ..., 9\})$, individuals have preferences over consumption, denoted c, and labor supply, denoted l and make consumption-savings decisions each period

$$u(c_{it}, l_{it}) = \frac{c_{it}^{1-\iota}}{1-\iota} - \chi(m)\frac{l_{it}^{1+\psi(m)}}{1+\psi(m)} + \varepsilon_{it}^{j} \tag{3}$$

subject to their budget and borrowing constraints

$$c_{it} + a_{i,t+1} = s_{it}h_{it}l_{it}\kappa(1-\tau_{it}) + a_{i,t}(1+r) + TR_{it} \tag{4}$$

$$a_{i,t+1} \geq B, \quad a_{it} \geq 0 \tag{5}$$

where ε^{j} denotes a choice-specific taste shock following a Type I extreme value distribution, ι denotes the intertemporal elasticity of substitution, $\chi(m)$ denotes the disutility of labor supply for type-m worker, $\psi(m)$ denotes the labor supply elasticity for type-m worker, a denotes assets, s denotes the worker's skill price, κ denotes the maximum hours worked per year (set to 5110), h denotes their human capital, r denotes the fixed interest rate, τ denotes the marginal tax rate, TR denotes transfers (e.g., unemployment insurance), and B denotes a per-period borrowing limit. The borrowing constraint in Equation 5 imposes that individuals cannot: (i) borrow more than B each period, and (ii) borrow against either their transfers or future earnings.[24]

[24]The fact that individuals make both labor supply and consumption-savings decisions means that wage changes will allow for both income and substitution effects.

Since Equation 4 only applies to individuals who are working up until age $T = 65$, individuals subsequently retire and simply optimize by choosing consumption optimally subject to the budget constraint[25]

$$c_{i,T+1} + a_{i,T+1} = a_{i,T}(1+r) + TR_{i,T} \tag{6}$$

3.2. Production of Human Capital and Skill Prices

The production function for human capital is based on a refinement of Heckman et al. (1998) where skill is a function of current labor supply and the existing stock of human capital

$$h_{i,t+1}(m) = f(h_{it}, l_{it}) = A_{it}(m) l_{it}^{\gamma_l} h_{it}^{\gamma_h} + (1 - \xi_1) h_{it} \tag{7}$$

where $A_{it}(m)$ allows the rate of human capital accumulation to vary by type-m (i.e., some individuals learn faster than others), γ_l governs the curvature of hours worked with respect to future human capital, γ_h governs the degree of complementarity, and ξ_1 denotes the depreciation of human capital. In contrast to the Ben-Porath (1967) approach to modeling human capital, Equation 7 embeds the insight from Shaw (1989), Imai and Keane (2004), and Michelacci and Pijoan-Mas (2012) that individuals accumulate skills through "learning by doing."[26] Equation 7 also allows for richer dynamics than are typically included by embedding the potential for not only static ($\partial^2 h/\partial h \partial l > 0$) and dynamic complementarities.[27]

The skill price is specified as a function of performance pay status, job-group dummies, their interactions, and an indicator for whether the individual just switched jobs

[25]This approach follows in the tradition of Gourinchas and Parker (2002), Kaplan and Violante (2010), and Blundell et al. (2013). However, Jorgensen (2017) shows that an additional tuning parameter can be introduced to scale the post-retirement value function to accommodate potential post-retirement motives associated with income uncertainty, retirement benefits, and bequest motives.

[26]There are two reasons for this choice. First, the dominant consensus in psychology is that deliberate practice (concentrated effort) is a crucial, if not the largest, determinant of skill accumulation; see Ericsson et al. (2006) for a comprehensive survey. Second, based on the microeconomic evidence provided earlier, performance pay workers are willing to work longer in $t-1$ and receive lower pay in t all in order to receive higher pay in the future. While not a direct proof for learning by doing, it is a prediction from a canonical learning by doing model and, therefore, provides a rationale for the modeling approach.

[27]The latter follows since higher investment in period t raises h_{t+1} since $f(h,l)$ is increasing in l, which in turn raises $h_{t'}$ because f is increasing in $h_{t''}$ for $t'' \in [t, t']$. While a richer specification would allow for a CES production function, this is a more than reasonable starting point, much like the literature on the technology of skill formation began with additive separability in Todd and Wolpin (2003) and Cunha and Heckman (2006) before moving towards a fully non-linear framework with dynamic complementarities in Cunha et al. (2010).

$$s_{it} = \alpha_0 + \alpha PP_{it} + \sum_j \zeta^j d_{it}^j + \sum_j \delta^j (d_{it}^j \times PP_{it}) + \xi_2 o_{ijt} + \mu_m + z_{it} \tag{8}$$

where α_0 denotes the utility of being employed,α captures the overall performance pay premium, ζ^j captures the earnings premium associated with working in job j, δ^j captures the job-specific performance pay premium, ξ_2 captures the specificity of human capital following an exit, μ denotes type-specific fixed effects, and z denotes heterogeneity in skill prices governed by the following AR(1) process

$$z_{it}^j = \rho^j z_{i,t-1}^j + \omega_{it}^j, \quad \omega_i^j \sim \mathcal{N}(0, \sigma_\omega^2) \tag{9}$$

where the worker knows the autoregressive component of their earnings process and the distribution of their next-period earnings shock, but not the actual value. What is not modeled in Equation 8, however, is the role of tenure. Since the debate about the returns to tenure and experience is still ongoing (Altonji and Shakotko, 1987; Topel, 1991; Buchinsky et al., 2010; Buhai et al., 2014) and not directly informative for the dynamics in this paper, I abstract from them and leave further analysis to future work.

3.3. Wage-setting Process

Whenever an individual receives a job offer, there is a probability that it is performance pay, denoted p_t^j, which are exogenous to the individual's decision.[28] The fact that these probabilities vary over time is important since their time series properties will govern the strength of incentives. The fact that they vary by industry-by-occupation also matters since younger workers might more likely to join certain types of jobs that are more demanding as a vehicle for accumulating skills, whereas these workers might eventually switch jobs. The solution involves integrating over the probability of receiving performance pay before integrating over the taste-specific shock.

[28]While an exploration of the underlying source of these changes in performance pay would be a fruitful and interesting exercise, it is beyond the scope of the current paper; here, the rise of performance pay is taken as a macro change in labor market institutions, much like prior literature has treated the rise of information technology as an exogenous force in both a non-stationary dynamic environment (Krusell et al., 2000) and static environment (Autor et al., 1998, 2003). As will become more clear when the equilibrium is characterized under rational expectations, individuals expect that the probability of joining a performance pay job equals the probability that actually manifests in the data.

3.4. Dealing with Selection and Heterogeneity

An integral component of understanding the provision and effects of performance pay is the presence of non-random sorting into performance pay—that is, individuals who sort into jobs with a higher probability of giving performance pay differ systematically from their counterparts. I address this concern in three ways. First, the initial distribution of $A_{it}(m)$, which governs the rate at which people learn, is drawn directly from the data. Since individuals with greater education are likely to learn more rapidly, and recognizing that human capital affects the optimal job choice, allowing for heterogeneity in learning induces heterogeneity in the selection of jobs among workers. Second, I allow for persistence in the skill price process, which captures the fact that wages exhibit significant persistence. Third, I apply a recent innovation from Bonhomme et al. (2016) whereby the sample is partitioned into $M (m = 1, 2, ..., M)$ types of individuals with features $X_{it} \subset \mathcal{F}$ where $\mathcal{F}$ denotes the feature space. I subsequently use a K-means algorithm to cluster individuals into similar groups on the basis of their observed features, subsequently estimating the model parameters separately for each group.[29]

3.5. Equilibrium Search and Value Functions

The model features on-the-job search and the potential for unemployment. Each period, individuals have a probability λ_u of being offered employment out of unemployment, λ_l of being laid off from current employment, λ_e for being offered a new job outside of their current firm, and $1 - \lambda_l - \lambda_e$ of staying within the same job.[30] Those who find new employment—that is, a mass of $\lambda_u + \lambda_e$ workers—make a discrete choice among a menu of nine different industry-by-occupation jobs, denoted j, each which vary in their earnings payoffs and probability of offering performance pay. Once an offer is accepted, an individual is either performance pay or fixed wage for the duration of their employment spell. In this sense, individuals face a discrete choice over the type of job to apply for and their probability of obtaining it depends on the job that they are currently working in.[31]

[29] This is an alternative to another approach of embedding unobserved heterogeneity using a Heckman and Singer (1984) method, typically using an expectation-maximization (EM) algorithm.

[30] Technically, there is also a probability of being laid off and receiving a new offer. However, empirically this is a small fraction of individuals (roughly 2%).

[31] One interpretation of this assumption is that the probability of getting a job based on their current job is a reduced-form approximation of specific human capital or social networks. Moving to investment banking for retail service, for example, is more difficult than moving from consulting to investment banking.

Denote $\Omega_{it} = (h_{it}, a_{it}, z_{it})$ as the set of state variables.[32] At any point in time $s = t$, individuals choose their job, labor supply, and consumption (and thus savings) to maximize their discounted utility

$$E\left[\sum_{s=t+1}^{T} \beta^{s-t} u(c_{is}, l_{is}, \Omega_{is})|c_{it}, l_{it}, \Omega_{it}\right]$$

where Bellman's principle of optimality implies that recursive utility varies based on whether the individual is currently unemployed or employment. These options are described below. While there is no analytic solution, the finite horizon dynamic program can be solved numerically through backwards induction and interpolation of the value function based on Keane and Wolpin (1994). Once each choice-specific value function is obtained, the maximum can be computed across each job.

3.5.1. Search for the Unemployed

Those who are unemployed have a probability λ_u of being offered an employment contract. Conditional on being offered a contract, they make a discrete choice about which j type of job to enter. The value of unemployment is given by

$$V^u(\Omega_{it}) = u(c_{it}, l_{it}) + b + \beta\left[\lambda_u \text{Emax}\left\{V^u(\Omega_{i,t+1}), V^e(\Omega^j_{i,t+1})\right\} + (1-\lambda_u)V^u(\Omega_{i,t+1})\right] \tag{10}$$

where $u(c_{it}, l_{it}) + b$ denotes the utility flow of unemployment.[33] The second term in brackets, $\text{Emax}\left\{V^u(\Omega_{i,t+1}), V^e(\Omega^j_{i,t+1})\right\}$, denotes the expected value of the better option between staying unemployed and taking a new job j in period $t+1$; the specific formulation of job j will be discussed in the next subsection. If, for example, the utility value of unemployment is sufficiently high or the disutility of labor supply is sufficiently high, individuals may prefer to simply stay unemployed.[34] The third term, $V^u(\Omega_{i,t+1})$, denotes the utility value of remaining unemployed if an offer does not arrive. Unemployed agents have a search strategy whereby they accept any

[32] ε^j_{it} is technically an exogenous state variable, but, since it is iid, it becomes known an integrated out immediately.

[33] There is a little abuse of notation here with ε^j_{it}, which equals zero when the individual is unemployed.

[34] Specifically, let $\tilde{j} = \{j\} \cup \{unemployed\}$ denote the new choice set. Following the notation in the next subsection, then

offer that provides a one-period flow utility that is greater than a specified reservation value. While models of duration dependence are important and realistic (Kroft et al., 2013), I abstract from them here.

3.5.2. Search for the Employed

Those who are already employed have a probability λ_l of being laid off, λ_e of taking a new job, and $1 - \lambda_l - \lambda_e$ of staying at their current job. Conditional on taking a new job, they will make a discrete choice about which j type of job to enter. The assumption here is that an individual offered a new job with probability λ_e is effectively being offered a job across any of the j categories and, therefore, must choose the one that delivers highest utility. The value of employment is given by

$$V^e(\Omega_{it}) = u(c_{it}, l_{it}) + \beta \left[\lambda_l V^u(\Omega_{i,t+1}) + \lambda_e \text{Emax}\left\{V^e(\Omega^j_{i,t+1}), V^e(\Omega^{j'}_{i,t+1})\right\} + (1 - \lambda_e - \lambda_l) V^e(\Omega^j_{i,t+1})\right] \tag{11}$$

The first term, $u(c_{it}, l_{it}) + \varepsilon^j_{it}$, denotes the flow value of being employed. The second term, $V^u(\Omega_{i,t+1})$, denotes the value of unemployment if the individual is laid off from their current employment. The third term, $\text{Emax}\left\{V^e(\Omega^j_{i,t+1}), V^e(\Omega^{j'}_{i,t+1})\right\}$, denotes the expected value of the better option between their current job j and their potentially new job $j' \neq j$.[35] The fourth term, $V^e(\Omega^j_{i,t+1})$, denotes the value of remaining in their current employment. With a slight abuse of notation of $V(\Omega_{i,t+1})$ as a stand-in for the maximum over the alternative-specific value functions in Equation 11, then the fact that ε^j_{it} means that

$$\begin{aligned} E\left[V(\Omega_{i,t+1}) | c_{it}, l_{it}, d^j_{it}, \Omega_{it}\right] &= E\left[\max V^j(\Omega_{i,t+1}) | c_{it}, l_{it}, d^j_{it}, \Omega_{it}\right] \\ &= \Gamma + E\left[\ln\left(\sum_{j'} \exp(V^j(\Omega_{i,t+1}) | c_{it}, l_{it}, d^j_{it}, \Omega_{it})\right)\right] \end{aligned}$$

where Γ is the Euler-Mascheroni constant and $V^{j'}(\Omega)$ is the expectation of the alternative

$$\begin{aligned} E\left[V(\Omega_{i,t+1}) | c_{it}, l_{it}, d^{\tilde{j}}_{it}, \Omega_{it}\right] &= E\left[\max V^{\tilde{j}}(\Omega_{i,t+1}) | c_{it}, l_{it}, d^{\tilde{j}}_{it}, \Omega_{it}\right] \\ &= \Gamma + E\left[\ln\left(\sum_{\tilde{j}'} \exp(V^{\tilde{j}}(\Omega_{i,t+1}) | c_{it}, l_{it}, d^{\tilde{j}}_{it}, \Omega_{it})\right)\right] \end{aligned}$$

[35] These terms within the maximization, $V^e(\Omega^j_{i,t+1})$ and $V^e(\Omega^{j'}_{i,t+1})$, are called alternative-specific value functions since they denote the value associated with a specific job j.

j' specific value function given the observed state, Ω, and the current alternative, j. However, because individuals enter into performance pay contracts based on the probability of their sector-occupation choice, the choice-specific value function must be solved under the two possible cases where $PP = 1$ and $PP = 0$, i.e.,

$$E\left[V(\Omega_{i,t+1})|c_{it}, l_{it}, d_{it}^{j}, \Omega_{it}\right] = \sum_{pp\in\{1,0\}} \left\{ \int \left[\Gamma + \ln\left(\sum_{j'} \exp(V^{j}(\Omega_{i,t+1})|c_{it}, l_{it}, d_{it}^{j}, \Omega_{it}) \right) \right] f_j(z)dz \right\} P^{j}(pp) \tag{12}$$

where $P^j(pp)$ in Equation 12 denotes the probability that job j is performance pay and where $f(z)$ is the probability density function for a normal distribution. Under normality of the earnings shock, the value function can be numerically integrated between using Gaussian quadrature.

3.6. Computation

Since the solution to the dynamic programming problem does not have an analytical solution, I turn to numerical approximations based on backwards induction. Since allowing for fully continuous states on both human and physical capital would lead to an intractable numerical solution, I follow Keane and Wolpin (1994) by choosing a coarse set of grid points on both state variables and interpolating between them to allow for the continuous choices of the agents in the model. Specifically, I place a ten-point grid on human capital between one and ten, capturing the fact that individuals move across different skill levels, which scale earnings accordingly. Following the standard in the literature, I place a grid on the *logarithm* of assets between zero between values of zero and 1.2 million dollars, concentrating the bulk of the grid points on lower ends of the asset distribution. Based on these grid points, interpolation is implemented following Sullivan (2006) by regressing the simulated Emax, denoted $E\left[\tilde{V}(\Omega_{i,t+1})\right]$, on a constant and the closed-form expression of the expected value of the maximum choice at $t+1$, denoted $\Psi\left[V^*(\Omega_{i,t+1})\right]$

$$E\left[\tilde{V}(\Omega_{i,t+1})\right] = \pi_{0t} + \pi_{1t}\Psi\left[V^*(\Omega_{i,t+1})\right]$$

As Sullivan (2006) explains, a feature of this regression is that collinearity will never be a problem regardless of the size of the choice set since there is only one regressor. Importantly, however, the regressor is defined at each point of the state space, so there is no need to estimate separate interpolating regressions. Moreover, since it leverages the presence of a closed-form expression for the optimal choice of jobs, the regression function converges to the exact solution of the Emax as the variances approach zero.

3.7. Calibration

3.7.1. Externally Calibrated

The discount rate, β, is set to 0.98 to match the fact that each time step is a year. The interest rate is fixed at $r = 0.04$ to match evidence on the risk-free rate of U.S. Treasury bonds as in McGrattan and Prescott (2000). The intertemporal risk aversion coefficient, ι, is set to 1.50, which is in line with the preferred macroeconomic estimates (Orazio, 1999; Hall, 2009) and was recently used by Gayle and Miller (2009) within the context of a moral hazard problem. The depreciation of human capital is set to $\xi = -0.05$ from Hendricks (2013). The per-period borrowing limit is set to $B = 22,000$, which is the 95th percentile of the savings distribution in NLSY79. The utility flow of unemployment is set to $b = 0.06$ based on results from Chodorow-Reich and Karabarbounis (2016).

The probabilities that an individual receives an offer out of unemployment (λ_u), out of employment (λ_e), and the probability that an individual gets laid off (λ_l) are based on the fraction of workers observed in the data who for each category (i.e., the fraction of people who are currently unemployed, but get an offer and become employed next period). The initial distribution of learning rates (A_{i0}) is calibrated by regressing logged hourly wages on person fixed effects.[36]

[36] As French (2005) discusses, using person fixed effects creates a selection problem with wages. In particular, if individuals leave the market at precisely the time they experience a sudden wage drop (e.g., job loss), then wage growth for workers will be greater than wage growth for non-workers. I account for this selection problem by requiring that the fixed effects estimated in the model match those from the data, thereby allowing for measurement error to enter the model the same as it enters in the data.

3.7.2. Income Dynamics

The earnings process is estimated externally to the model, but based on the same underlying equations that are in the model. In particular, I use an earnings process of $w_{it}^j = \mu_i^j + z_{it}^j + \varepsilon_{it}^j$ where $z_{it}^j = \rho^j z_{it-1}^j + \omega_{it}^j$.[37] Following the advice from Daly et al. (2014), I restrict the sample to individuals who are observed in six consecutive years, rather than people who suddenly disappear and reappear.[38] I subsequently use logged earnings and its four lags to construct and match the entire autocovariance matrix using a method of moments estimator.

3.7.3. Internally Calibrated

The remaining parameters are estimated and identified explicitly from the model using simulated method of moments (SMM) and indirect inference based on recent advances from Creel et al. (2015). The starting values for the earnings parameters are obtained by estimating Equation 7 using least squares (see Appendix Section A8.3. for these in Table 16 across several different sample restrictions). The starting value for the labor supply elasticity is set to $\psi = 0.5$ to match Keane and Rogerson (2012) and the disutility of labor supply is set to $\chi = 2.13$.

Given these initial parameter values, the dynamic program can be solved and simulated forward to produce a sequence of simulated moments. These moments, denoted $\Psi^S(\vartheta)$, are written as a function of the parameters since they depend on the iteration or guess of the $\vartheta \in \Theta$ parameter values. Given these simulated moments for a given vector of parameters, the optimization problem is to search over the parameter space to minimize the distance between the simulated moments and the actual (data) moments, which are denoted Ψ^A, using the following moments estimator

$$\hat{\vartheta} = \arg\min_{\vartheta \in \Theta} \left[\frac{\Psi^A - \Psi^S(\vartheta)}{\Psi^A} \right]^T \Lambda \left[\frac{\Psi^A - \Psi^S(\vartheta)}{\Psi^A} \right]$$

where Λ denotes the weighting matrix, set to the identity matrix. While the standard

[37]The theoretical autocovariances implied by this income process are

$$Var(w_{it}^j) = \Sigma_\mu + Var(z_{it}^j) + \Sigma_\varepsilon, \quad Var(z_{it}^j) = \sum_s \rho^{2s} \Sigma_\omega^2, \quad Cov(w_{it}^j, w_{it+n}^j) = \Sigma_\mu + \rho^n Var(z_{it}^j)$$

[38]However, in future work, I also will use the NCS to decompose permanent and transitory shocks to financial compensation and non-wage benefits.

approach is to simply take the ϑ that minimizes the simulated and actual moments difference, I follow the recent results from Creel et al. (2015) whereby I run a quantile regression of the top 50 parameter values (for each ϑ) on the corresponding distance matrix $((\Psi^A - \Psi^S(\vartheta))/\Psi^A)$, taking the constant in the regression as the optimal parameter value. As Creel et al. (2015) discuss, this approach has much more robust properties.

Before outlining the moments that are used for identification, I briefly discuss my approach to the "initial conditions problem." In particular, since I only model and feed in moments beginning at age 25, initial conditions that are not exogenous (e.g., college attainment correlated with performance pay) could produce bias. First, I incorporate permanent unobserved heterogeneity through persistence in the earnings process and through the discrete M types of individuals. For example, μ_m in Equation 8 deals with the fact that unobserved heterogeneity affects selection into performance pay through their skill prices. Second, I take the initial distribution of learning rates directly from the data. For example, $A_{it}(m)$ allows for different types of workers to vary with respect to their on-the-job learning process. Third, the fact that my estimation strategy is also based off of a moments estimator, rather than a likelihood function, allows me to deal with the fact that not all individuals have non-missing data throughout the sample. I now discuss the specific moments used to achieve identification.

The learning curvature and elasticity of current human capital to future human capital are identified through the covariance between earnings, hours, and cumulative hours. Consider an increase in hours worked in period t. If earnings grows in period $t+1$, then this variation will be attributed to learning. Furthermore, differences in the cumulative hours profiles across workers will help identify the complementarity between the stock of human capital and investment. For example, if individuals who have over 5,000 hours worked already completed by age 27 have higher earnings growth, then the correlation will help identify the curvature on the stock of human capital. The depreciation of human capital is matched through the decline in earnings following unemployment or job transitions separately for performance pay and fixed wage workers.

The parameters in the skill price equation are identified from the cross-sectional differences across industries, occupations, and performance pay jobs. For example, the indicator on performance pay is matched by comparing the mean hourly wage for a performance pay worker with a fixed wage worker. Job mobility rates also help in the identification of some of these differences across workers. For example, if an individual moves from one job to another and does not experience an earnings decline, then the model will infer that human capital is fairly general (rather than job-specific). Similarly, if an individual moves from one job to another and is working greater hours without experiencing a simultaneous rise in pay, but does experience a future pay raise, then the model will infer that the individual is investing in human capital. The rest of the section will compare the parameter estimates with those in the literature, focusing on the labor supply elasticity and learning curvature.[39],[40]

4. Quantitative Results

[TBD UPDATE IN PROCESS]

5. Conclusion

The United States labor market has undergone a profound transformation. Using micro-data from the Panel Study of Income Dynamics (PSID) and National Longitudinal Survey of Youth (NLSY), I document the rise of performance pay contracts in the labor force, growing from roughly 15% in 1970 to 50% by the early 2000s. Given the difficulty in reliably measuring performance pay status in survey micro-data, I subsequently validated the time series and cross-sectional patterns using restricted micro-data from the National Compensation Survey (NCS) maintained by the Bureau of Labor Statistics (BLS). Using these data, I also document systematic differences in annual income and hours worked between performance pay and fixed wage workers on the order of 8-12%. These results are robust to controlling for time-invariant person heterogeneity, as well as comparing similarly ranked performance pay versus fixed wage jobs in the same establishment.

Motivated by these robust conditional correlations, I subsequently develop a dynamic Roy model with searching and matching in the labor market. Individuals choose one of nine different possible jobs each period with the outside option of unemployment and, conditional on having a job, decide how much to work, consume, and save. The model allows for income fluctuations and skill accumulation through a learning-by-doing human capital production function. Im-

[39]Estimates of the human capital curvature between 0.80 and 0.95 (Guvenen and Kuruscu, 2010), about 0.93 Manuelli and Seshadri (2014).

[40]Kim and Lee (2007) and Wallenius (2011) conduct similar exercises over on the job training and on the job learning / Ben-Porath human capital accumulation; they all show that there is major downward bias when human capital is not included due to omitted variables bias.

portantly, jobs vary based on their probability of providing performance pay contracts, which allows workers to indirectly sort into jobs based on their career preferences and returns to accumulating skill. I allow the probability of receiving a performance pay job to vary over time and in the cross-section based on the available data. Using a new set of computational tools, I subsequently solve the model, compare the simulated series to the data, and use the simulations to conduct counterfactual exercises.

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6. Figures and Tables

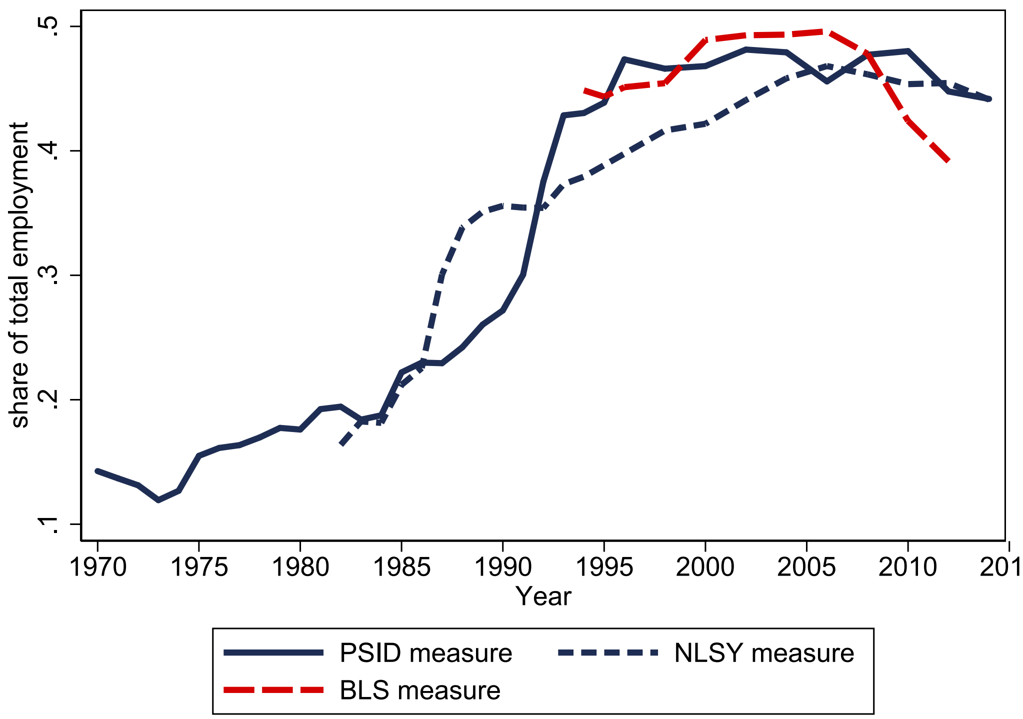


Figure 1: The Rise of Performance Pay and Decline of Union Contracts

Notes.–Source: Panel Study of Income Dynamics (PSID, 1970-2014), National Longitudinal Survey of Youth (1980-2014), and National Compensation Survey (1994-2014). The figure plots the share of performance pay workers in the labor force. Using both the PSID and NLSY, performance pay workers are those who receive bonus, tip, or commission at least once with the same employer. Using the NCS, performance pay jobs are identified as those with bonus or incentive pay.

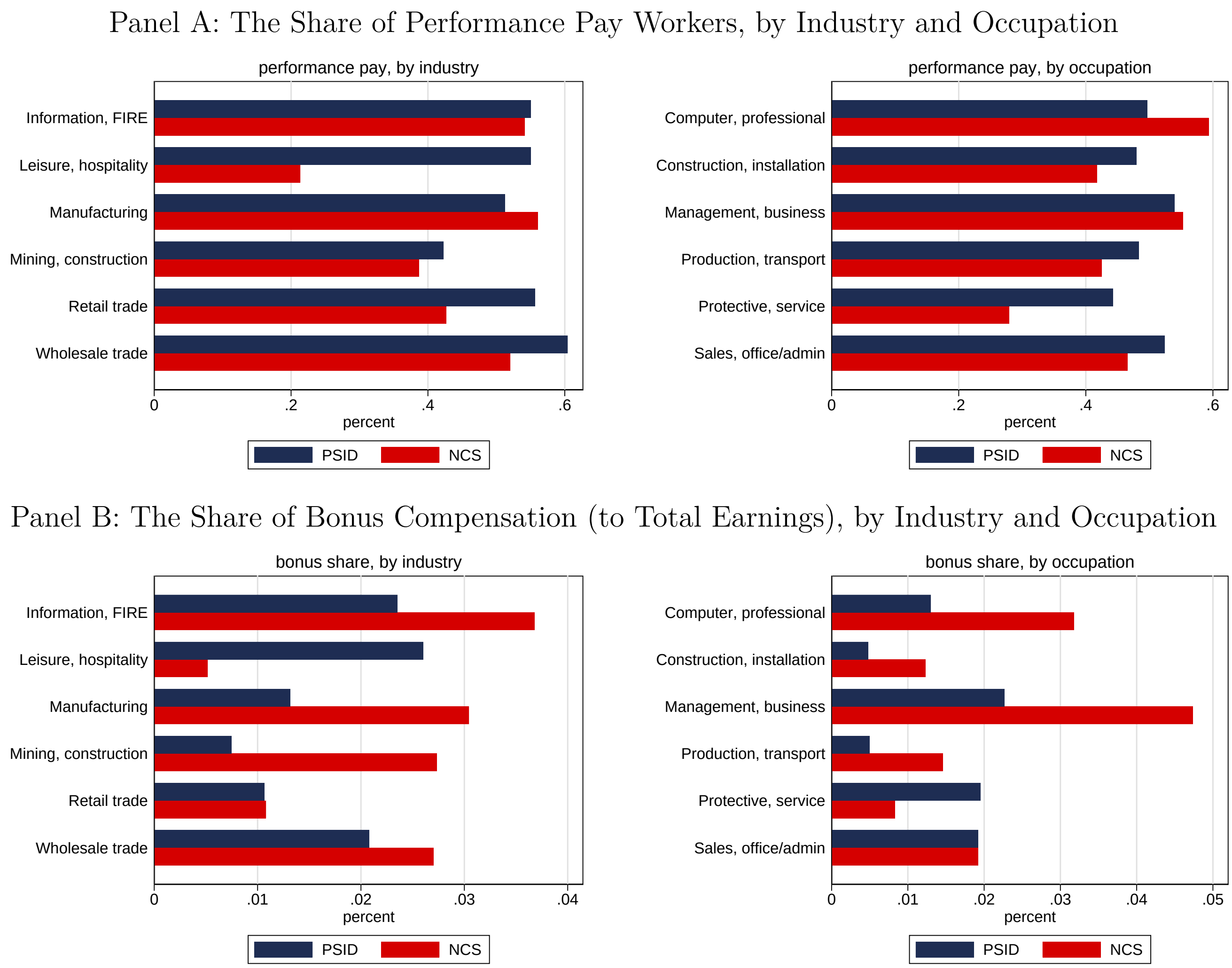


Figure 2: Validating Performance Pay with the National Compensation Survey, 2002-2014

Notes.–Source: Panel Study of Income Dynamics (PSID) and National Compensation Survey (NCS), 2004-2014. Panel A plots the fraction of performance pay workers in the labor force across major industry and occupation classifications between 2004 and 2014 data. Panel B plots the share of bonus compensation, relative to total compensation, using PSID sample weights to produce the averages. Performance pay workers in the PSID are those who receive bonus, tip, or commission at least once with the same employer. Performance pay jobs in the NCS are those with incentive pay or receiving non-production bonuses. Military, public administration, and education and health workers are omitted.

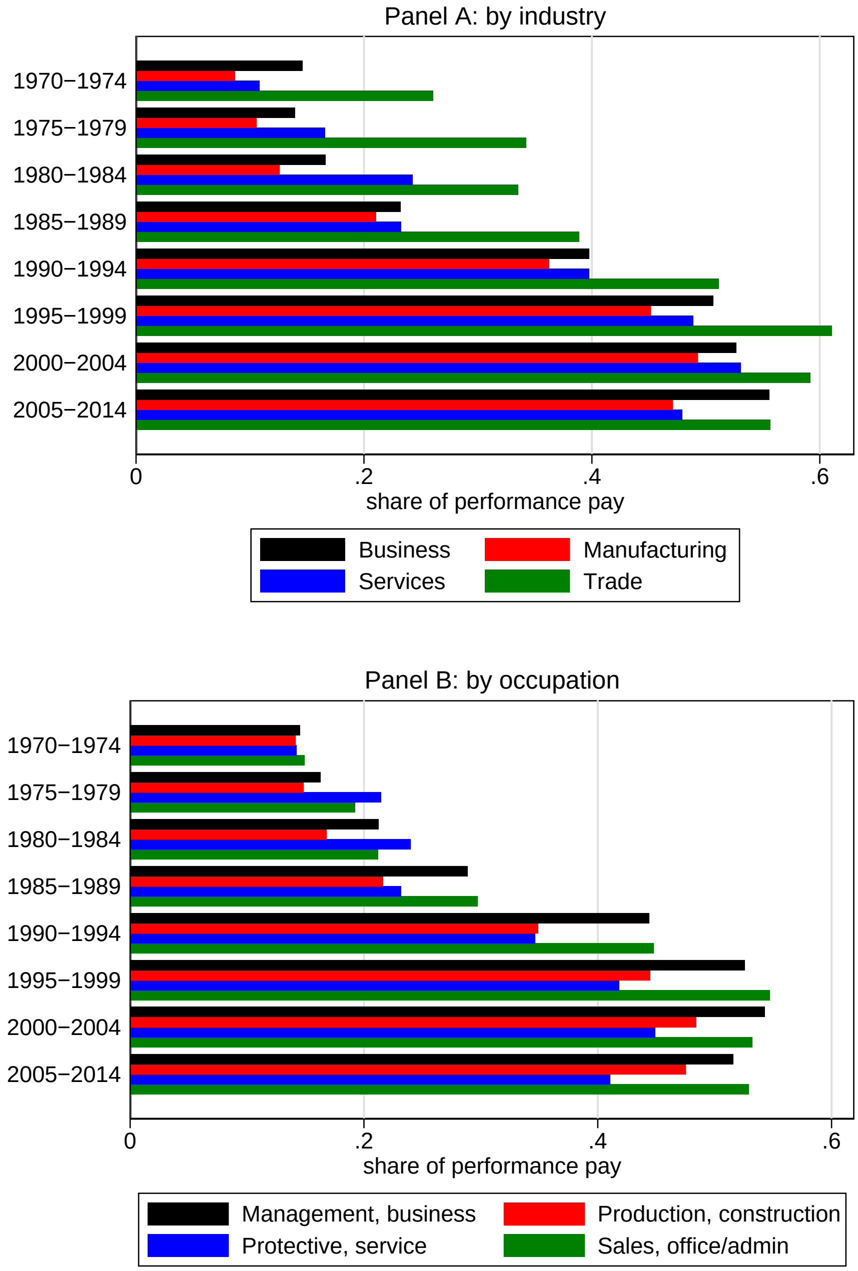


Figure 3: Performance Pay by Industry and Occupation, 1970-2012

Notes.–Source: Panel Study of Income Dynamics (PSID, 1970-2014). The figure plots the share of performance pay workers by industry and occupation. Performance pay workers are those who receive bonus, tip, or commission at least once with the same employer. The industry categories distinguish among (i) construction, transportation, and utilities, (ii) manufaturing (durables and non-durables), wholesale trade, and retail trade, (iii) business, information, finance and real estate, and other professional business services, and (iv) social assistance, leisure and hospitality, food preparation, and other services. Military, public administration, and education and health workers are omitted. The occupation categories distinguish among: (i) management, executives, management related occupations, and professional specialty occupations, (ii) technicians and related support occupations, sales occupations, administrative support occupations, (iii) social workers, protective service occupations, and (iv) mechanics and repairers, construction trades, extractive operations, precision production operations, machine operators, and transportation and material moving occupations. Observations are weighted by the PSID sample weights.

Table 1: Earnings and Hours Differences, Performance Pay and Fixed Wage

Dep. var. =	ln(annual earnings)									
	PSID	PSID	PSID	PSID	PSID	NLSY	NLSY	NLSY	NLSY	NLSY
Panel A										
perf. pay	0.13***	0.12***	0.06***	0.04**	0.07***	0.22***	0.17***	0.11***	0.12***	0.11***
	[0.02]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
R-squared	0.32	0.44	0.71	0.70	0.70	0.32	0.42	0.64	0.65	0.61
Sample Size	47786	47526	47786	12560	35226	125809	107123	125809	31769	94040
Dep. var. =	ln(annual hours worked)									
Panel B										
perf. pay	0.06***	0.05***	0.03***	0.01	0.04***	0.07***	0.06***	0.11***	0.06***	0.05***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]
R-squared	0.06	0.12	0.39	0.39	0.40	0.14	0.19	0.64	0.44	0.39
Sample Size	47780	47521	47780	12561	35219	135882	114630	125809	33576	102306
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	No	No	No	Yes	No	No	No
Person FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Sample	pooled	pooled	pooled	college	non-college	pooled	pooled	pooled	college	non-college

Notes.–Sources: Panel Study of Income Dynamics (PSID, 1970-2014) and National Longitudinal Survey of Youth (NLSY, 1985-2014). The table reports the coefficients associated with regressions of logged annual earnings and logged hours worked on an indicator for performance pay, conditional on controls. Performance pay in the PSID and NLSY is defined as those receiving bonus, tip, or commission at least once with the same employer. Controls include a quadratic in age and educational attainment, gender, marital status, race (black and white), and family size. The sample is restricted to workers between ages 20 and 65 in the PSID, whereas it is restrict to workers between ages 25 and 55 in the NLSY. Observations are weighted by the survey sample weights and standard errors are clustered at the person-level.

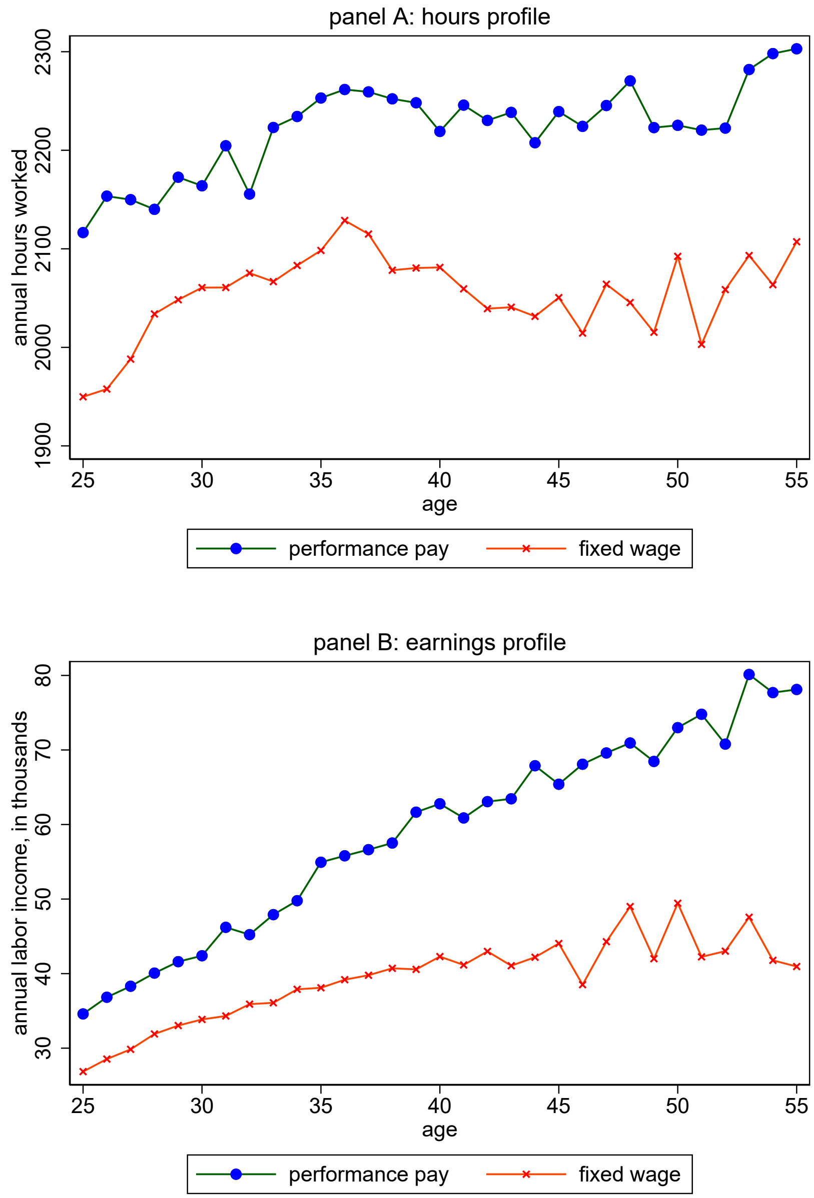


Figure 4: Heterogeneity in Hours and Earnings over the Life Cycle

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The figure plots average annual hours worked and earnings (deflated using the 2009 consumer price index) over the life cycle for performance pay and fixed wage workers. Performance pay workers are defined as those who earn bonus, tip, or commission at least once with the same employer. The sample is restricted to full-time workers (over 500 hours per year, over $5000 per year). Observations are weighted by survey sample weights.

	ρ	σ_m^2	σ_ε^2	σ_ω^2
PP	0.964	0.056	0.027	0.051
FW	0.939	0.046	0.056	0.079

Table 3: Earnings Decomposition of Income Dynamics

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The table reports the presistence parameters and standard deviations of the shocks associated with the income processes for performance pay and fixed wage workers.

Table 2: Human Capital Accumulation and Learning in Performance Pay Jobs

Dep. var. =	logged annual earnings					
	NLSY	NLSY	NLSY	PSID	PSID	PSID
$\ln(\text{hours})^{t-1}$	.57***	.06***	.38***	.45***	-.26***	.20***
	[.01]	[.01]	[.01]	[.02]	[.02]	[.02]
performance pay	-.26**	-.25***	-.07	-.40	-.84***	-.37
	[.11]	[.09]	[.09]	[.33]	[.25]	[.27]
$\times \ln(\text{hours})^{t-1}$	.06***	.05***	.02*	.06	.11***	.06
	[.01]	[.01]	[.01]	[.04]	[.03]	[.04]
$\ln(\text{earnings})^{t-1}$		.56***			.77***	
		[.01]			[.01]	
R-squared	.45	.61	.68	.36	.71	.80
Sample Size	154242	143107	154242	41492	41490	41492
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79 and NLSY97) and Panel Study of Income Dynamics (PSID, 1970-2014). The table reports the coefficients associated with regressions of logged earnings on an indicator of performance pay, logged contemporaneous hours worked, lagged logged hours worked, and their interaction. Controls include a quadratic in age and education, gender ,race, marital status, and family size.Observations are weighted by the survey sample weights and standard errors are clustered at the person-level.

Parameter	Value	Description	Parameter	Value	Description
χ	2.13	Disutility of labor	ζ_7	-0.51	1[job 7] from ln(skill price)
ψ	0.50	Labor elasticity	ζ_8	-0.16	1[job 8] from ln(skill price)
γ_l	0.7	Learning curvature	ζ_9	-0.22	1[job 9] from ln(skill price)
γ_h	0	Learning complementarity			
ξ_1	-0.05	General skill depreciation			
ξ_2	-0.08	Specific skill depreciation			
σ_ω^2	0.03	Variance of skill price shock			
ρ	0.97	Persistence of skill process			
α_0	2.72	Constant from ln(skill price)			
α	0.28	PP premium from ln(skill price)			
ζ_2	0.21	1[job 2] from ln(skill price)			
ζ_3	-0.11	1[job 3] from ln(skill price)			
ζ_4	-0.17	1[job 4] from ln(skill price)			
ζ_5	0.13	1[job 5] from ln(skill price)			
ζ_6	-0.01	1[job 6] from ln(skill price)			

Table 4: Initial Parameter Estimates for Structural Model

A Online Appendix (Not for Print)

A1. Supplement to Data Description

A1.1. Panel Study of Income Dynamics (PSID)

Following the tradition from prior papers, the sample is restricted to full-time workers and heads of households due to a combination of concerns about the data reliability of other household members and their relevance to the analysis (since performance pay only applies to employed individuals). I follow Blundell et al. (2008) in their construction of the file, but retain self employed workers. While all the reduced-form results are robust to excluding these workers, they are included since they tend to receive some type of performance pay even though they are likely to be very different types of workers than others. For example, a probit of self employment on performance pay, conditional on education, marital status, gender, age, and family size produces a correlation of 0.64 on performance pay. I recode all the variables and make them uniform across all the years (since their meaning changes at times throughout the survey). I deflate all financial variables (wages, income, bonuses, etc) by the consumer price index in annual terms using the OECD dataset on consumer prices/products. I winsorize the data by year at the 1 and 99 percentiles and recode all variable values equal to “dont know” (DK) and “inappropriate” to zero.

Working with the PSID requires linking households, which I do for hte full sample (1967 to 2014). To do this, researchers must link the interview identifier that corresponds to the observations in that year’s family file.[41] These can all be combined and matched to measure the same household over time. After extracting all the .txt files from the PSID site, save them in the desired format. University of Michigan has a “variable search” feature on their site, which enables researchers to quickly find their variable of interest and examine whether the definition is constant over time, or whether the question (and corresponding answer key) changes in some years. To link these all together, researchers must use the “individual” file (“INDYYYER”) where YYYY denotes the most recent year.

Since the PSID contains a significant amount of measurement error (Bound and Krueger,

[41] An efficient way of keeping track of the same household is to simply take the new year’s interview ID, and then name that variable “ID” in the dataset for the matching. For example, in 1979, there is an interview id equal to “V6902” in the data; I label this as “id”; the interview id in 1978 is “V6302” and I label it “id”.

1991; Bound et al., 1994), I clean a number of the variables: education, age, earnings, experience, and tenure. Since sometimes individuals report having fewer years of education in a future year, I correct all records by simply taking the maximum value that an individual reports for years of schooling. Similar mis-reporting takes place with age where some individuals appear to get younger over time (!). To deal with these, I tag observations as wrong if the value in $t+1$ is larger than in t. For these incorrect observations, I interpolate.[42]

Consumption is not measured in the PSID until 1998 and onwards. In order to obtain measures of consumption that are informative in the other years, it is important to take seriously the prediction strategy.[43] Using a simple sieve estimator, I regress log consumption (over the years it is available) on demographics (occupational task concentrations, CPI, number of children, family size, educational attainment, major industry dummies, age, male, race dummies, union, and marital status), interactions between log food expenditures and three bins for the number of children in the family (setting 3+ children as the omitted group), and interactions between log rent expenditures and three bins of age (setting 20-30 as the omitted group).

Figures 5 and 6 provide measures of fit for the imputation. Figure 5 shows that the both the conditional means and quantiles between the actual and imputed values match up closely. The actual values are known only for 1999-2012. Similarly, Figure 6 shows that the aggregates matche each other well over the known time series.

[42]Specifically:

$$AgeNew_i = Mean(Age_i) - Mean(Year_i) + Year$$

which says that, for each worker, I take their mean age, then subtract the mean year (for those times they're observed) and add the year. This approach is equivalent to regressing age on year for each worker separately and restricting the slope equals one.

[43]Consumption is defined as the sum of expenditures on food, schooling tuition, water, gasoline, heat, electricity, car insurance, home insurance, rent (6% of home value from Flavin and Yamashita (2002)), childcare, health spending, parking, and transportation.

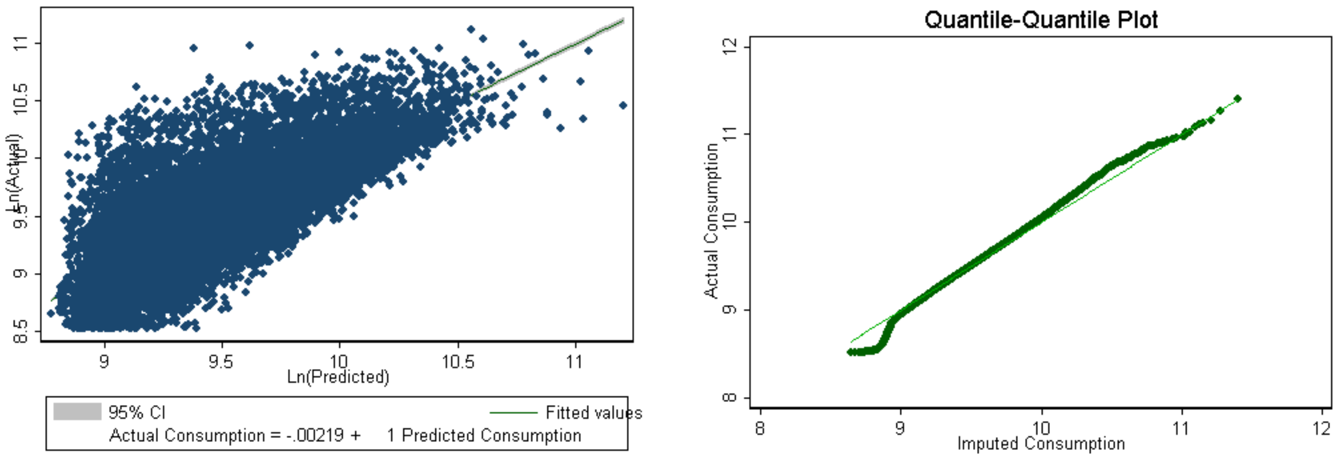


Figure 5

Notes.–Sources: PSID. The figures ploted the mean and quantiles of actual / imputed values of log consumption over the period of time that the consumption is explicitly reported in the PSID. Consumption is defined according to Attanasio and Weber (1995) and follows a similar strategy as in Orazio and Pistaferri (2014). Specifically, consumption is defined as the sum of expenditures on food, schooling tuition, water, gasoline, heat, electricity, car insurance, home insurance, rent (6% of home value from Flavin and Yamashita (2002)), childcare, health spending, parking, and transportation. The predicted values of consumption are obtained by regressing log consumption (over the years it is available) on demographics (occupational task concentrations, CPI, number of children, family size, educational attainment, major industry dummies, age, male, race dummies, union, and marital status), interactions between log food expenditures and three bins for the number of children in the family (setting 3+ children as the omitted group), interactions between log rent expenditures and three bins of age (setting 20-30 as the omitted group), and year and state fixed effects.

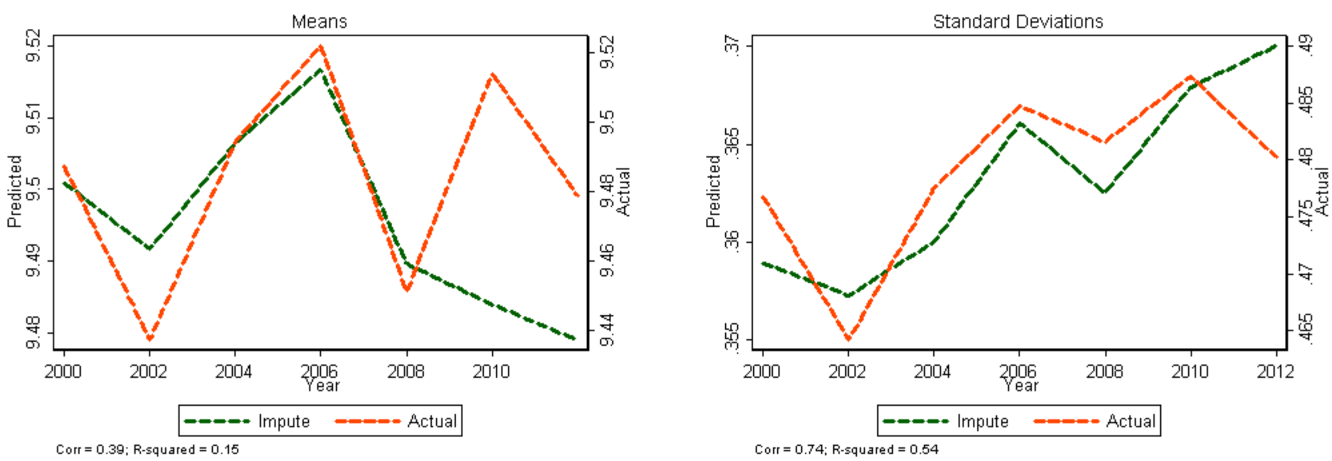


Figure 6: Comparison of Actual and Imputed Consumption, 1999-2012

Notes.–Sources: PSID. The figures ploted the imputed mean and standard deviation of consumption over the period of time that the consumption is explicitly reported in the PSID. Consumption is defined according to Attanasio and Browning (1995) and follows a similar strategy as in Orazio and Pistaferri (2014). Specifically, consumption is defined as the sum of expenditures on food, schooling tuition, water, gasoline, heat, electricity, car insurance, home insurance, rent (6% of home value from Flavin and Yamashita (2002)), childcare, health spending, parking, and transportation. The predicted values of consumption are obtained by regressing log consumption (over the years it is available) on demographics (occupational task concentrations, CPI, number of children, family size, educational attainment, major industry dummies, age, male, race dummies, union, and marital status), interactions between log food expenditures and three bins for the number of children in the family (setting 3+ children as the omitted group), interactions between log rent expenditures and three bins of age (setting 20-30 as the omitted group), and year and state fixed effects.

To match occupations with task data, occupations in the PSID must be harmonized. They change occupational codes from the original 1967-1979 in 1980 until 1983 (or, in the family files, from 1981-1984). However, they have another occupation variable that seems to be consistently reported in surveys from 1974-2001 family files; I use these latter starting in 1980 ("B15-16 MAIN OCC:3DIG H-E") when the other occupation variable is no longer asked. Because the occupational titles change in the PSID in 2002 (or, 2003 in the family files)—that is, from 2002 onward, occupations follow the 2000 Census—I must make a cross-walk with prior years. Fortunately, Autor and Dorn (2013) provide crosswalks for the different censuses. Converting to a comparable occupational measure for 1990, there are some duplicates because the comparable measure is not as fine as the actual occupation codes. I collapse on the year group and occ1990dd variables, which is not ideal since occupational tasks may differ within the occ1990dd measure. At worst, this will attenuate the occupational measures, but there is no other alternative solution to my knowledge. When merging the occupational tasks with the PSID, I keep all the observations even if the merge is not complete. Those observations with incomplete merges are ones where the occupation is missing or equal to 999, which denotes the worker is unemployed; discarding these observations would be wrong since the household information is fine—only the occupation changed.

For the 1970 census, the missing 1990 occupation codes that were available in the 1970 survey are: 280 (salesman and sales clerks, n.e.c.), 600 (operatives, except transport), 810 (farmers and farm managers), 999 (non-classified workers). I change these to 285 (an exact change), 815 (to transport equipment operatives–allocated), 473 (farmers, except horticultural), and 0. For the 2000 census, the missing 1990 occupation codes that were available in the 2000 survey are: 0 (not in labor force), 121 (mathematician), 123 (statistician), 134 (biomedical), 150 (mining/geological), 183 (sociologists), 245 (librarian technician), 310 (physician assistant), 386 (transit and railroad police), 416 (food preparation and service worker), 521 (correspondence clerk), 602 (animal breeders), 615 (logging worker), 650 (reinforcing iron and rebar workers), 705 (electronic repairers), 752 (commercial drivers), 787 (food and cooking operators), 802 (milling and planing machine setters), 843 (extruding and forming machine setters/operators), 844 (fabric and apparel patternmakers), 884 (semiconductor processors), 890 (cooling and freezing equipment operators), 911 (ambulance drivers), 944 (misc transportation), 950 (conveyeor operators and tenders), 974 (tank, car, ship loaders), 980 (military officer specialists), 981 (first line military supervisers/managers), 982 (military enlisted tactical operations and air/weapons specialists), 983 (military non-specified), 999 (not classified). Since the 1990 codes are more coarse, the conversion is approximate, displayed in Table 5.

1990 Codes	0	068	067	083	075	168	329	089	426	439	326	496	723	213	804	433	705
2000 Codes	0	121	123	134	159/150	183	245	310	386	416	521	615	650	705	752	787	802

1990 Codes	487	724	717	750	213	814	815	904	903	903	903	903	905	0
2000 Codes	602	890	843	844	884	911	944	950	974	980	981	982	983	999

Table 5: Conversion of 1990 to 2000 Occupation Codes

From the Dictionary of Occupational Tasks (DOT), I use Autor's files "dot77-70-gen" and "dot91-70-gen" to cover the intervals 1966-1977 and 1978-1990, respectively. While women's introduction into the labor force was most pronounced pre-1990, individual level and year fixed effects should control for this without having to complicate the weighting process further with gender. For earlier subperiods, I use Acemoglu and Autor (2011) cleaned O*NET files to cover the post-1990 period; I am grateful to Melanie Wasserman for assisting me with these files. Their "onet-task-occ2000" contains the combined task measures for each occupation in the Census 2000 occupation classification scheme, whereas "onet-task-1990dd" contains the combined task measures for each occupation in the occ1990dd occupation classification scheme; the latter is a more consistent version of occ1990, used in IPUMS Census/ACS data. A major empirical challenge is linking ONET with DOT data since the former contains different measures and importance weights. The measures can be made "approximately" similar in classification, but the importance weights do not exist for the DOT. The importance weights supposedly—their documentation is not ideal—characterize the aggregate composition of occupations with respect to output in the economy. Failing to weight properly will attribute variation in output or labor income incorrectly to a change in task when really it is just a sectoral reallocation. To implement a similar "importance weight", I begin by running regressions of the form $\log w_{it} = X_{it}\beta + \epsilon_{it}$, where X consists of a quadratic in age, male, race, marital, and years of schooling dummies, family size, number of children, wife's wage, wife's age, and union status. Purging wages of all demographic variation allows me to re-weight occupations in the process of the standardization according to their relative "importance" measured through "efficiency". To address the comparability between O*NET and DOT data, the main category that does not fit is “nonroutine manual personal”: tasks that are interactive, nonroutine, and physically demanding. However, the others nearly align perfectly. Like MacLeod and Parent (2014), I standardize all these occupational task measures to have a mean of 0 and standard deviation of 1 such that the interpretation on the coefficients can be interpreted as a one standard deviation of task type X on the probability that a worker is in a job with pay for performance compensation.

A1.2. National Longitudinal Survey of Youth (NLSY)

The National Longitudinal Survey of Youth (NLSY) is a survey implemented on 14-21 year olds starting in 1979 on one cohort of individuals and again in 1997 on another cohort, which they survey each year. All the specifications restrict individuals to ages 25 and 55 and individuals with less than 500 hours worked per year or less than $5,000 in annual earnings are omitted.

A1.3. National Compensation Survey

Administered by the Bureau of Labor Statistics (BLS), the NCS is unique in that it is the only source that contains detailed data on not only various labor outcomes (e.g., employment and compensation), but also non-wage compensation (e.g., benefits) and the type of contractual arrangement across a subset of sampled jobs within each establishment. The sample is restricted to private establishments, which tend to be observed for five years. Observations are weighted by the NCS job-level sample weights. The data are collected from a three-stage probability sample: local areas (metropolitan), establishments within the sampled areas, and jobs within the sampled establishments. Some areas are selected with certainty according to their size, whereas others are selected based on a probability. Establishments and jobs within each establishment are also sampled probabilistically based on their size and number of employees working in each job, respectively.

Approximately four to eight unique types of jobs are sampled within each establishment, each of which are labeled as having either an incentive pay component or not, providing within-establishment and within-job variation over time. Jobs are selected in the following fashion. When a BLS field economist comes to an establishment, the employer will provide a list of all employees, which is translated by the surveyer to match the NCS scope. Individuals are randomly selected with their corresponding job and the surveyer classifies the job with the appropriate Standard Occupational Classification (SOC) code, together with a number of other characteristics about the job, ranging from job duties to compensation. We do not leverage the information on job duties in this paper.

A2. Supplement to Descriptive and Empirical Evidence

A3. Data Validation

The main text compares the share of performance pay workers across partially aggregated two-digit industries and occupations with the share implied from the PSID. There is broad alignment. Here, I also implement a similar comparison for the NLSY against the NCS. Figure 7 shows that there is, again, broad alignment with a correlation of 0.62. Figure 8 also implements a year-to-year comparison between the PSID, NLSY, and NCS. While the NLSY is included in the plot for completeness, it is a cohort-based study and, therefore, less comparable to either the PSID or NCS. The national share implied by the PSID has a correlation of 0.62 with the national share from the NCS between 1994-2014.

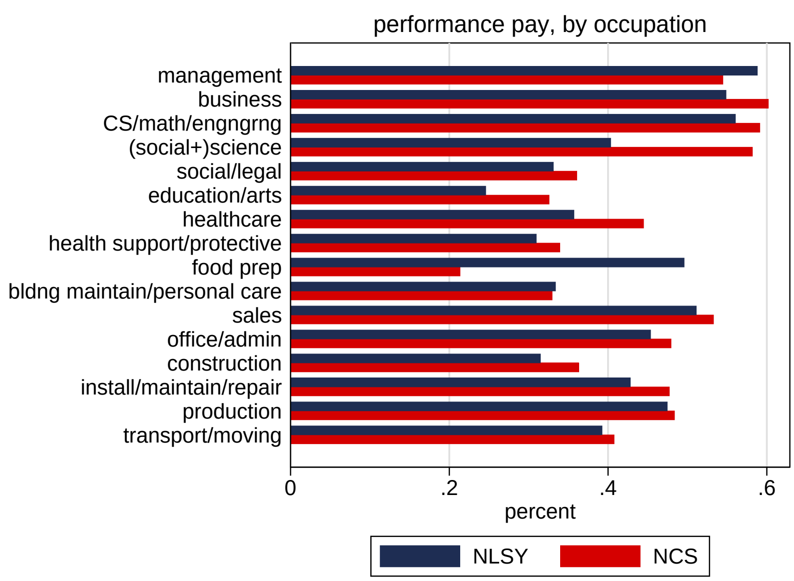


Figure 7: Comparison of Performance Pay in the NLSY and NCS

Notes.–Source: National Longitudinal Survey of Youth (NLSY) and National Compensation Survey (NCS), 2004-2014. The figure plots the share of performance pay, by major SOC occupation code, in the NLSY and NCS datasets. Observations are weighted by the NLSY sample weights.

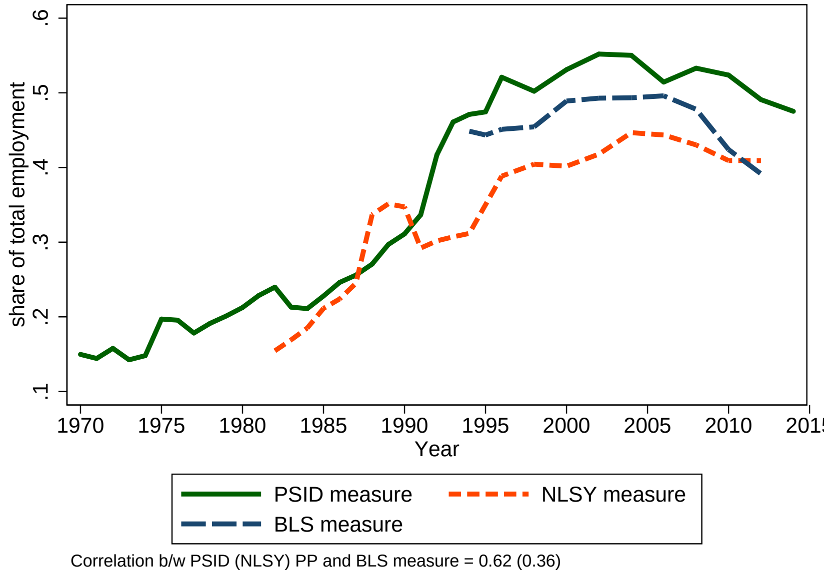


Figure 8: Comparison of Performance Pay in PSID, NLSY, NCS

Notes.–Source: Panel Study of Income Dynamics, National Longitudinal Survey of Youth and National Compensation Survey. The figure plots the shares of performance pay workers in the PSID, NLSY, and NCS. They are observed directly in the NCS data.

A3.1. Descriptive Evidence

Beginning with variation by decade, Table 6 plots the differences between performance pay and fixed wage workers. There are minor demographic differences between performance pay and fixed wage workers with the exception of college attainment and gender composition. For example, between 1970 and 1979, 29% of performance pay workers had a college degree (versus 21% of fixed wage workers). However, it is interesting to note that the gap does not widen—with 40% of performance pay workers having a college degree versus 32% of fixed wage workers between 2000-2014, suggesting that differences in educational attainment cannot explain earnings premia. While non-durable consumption expenditure information only begins in the 1990s, it is interesting to note that there are not substantial differences between the two groups—although they are higher among performance pay workers (e.g., roughly $14,000 versus $12,600 per year). However, there are more significant differences in housing consumption expenditures, which suggests that performance pay workers might be allocating their larger labor income towards durable assets (versus non-durables).

Turning towards the labor market variables, performance pay workers are much less likely to be union and relatively less likely to be paid by the hour. As will be shown shortly, there is a slight disagreement with the NLSY where there are not significant differences in selection into hourly pay jobs between the two groups. Not surprisingly, and consistent with the evidence in the main text, there are large differences in income and hours worked between the two groups. While hours spent in home production is also reported for completeness, these measures are likely to contain especially high measurement error, but generally support the claim that performance pay workers spend less time in these home activities. There are, however, large differences in the skill intensity of performance pay jobs. For example, the skill intensity of non-routine tasks (cognitive and interactive) is roughly 0.25 on average versus 0.08 on average in fixed wage jobs. Conversely, performance pay jobs have much lower skill intensities in routine based jobs.

Table 7 documents similar summary statistics in the NLSY data, separating between performance pay and fixed wage workers over the life cycle. Starting with the demographic variables, there are surprisingly no statistically significant results with the exception of college attainment—performance pay workers are more likely to have a college degree than their counterparts. There are also marginal differences in the share of male workers.

Turning towards the labor market variables, fixed wage workers are much more likely to be covered by a union, but hourly workers are almost equally as likely to be in performance pay and fixed wage jobs. As discussed in the main text, performance pay workers earn and work considerably more than their counterparts, which grows over the life cycle. For example, between ages 25 and 34, performance pay workers earn only $10,000 more than their counterparts, but by ages 45 and 55 they earn nearly $30,000 more. It is also interesting to point out that the variance of earnings for performance pay workers is much larger than their counterparts, consistent with the fact that the returns to offering these contracts are greater in heterogeneous work environments (Lazear, 1986).

There are relatively insignificant differences in tenure and experience between the two workers, although performance pay workers have slightly higher years of experience, consistent with the fact that fixed wage workers are more likely to get laid off (Gittleman and Makridis, 2017). It is also interesting to point out that performance pay workers have considerably higher job satisfaction—for example, a standard deviation of 0.08 for performance pay workers versus 0.02 for fixed wage workers between ages 25 and 34, which is consistent with the complementarity between performance pay and organizational practices (Makridis, 2016).

Having described the details of both the PSID and NLSY, I now turn to an additional set of descriptive statistics from the NCS. Figure 9 plots the number of establishments in the

Table 6: Descriptive Statistics in the Panel Study of Income Dynamics, by Decade

	performance pay								fixed wage							
	1970-1979		1980-1989		1990-1999		2000-2014		1970-1979		1980-1989		1990-1999		2000-2014	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
demographics																
age	38.9	13.0	37.0	11.3	38.3	11.3	42.8	11.6	40.6	13.8	39.5	12.5	41.0	11.4	44.0	11.8
male	0.77	0.42	0.79	0.41	0.79	0.41	0.75	0.43	0.72	0.45	0.72	0.45	0.70	0.46	0.66	0.47
married	0.47	0.50	0.38	0.49	0.36	0.48	0.41	0.49	0.45	0.50	0.39	0.49	0.37	0.48	0.35	0.48
education	13.4	2.5	13.9	2.1	13.9	2.1	14.1	2.2	12.7	2.8	13.5	2.2	13.9	2.2	14.2	2.3
college	0.29	0.45	0.34	0.47	0.35	0.48	0.40	0.49	0.21	0.41	0.27	0.45	0.32	0.47	0.42	0.49
white	0.88	0.33	0.89	0.31	0.85	0.36	0.80	0.40	0.84	0.37	0.84	0.37	0.83	0.38	0.78	0.41
Black	0.09	0.29	0.09	0.29	0.11	0.31	0.14	0.34	0.13	0.34	0.14	0.35	0.14	0.35	0.16	0.37
family size	2.0	1.3	1.9	1.1	1.8	1.1	2.0	1.3	2.0	1.3	1.9	1.2	1.8	1.1	1.9	1.2
non-durables cons.	.	.	.	.	11839	6879	13980	8030	.	.	.	.	11852	6960	12637	7489
housing cons.	2179	1746	4749	4849	5027	6691	10179	17922	1842	1368	4118	3519	4324	5080	7910	11244
labor																
union	0.22	0.41	0.11	0.32	0.11	0.31	0.09	0.28	0.27	0.44	0.21	0.41	0.20	0.40	0.17	0.37
hourly	0.19	0.39	0.23	0.42	0.39	0.49	0.42	0.49	0.43	0.49	0.49	0.50	0.51	0.50	0.54	0.50
labor income	51769	34081	54086	56781	58296	50660	71693	118754	47269	30335	50158	65693	48681	39469	51601	44319
hours worked	2120	642	2169	655	2241	628	2197	634	2022	580	2042	567	2055	597	2082	632
home production	629	633	389	343	391	323	414	352	658	668	433	360	427	362	436	373
non-routine, cognitive	0.28	1.03	0.20	0.97	0.13	0.98	0.24	0.96	0.15	1.03	0.16	1.00	0.15	1.02	0.21	0.98
non-routine, interactive	0.22	1.13	0.13	1.04	0.07	1.02	0.16	1.02	0.07	1.04	0.13	1.05	0.11	1.04	0.15	1.02
routine, cognitive	-0.28	0.98	-0.22	0.98	-0.08	0.99	-0.03	0.89	0.06	1.01	0.05	1.01	0.04	1.01	0.08	0.93
routine, manual	-0.14	0.98	-0.19	0.93	-0.07	1.00	-0.16	0.96	0.08	1.03	0.09	1.02	0.07	1.04	-0.11	0.96
non-routine, manual	-0.19	1.00	-0.12	0.99	-0.08	1.01	-0.10	1.01	-0.10	0.97	-0.12	0.91	-0.07	0.94	-0.12	0.99
Observations	1689		3359		4774		7612		7506		10393		7673		8273	

Notes.–Sources: Panel Study of Income Dynamics (PSID, 1970-2014). The table reports the means and standard deviations of various demographic and labor market variables separately for performance pay and fixed wage workers, partitioned by age bracket. Performance pay workers are those who earn bonus, tip, or commission at least once with the same employer. Earnings and consumption expenditures are deflated using the 2010 personal consumption expenditure index. Non-durables measured following Attanasio and Browning (1995), rental expenditures following Flavin and Yamashita (2002) to impute rent for homeowners using their self-reported property values. Observations are weighted by the PSID sample weights.

Table 7: Descriptive Statistics in the National Longitudinal Survey of Youth, by Age Bracket

	performance pay						fixed wage					
	25-34		35-44		45-55		25-34		35-44		45-55	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
demographics												
age	29.1	2.7	39.7	2.9	49.2	3.0	28.9	2.8	39.2	3.0	49.2	3.0
family size	2.8	1.5	3.2	1.5	2.8	1.4	2.9	1.5	3.2	1.5	2.8	1.4
education	13.8	2.4	13.8	2.5	14.0	2.5	13.4	2.5	13.3	2.5	13.7	2.6
college	0.33	0.47	0.32	0.46	0.33	0.47	0.26	0.44	0.22	0.42	0.27	0.44
male	0.56	0.50	0.57	0.49	0.56	0.50	0.52	0.50	0.51	0.50	0.49	0.50
married	0.52	0.50	0.68	0.47	0.67	0.47	0.54	0.50	0.64	0.48	0.63	0.48
white	0.64	0.48	0.83	0.37	0.84	0.37	0.66	0.47	0.79	0.40	0.80	0.40
black	0.10	0.31	0.11	0.31	0.11	0.31	0.13	0.33	0.14	0.35	0.14	0.35
labor												
hourly	0.19	0.39	0.14	0.35	0.19	0.39	0.19	0.40	0.15	0.35	0.16	0.37
union	0.08	0.28	0.10	0.30	0.11	0.31	0.14	0.34	0.18	0.38	0.20	0.40
labor income	41042	28875	59890	54622	68263	70438	31750	22384	39375	36709	43924	48693
hours worked	2141	681	2216	688	2209	656	1982	732	2043	816	2021	835
tenure	3.7	3.4	7.5	6.3	11.5	8.9	3.5	3.4	6.3	5.8	9.3	8.6
experience	10.0	3.3	17.6	4.4	26.2	5.4	9.2	3.5	16.2	4.8	24.7	6.2
job satisfaction	0.08	0.67	0.12	0.65	0.09	0.67	0.02	0.70	0.08	0.69	0.09	0.70
Observations	25786		12286		10627		55423		18620		13889	

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79 and NLSY97). The table reports the means and standard deviations of various demographic and labor market variables separately for performance pay and fixed wage workers, partitioned by age bracket. Performance pay workers are those who earn bonus, tip, or commission at least once with the same employer. Earnings is deflated using the 2010 personal consumption expenditure index. Observations are weighted by the NLSY sample weights.

NCS over the sample; each establishment is observed for roughly four to five years. Table 8 documents employment, earnings, hours, and non-wage benefits separately for performance pay and fixed wage jobs by one-digit occupation. Starting with business and professional technical occupations, there is a large difference in earnings—roughly $85,000 on average for performance pay jobs versus $68,000 for fixed wage jobs. While annual hours worked are not very different between the two, the NCS generally does not measure hours worked very reliably since it simply records the hours requirement for the posted job—not how much given employees end up working in reality. The hourly bonus is $2.81 versus a $37.61 hourly wage, which is roughly 7%. However, the variance is much larger—$12.32/hour.

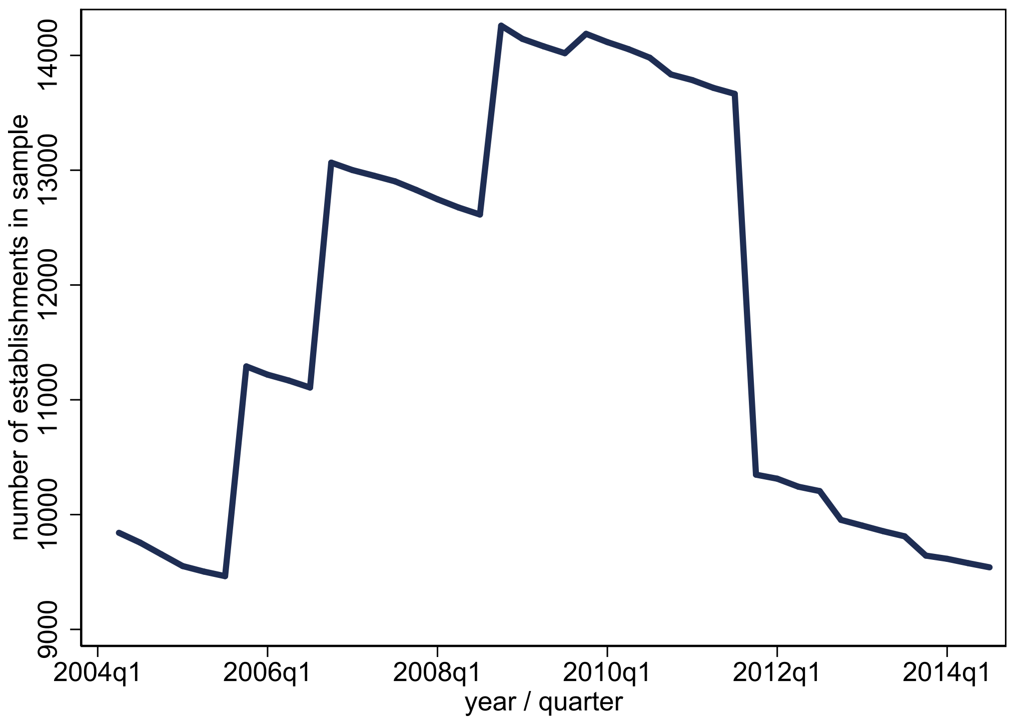


Figure 9: Number of Establishments in the National Compensation Survey
Notes.–Sources: National Compensation Survey, 2004-2014. The figure plots the number of establishments observed in the sample over time. Each establishment is observed for roughly 4-5 years.

Turning towards non-wage benefits or other forms of payments, overtime pay is low, but vacation pay is non-trivial—roughly 6% of overall compensation for both performance pay and fixed wage jobs. Both holiday pay and sick pay are also quite similar, but smaller, between the two. The most significant non-wage benefit is health insurance, which comes to 10.4% of earnings for performance pay workers and 11.4% for fixed wage workers. This is just above the share for social security payments. Direct benefit plans and direct contributions are non-trivial, but only come to roughly 3%. Overall, non-wage benefits do not differ much between these two sets of jobs, although there appears to be greater variance in performance pay jobs.

Turning towards community, social, legal, education, and entertainment / arts occupations, we see an even larger earnings gap of roughly \$61,500 for performance pay workers and \$47,000 for fixed wage workers. Non-wage benefits are relatively similar in their shares and trends as discussed above for business and professional occupations, but health insurance is roughly 2% higher in earnings for these workers, which is consistent with the claim that many middle-income workers are not necessarily compensated through higher pay, but rather higher amenities. The remaining occupations have similar trends as well. Healthcare support, protective service, food preparation, and grounds cleaning all have a much lower performance pay earnings gap (\$25,000 versu \$17,000), but the non-wage amenities shares tend to be similar. The sales, construction, extraction, installation occupations have a higher performance pay earnings premium, but this is largely driven by the fact that sales workers are almost exclusively performance pay and earn more than their production-based worker counterparts.

While discussed briefly above, it is also useful to point out differences in standard deviations. In every occupation, performance pay jobs have considerably higher variance in earnings, relative to their counterparts. The variance in employment is, however, much larger in fixed wage jobs, which reflects the fact that many of these positions involve lots of workers for often times routine tasks. For many of the non-wage amenity shares, however, there are not substantial differences in the variance for the two job types.

Table 9 now documents these summary statistics across industries. Like in the case of occupations, there is a large performance pay earnings premium in each sector. While the premium is small in some sectors—for example, it is roughly 8% in mining and construction—it is very large in other sectors—for example, nearly 94% in trade and FIRE. It ranges between 25-37% in manufacturing / transportation and services sectors. There is also an hours premium, but generally a smaller one in comparison to earnings since the NCS tends to measure the hours required for a job, rather than the hours actually worked by individuals. Moreover, like before when the summary statistics were presented by occupation, performance pay jobs contain greater dispersion in annual earnings than their counterparts. As a break down of industries, the employment share in mining and construction is 10%, manufacturing is 20%, trade and FIRE is 28%, and services is 40%. Turning towards the non-wage benefits, there is again only a meager difference between performance pay and fixed wage jobs. Performance pay jobs have

Table 8: Descriptive Statistics in the National Compensation Survey, by Occupation

	SOC1, PP		SOC1, FW		SOC2, PP		SOC2, FW		SOC3, PP		SOC3, FW		SOC4, PP		SOC4, FW		SOC5, PP		SOC5, FW	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
employment	1908	4712	2106	10355	2780	9701	3894	15440	949	3283	1297	9932	632	2702	955	7815	899	3040	707	5135
annual earnings	84759	52190	68862	32970	61468	44793	46948	34025	24872	17979	16773	13326	39875	31116	29378	19282	37892	19815	28884	18195
annual hours worked	1849	225	1814	256	1609	413	1431	499	1664	506	1431	547	1805	403	1667	487	1935	423	1787	490
hourly wage	37.61	19.71	33.53	15.43	33.51	22.31	29.86	17.35	12.58	6.96	10.28	5.24	18.71	12.86	15.35	7.73	17.20	11.83	14.70	10.67
hourly bonus	2.81	12.32	.	.	0.88	3.85	.	.	0.27	0.49	.	.	0.73	5.60	.	.	0.57	1.13	.	.
overtime pay, share	0.005	0.014	0.004	0.011	0.009	0.015	0.007	0.015	0.017	0.024	0.010	0.019	0.015	0.024	0.013	0.023	0.034	0.036	0.028	0.031
vacation pay, share	0.066	0.025	0.061	0.030	0.049	0.037	0.033	0.038	0.035	0.031	0.022	0.029	0.042	0.029	0.034	0.030	0.043	0.028	0.034	0.029
holiday pay, share	0.041	0.013	0.039	0.016	0.031	0.024	0.026	0.028	0.023	0.021	0.015	0.022	0.028	0.017	0.024	0.019	0.032	0.018	0.025	0.018
sick pay, share	0.017	0.028	0.017	0.018	0.020	0.019	0.020	0.019	0.010	0.014	0.007	0.013	0.011	0.012	0.009	0.013	0.008	0.013	0.007	0.013
bonus pay, share	0.067	0.154	.	.	0.025	0.068	.	.	0.021	0.029	.	.	0.034	0.088	.	.	0.031	0.055	.	.
health ins, share	0.104	0.062	0.114	0.079	0.122	0.100	0.126	0.121	0.119	0.134	0.080	0.134	0.124	0.109	0.115	0.127	0.153	0.109	0.136	0.145
def benefits, share	0.037	0.083	0.032	0.065	0.041	0.067	0.052	0.074	0.027	0.074	0.018	0.061	0.022	0.068	0.026	0.064	0.028	0.072	0.025	0.060
def contrib, share	0.039	0.036	0.031	0.036	0.026	0.035	0.018	0.030	0.013	0.027	0.007	0.021	0.026	0.035	0.017	0.033	0.022	0.032	0.014	0.028
social security, share	0.070	0.012	0.066	0.013	0.065	0.019	0.061	0.020	0.071	0.031	0.073	0.044	0.069	0.008	0.066	0.008	0.071	0.008	0.068	0.008
medicare, share	0.017	0.002	0.016	0.001	0.017	0.002	0.016	0.002	0.017	0.007	0.017	0.010	0.016	0.002	0.016	0.001	0.017	0.002	0.016	0.002
Observations	221124		155035		139304		251779		97124		222591		360549		432133		152892		185013	

Notes.–Sources: National Compensation Survey, 2004-2015. The table reports the mean and standard deviation of performance pay and fixed wage job employment, earnings, hours, and non-wage benefits. Performance pay jobs are those that receive bonus compensation or are classified as incentive pay. SOC1 includes management, business / finance, computer / math, architecture / engineering, life / physical / social science. SOC2 includes community / social, legal, education / training / library, arts / design / entertainment / sports / media, healthcare practitioners / technical. SOC3 includes healthcare support, protective service, food preparation / serving related, building / grounds cleaning / maintenance, and personal care / service. SOC4 includes sales / related, office / administrative support, farming / fishing / forestry, construction / extraction, installation / maintenance / repair. SOC5 includes production, transportation / material moving. https://www.bls.gov/soc/major_groups.htm slightly higher shares of health benefits, but not systematically or in an economically significant fahsion.

Having described these basic statistics, I now turn towards several additional features of the data. Figure 10 plots the share of bonus compensation to total income together with the share of jobs that are classified as performance pay, separately by job level. Not surprisingly, both are increasing in the distribution of job levels, reflecting the fact that the role of incentives grows as monitoring becomes more important in more senior positions (Prendergast, 2002). However, the bonus share of income is an underestimate since, as discussed in the main text, it only covers non-production bonuses. Most senior leadership jobs have other forms of compensation, including both traditional incentive pay bonuses and stock options, neither of which are explicitly measured in the dataset. Despite the limitation in the measurement of bonus compensation, there is still considerable variation in the distribution of non-production bonuses (see Figure 11).

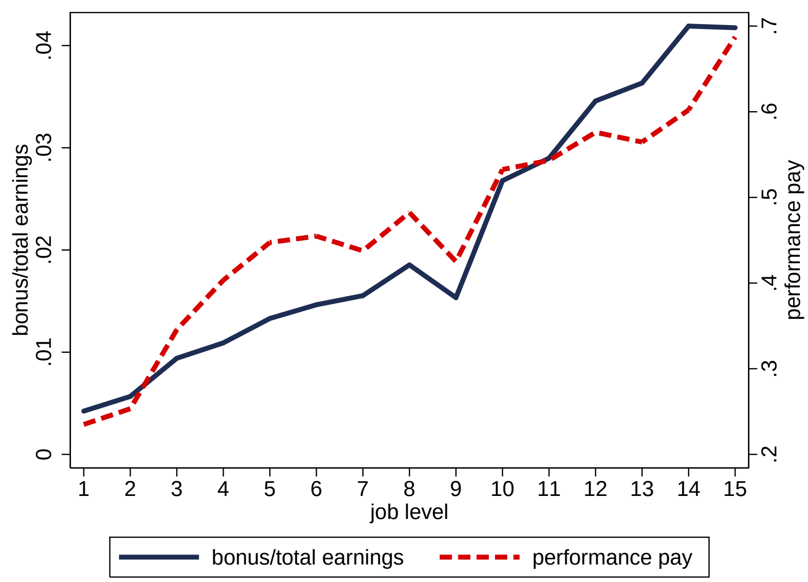


Figure 10: Bonus and Performance Pay Shares, by Job Level

Notes.–Source: National Compensation Survey, 2004-2015. The figure plots the share of performance pay workers and share of bonus to total earnings for performance pay workers across job levels.

Table 9: Descriptive Statistics in the National Compensation Survey, by Industry

	SIC12, PP		SIC12, FW		SIC34, PP		SIC34, FW		SIC56, PP		SIC56, FW		SIC78, PP		SIC78, FW	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
employment	459	1314	290	849	2270	4960	1112	2681	395	1240	159	843	1163	2494	911	2526
annual earnings	44591	31192	41410	23956	53590	30900	42808	25006	38162	41917	19630	18334	44158	38060	32038	28842
annual hours worked	1962	354	1959	375	1908	381	1855	405	1720	463	1495	530	1723	453	1566	536
hourly wage	19.58	13.08	19.21	10.32	24.07	16.03	20.84	15.19	17.82	15.76	11.22	7.75	21.70	16.84	17.99	13.79
hourly bonus	0.99	3.90	.	.	1.05	2.37	.	.	1.06	9.04	.	.	0.68	4.11	.	.
overtime pay, share	0.032	0.035	0.031	0.036	0.028	0.032	0.029	0.032	0.011	0.021	0.010	0.019	0.013	0.021	0.010	0.017
vacation pay, share	0.041	0.031	0.033	0.032	0.057	0.027	0.052	0.032	0.038	0.030	0.022	0.025	0.047	0.030	0.034	0.032
holiday pay, share	0.028	0.016	0.023	0.018	0.039	0.018	0.035	0.016	0.026	0.017	0.016	0.017	0.030	0.018	0.026	0.023
sick pay, share	0.006	0.010	0.005	0.008	0.013	0.015	0.012	0.015	0.010	0.011	0.006	0.010	0.013	0.012	0.011	0.014
bonus pay, share	0.042	0.155	.	.	0.039	0.060	.	.	0.041	0.133	.	.	0.025	0.067	.	.
health insurance, share	0.122	0.098	0.117	0.114	0.160	0.096	0.166	0.138	0.106	0.106	0.073	0.114	0.106	0.101	0.094	0.113
defined benefits, share	0.032	0.094	0.041	0.081	0.047	0.108	0.038	0.074	0.015	0.045	0.008	0.030	0.011	0.031	0.011	0.033
defined contributions, share	0.025	0.035	0.020	0.038	0.029	0.032	0.025	0.036	0.027	0.039	0.012	0.024	0.024	0.034	0.018	0.031
social security, share	0.070	0.007	0.067	0.005	0.072	0.009	0.069	0.008	0.070	0.018	0.074	0.041	0.070	0.018	0.068	0.015
medicare, share	0.016	0.002	0.016	0.001	0.017	0.002	0.016	0.001	0.017	0.004	0.017	0.010	0.017	0.004	0.016	0.003
Observations	60259		72407		151449		99562		203363		159773		204691		304031	

Notes.–Sources: National Compensation Survey, 2004-2015. The table reports the mean and standard deviation of performance pay and fixed wage job employment, earnings, hours, and non-wage benefits. Performance pay jobs are those that receive bonus compensation or are classified as incentive pay. SIC12 includes mining and construction; SIC34 includes manufacturing, transportation, utilities, and telecommunication; SIC56 includes wholesale / retail trade and finance / insurance / real estate; SIC78 includes services. https://www.naics.com/sic-codes-industry-drilldown/

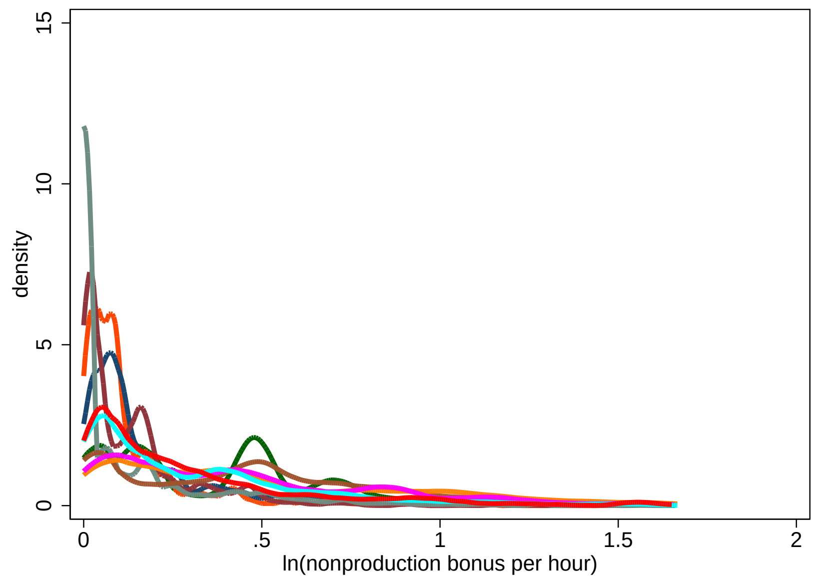


Figure 11: Dispersion in Bonus Compensation, by two-digit SOC
Notes.–Source: National Compensation Survey, 2004-2015. The figure plots logged bonus compensation (for only non-production bonuses) across two-digit occupations.

The main text discusses the differences in returns to human capital formation between performance pay and fixed wage jobs. An important characteristic of this pattern is the fact that workers in performance pay jobs allocate much more time to labor supply—and these differences are stark over the life cycle. Figure 12 partitions observations into 100 bins over the hourly earnings distributions, subsequently plotting it with annual hours worked. The gradient between hourly earnings and hours is much stronger in performance pay jobs and does not dampen off nearly as much as it does in fixed wage jobs. For example, towards the top of the hourly earnings distribution, there are some instances where hours worked is actually quite a bit lower to trend. In fact, the gap between annual hours worked and hourly earnings is largest at the top of the wage distribution, consistent with the claim that there are large differences in the returns to human capital formation.

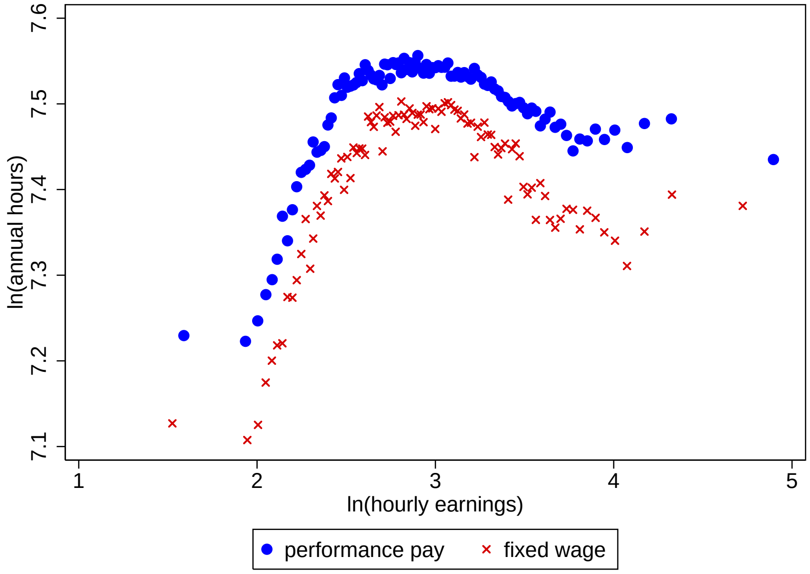


Figure 12: The Hump Shape of Hours and Wages, by Performance Pay and Fixed Wage

Notes.–Source: National Compensation Survey, 2004-2015. The figure plots logged annual hours and hourly earnings in performance pay and fixed wage jobs by income bracket (separated into 100 equally spaced hourly earnings bins).

Figure 13 plots the standard deviation of both raw and residualized earnings and benefits in performance pay and fixed wage jobs. While there is broad similarity between the two series for earnings dispersion, there is a persistent and growing wedge in the dispersion of benefits among the two sets of jobs—dispersion is growing rapidly in fixed wage jobs, whereas it is remaining close to constant in performance pay jobs.

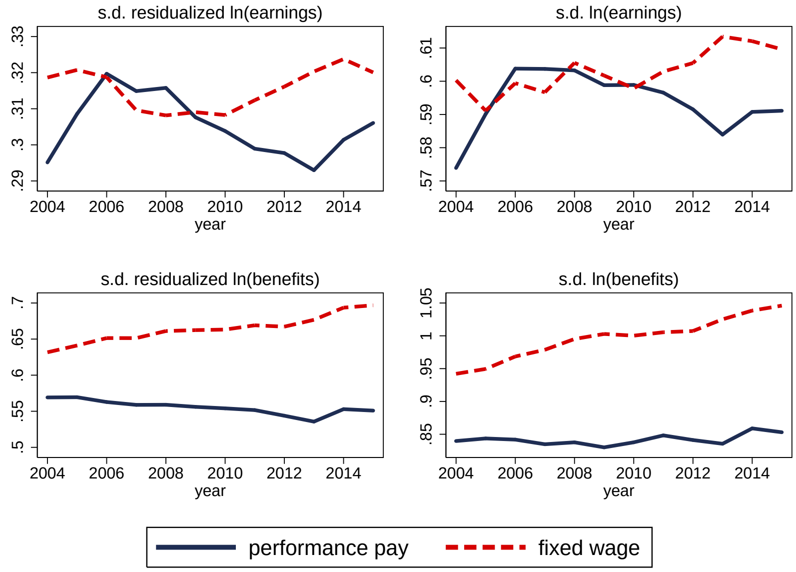


Figure 13: Dispersion in Earnings and Benefits, by Performance Pay and Fixed Wage
Notes.–Source: National Compensation Survey, 2004-2015. The figure plots the standard deviation of raw and residualized logged annual earnings and benefits where the residualized series is obtained by regressing the variable on establishment and job level fixed effects with the survey sample weights.

A4. Supplement to Differences in Earnings and Allocation of Time

A4.1. Life Cycle Profiles and Intertemporal Returns

The main text presents the returns to performance pay and fixed wage jobs over the life cycle. However, one concern is that these returns are driven by composition and selection effects. To address these concerns, I residualize logged annual hours worked and earnings on a vector of demographic controls, including a quadratic in education, race, gender, marital status, and family size. Panel A of Figure 14 plots residualized hours over the life cycle. The resulting plot is nearly indistinguishable in patterns when three-digit occupation fixed effects are included. Just as the main text illustrates with the raw data, hours worked for fixed wage workers peaks in their early 30s and subsequently declines back to levels observed at the start of their careers, whereas hours for performance pay workers plateaus in their late 30s and does not subsequently decline.

Panel B of Figure 14 plots residualized earnings, which again follows a similar pattern. In fact, the qualitative fact is even stronger than in the raw data—residualized earnings are flat from age 40 onward for fixed wage workers, whereas they continue to grow for performance pay workers. Panels A and B in Figure 15 plot analogous life cycle profiles for hourly wages, showing that the life cycle effect of earnings is greater than for hours, which is also consistent with models of human capital accumulation where the skill price is growing.

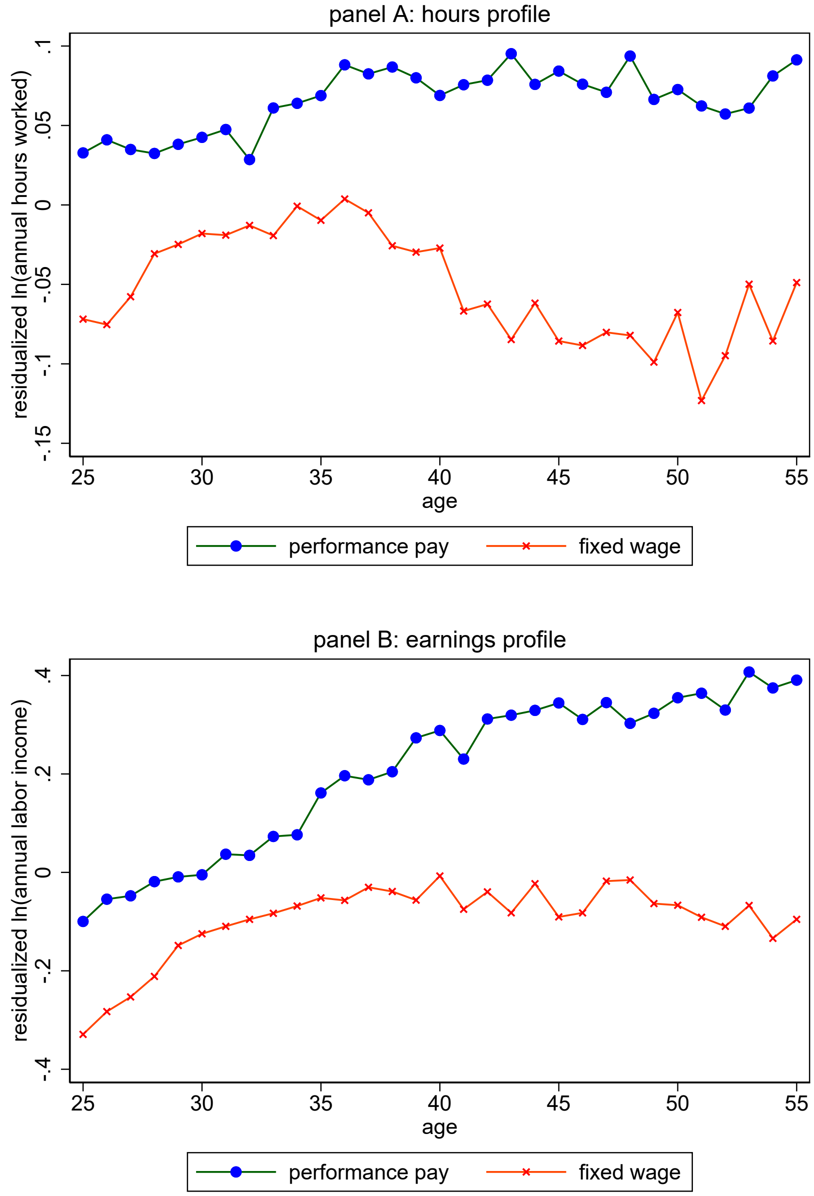
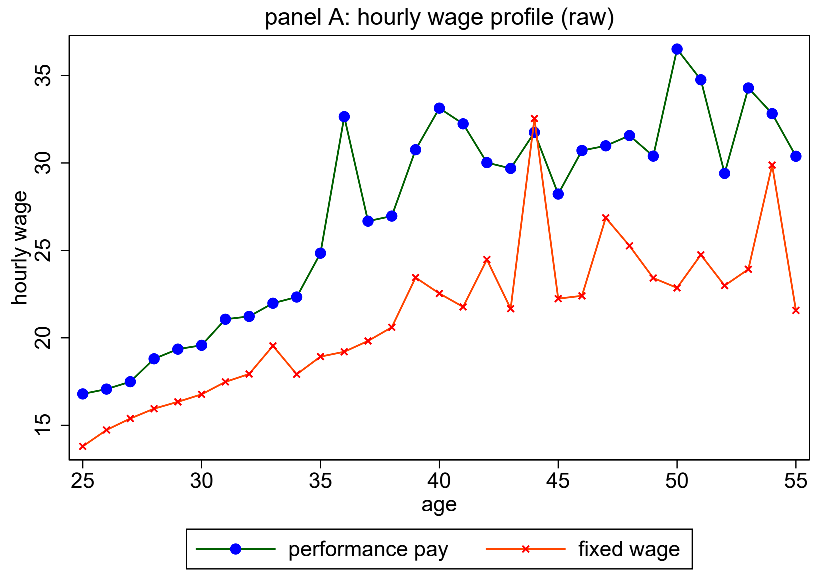


Figure 14: Residualized Heterogeneity in Hours and Earnings over the Life Cycle

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The figure plots residualized logged average annual hours worked and logged earnings (deflated using the 2009 consumer price index) over the life cycle for performance pay and fixed wage workers. Controls include: a quadratic in education, race, gender, marital status, and family size. Performance pay workers are defined as those who earn bonus, tip, or commission at least once with the same employer. The sample is restricted to full-time workers (over 500 hours per year, over $5000 per year). Observations are weighted by survey sample weights.



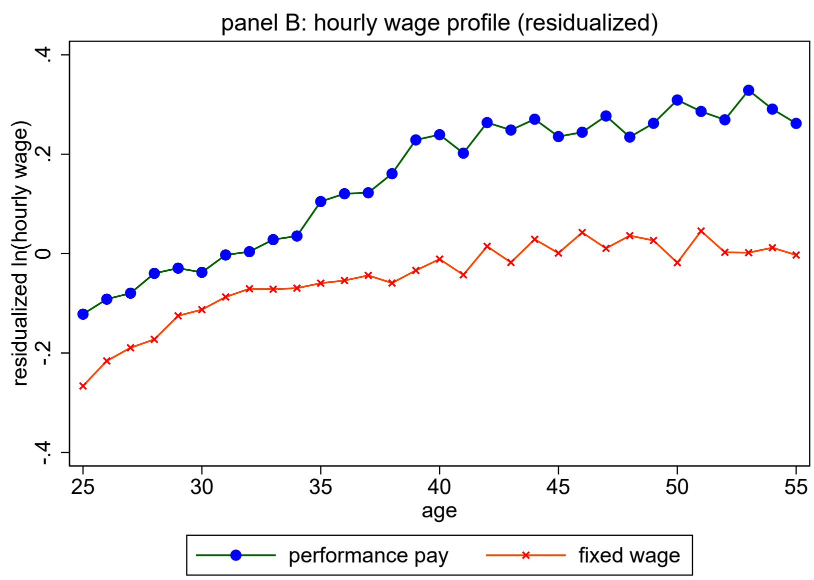


Figure 15: Heterogeneity in Hourly Wages over the Life Cycle

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The figure plots raw hourly wages and residualized logged hourly wages (deflated using the 2009 consumer price index) over the life cycle for performance pay and fixed wage workers. Controls used to residualize include a quadratic in education, marital status, gender, race, and family size. Performance pay workers are defined as those who earn bonus, tip, or commission at least once with the same employer. The sample is restricted to full-time workers (over 500 hours per year, over $5000 per year). Observations are weighted by survey sample weights.

While these life cycle patterns are stark, the main text also emphasizes the increase in performance pay over time, which is associated with the skill premium for these jobs. Figure 16 plots the logged earnings and hours for performance pay and fixed wage workers using the raw and residualized data from 1970 to 2014. While there is always a premium—that is, performance pay workers earning and working more than fixed wage workers—it begins widening in the 1980s. The earnings premium is larger than the hours premium.

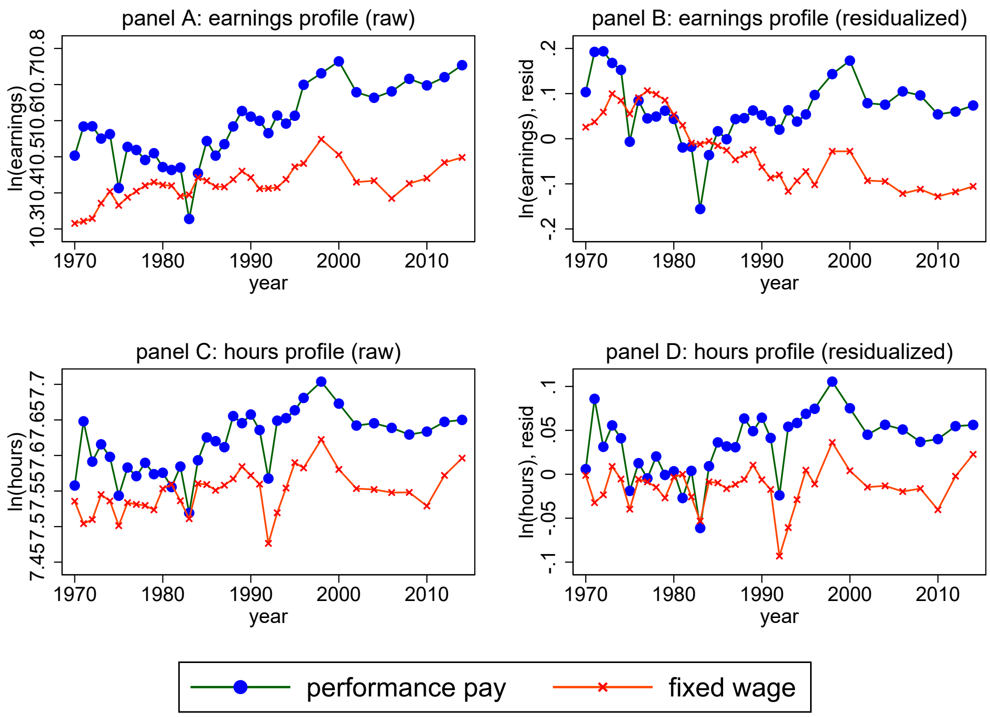


Figure 16: Heterogeneity in Earnings and Hours over Time, 1970-2014

Notes.–Sources: Panel Study of Income Dynamics (PSID, 1970-2014). The figure plots both raw and residualized logged earnings and hours worked (deflated using the 2009 consumer price index) over time for performance pay and fixed wage workers. Controls used to residualize include a quadratic in education, marital status, gender, race, and family size. Performance pay workers are defined as those who earn bonus, tip, or commission at least once with the same employer. The sample is restricted to full-time workers (over 500 hours per year, over $5000 per year). Observations are weighted by survey sample weights.

A4.2. Detailed Life Cycle Patterns

Figures 17, 18, and 19 plot the pattern of logged earnings and hours worked performance pay premia over the life cycle separately for each major two-digit occupation. The general pattern that emerges is an increasing premium over the life cycle except in a few occupations: education and healthcare; sales also has random fluctuations largely because the share of performance pay is already quite high and those with it have idiosyncratic earnings (by the nature of their job).

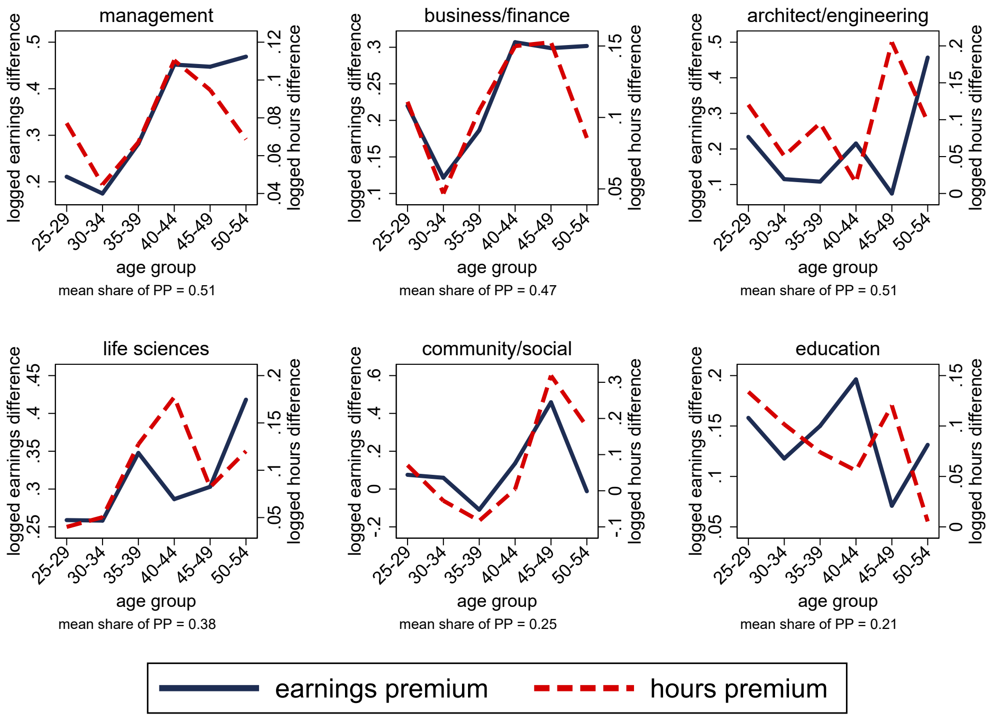


Figure 17: Earnings and Hours Premia over the Life Cycle, by SOC 2-Digit Part 1

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The figure plots the logged earnings and hours worked difference between performance pay and fixed wage workers over the life cycle by two-digit occupations. Observations are weighted by the survey sample weights and the sample is restricted to full-time employed workers.

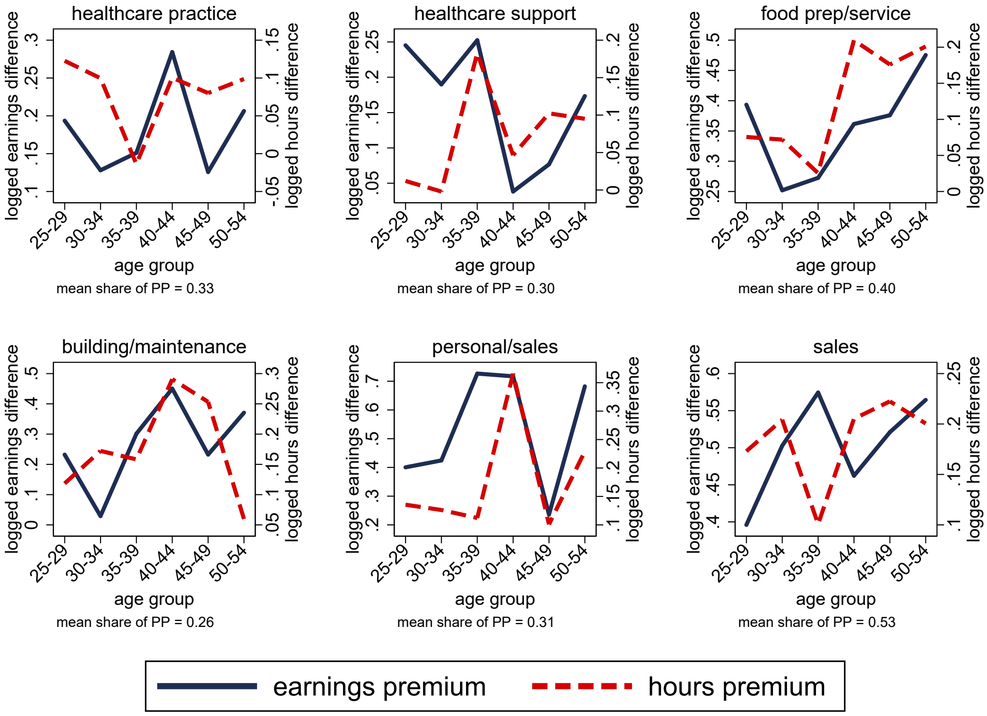


Figure 18: Earnings and Hours Premia over the Life Cycle, by SOC 2-Digit Part 2

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The figure plots the logged earnings and hours worked difference between performance pay and fixed wage workers over the life cycle by two-digit occupations. Observations are weighted by the survey sample weights and the sample is restricted to full-time employed workers.

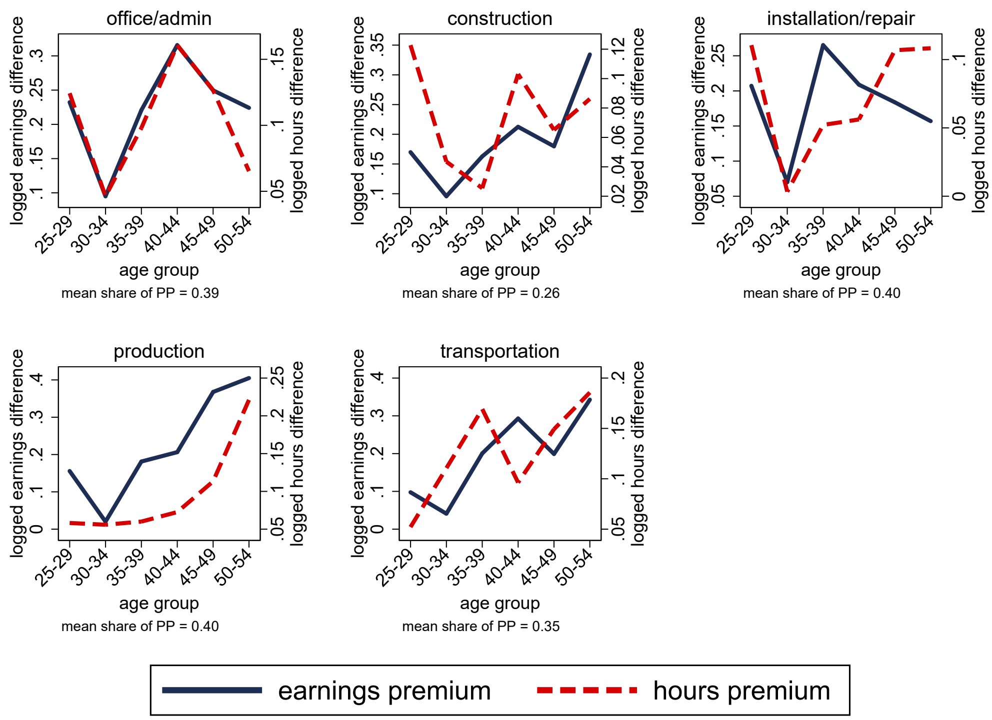


Figure 19: Earnings and Hours Premia over the Life Cycle, by SOC 2-Digit Part 3

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The figure plots the logged earnings and hours worked difference between performance pay and fixed wage workers over the life cycle by two-digit occupations. Observations are weighted by the survey sample weights and the sample is restricted to full-time employed workers.

Having documented these life cycle earnings and hours premia by occupation, I now document the premia by industry. Figure 20 documents these. Beginning with Panel A, the professional services sector has the largest earnings premium, growing from roughly 20% at age 25 to 60% by age 55. However, other sectors, like the agricultural / mining / construction sector, has a lower premium, which tends to stay at 20% over the life cycle. The manufacturing sector also exhibits an increasing earnings premium of the life cycle, growing from 20% to 45%. The premium finance, insurance, and real estate sector also exhibits a large premium on par with the manufacturing sector. Turning towards Panel B, there are also large hours differences between performance pay and fixed wage workers, but they tend to be more stable over the life cycle. For example, while the hours premium grows from 7% to 12% in the professional services sector and from 4% to 10% in the manufacturing sector over the life cycle, surprisingly it stays relatively constant in other sectors.

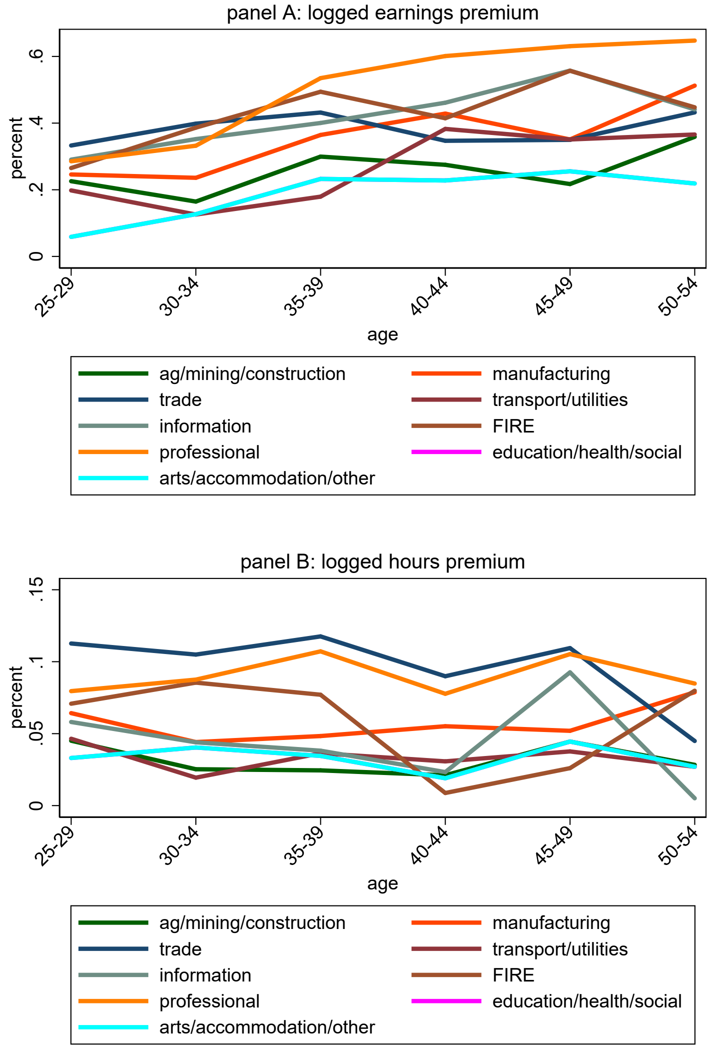


Figure 20: Earnings and Hours Premia over the Life Cycle, by Industry

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79 and NLSY97). The figure plots the logged difference between performance pay and fixed wage earnings and hours worked per year. Observations are weighted by the survey sample weights and the sample is restricted to full-time employed workers.

A4.3. Addressing Selection on the Firm-side

The main text underscores systematic differences between performance pay and fixed wage workers. While these results are identified off of variation within occupation and within person, selection and other endogeneity concerns are still possible. One of the primary threats to identification is the presence of other firm-level amenities that are correlated with performance pay and also influence learning. For example, since performance pay workers report higher development and training opportunities, it could be that performance pay workers are simply clustered in firms with different organizational practices.

The ideal natural experiment would be to randomize the provision of performance pay across a set of jobs that vary in these unobserved characteristics. While such an experiment is clearly not available, I can implicitly gauge the potential role that other amenities play in influencing human capital investments by using the job-level NCS micro-data to estimate the prices on different amenities

$$w_{ift} = \gamma PP_{ift} + \alpha A_{ift} + \delta(PP_{ift} \times A_{ift}) + \phi_i + \psi_f + \lambda_t + \epsilon_{ift} \tag{13}$$

where i now denotes the job, f denotes the establishment, and t denotes the period, w denotes the logged hourly earnings, PP denotes an indicator for whether the job is defined as performance pay, A denotes a vector of other relevant organizational amenities, and ϕ, ψ, and λ denote fixed effects on job-level (15 categories), establishment, and time, respectively. The vector of non-wage amenities, which are each measured as dollars per hour, includes: life insurance, health insurance, defined benefits, defined contributions, and vacation pay.[44]

Estimating Equation 13 is a variant of the coefficient comparisons test, therefore, identified off of comparisons of jobs of the same level within the same establishment. The magnitude and sign of $\delta > 0$ will provide insight into the potential for omitted variables.

Appendix Section X also provides an analogous table when the outcome variable is logged annual hours worked, which helps characterize the extent of omitted variables with respect to the intensive margin of effort.

A4.4. Sources of Heterogeneity

While the main text presented average treatment effects, there are potentially interesting sources of heterogeneity in the returns to performance pay across different partitions of the labor market. Using the NLSY, I consider regressions of the form

$$y_{it} = \beta X_{it} + \gamma PP_{it} + \phi^k d_{it}^k + \delta^k (PP_{it} \times d_{it}^k) + \eta_o + \lambda_t + \epsilon_{it}$$

where now d_{it}^k denotes a dummy variable for the k-th group (e.g., college, race, male) and

[44]Unfortunately, there is no measurement of promotions or skill intensities, although a recent version of the Occupational Requirements Survey (ORS) was piloted.

Table 10: Gauging Bias Through the Coefficient Comparison Test on Performance Pay

	ln(total hourly earnings)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
performance pay	.31***	.11***	.10***	.09***	.10***	.10***	.09***	.07***
	[.01]	[.00]	[.00]	[.01]	[.01]	[.00]	[.00]	[.01]
ln(life insurance)				.60***				
				[.09]				
× pp				-.05				
				[.10]				
ln(health insurance)					.10***			
					[.00]			
× pp					-.02***			
					[.00]			
ln(defined benefits)						.14***		
						[.01]		
× pp						-.05***		
						[.00]		
ln(defined contributions)							.21***	
							[.01]	
× pp							-.01	
							[.01]	
ln(vacation pay)								.22***
								[.01]
× pp								.01
								[.01]
R-squared	.07	.74	.92	.92	.92	.92	.92	.92
Sample Size	2220696	2220696	2220637	2220637	2220637	2220637	2220637	2220637
Job level FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year/Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: National Compensation Survey. The table reports the coefficients associated with regressions of the logged hourly earnings on an indicator for performance pay status and various measures of amenities measured as costs per hour worked. Job level fixed effects are defined over 15 levels of seniority, normalized to the first level. The sample excludes all public institutions, such as government entities and non-profits. Standard errors are clustered by establishment and observations are weighted by the NCS sample weights.

where η and λ denote fixed effects on three-digit occupation and year. Table 11 documents these results. Consistent with the results in the main text, performance pay workers earn approximately 20-23% more and work 9-12% more than their counterparts, controlling for time-invariant differences across occupations and the usual covariates. However, the more interesting results are the interactions with demographic characteristics. Performance pay workers with a college degree earn roughly 6% more than their counterparts, but it is important to point out that the interaction is almost a quarter as large as the direct effect, suggesting that the contract plays an especially important role. Looking at variation in hours worked, it is even more interesting that the interaction is insignificant, suggesting that college degree performance pay workers do not allocate more time to labor supply.

Turning towards heterogeneity in gender, while males earn roughly 44% more and work 23% than females, the interaction in the earnings regression is insignificant. The fact that the interaction in the hours worked regression is negative is puzzling at first. However, through further diagnostics, the differences appear to be driven by heterogeneity in the allocation of time among married males—those who are married spend less time at work. Finally, turning towards heterogeneity in race, while blacks tend to earn 8% less, the interaction with performance pay is statistically insignificant. However, black performance pay workers do tend to work 3% more than their counterparts, potentially reflecting the fact that they may face greater pressure to outperform their peers due to statistical discrimination in the labor market.

A4.5. Performance Pay Consumption Premia

Table 12 regresses different measures of consumption on an indicator of performance pay status, conditional on controls and with / without three-digit occupation fixed effects. Consumption is measured using non-durables following Attanasio and Browning (1995), using rental expenditures following Flavin and Yamashita (2002) to impute rent for homeowners' self-reported property values, and using car purchases. While there are some differences in non-durables expenditures between the two sets of workers, their durable purchases—housing and cars—are more significant.

Table 11: Estimating Heterogeneity in the Returns to Performance Pay Jobs

Dep. var. =	ln(earnings)			ln(hours worked)		
	(1)	(2)	(3)	(4)	(5)	(6)
performance pay (pp)	.20***	.23***	.22***	.09***	.12***	.09***
	[.01]	[.01]	[.01]	[.01]	[.01]	[.01]
college	.29***			.01		
	[.02]			[.01]		
college × pp	.06***			-.01		
	[.02]			[.01]		
male	.44***	.44***	.43***	.21***	.23***	.21***
	[.01]	[.02]	[.01]	[.01]	[.01]	[.01]
male × pp		-.02			-.05***	
		[.02]			[.01]	
black	-.07***	-.10***	-.08***	.02*	.01	.00
	[.02]	[.02]	[.02]	[.01]	[.01]	[.01]
black × pp			-.01			.03***
			[.02]			[.01]
R-squared	.34	.34	.34	.13	.13	.13
Sample Size	107747	107646	107646	115192	115085	115085
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: NLSY 79 and 97, 1979-2014. The table reports the coefficients associated with regressions of logged annual earnings and hours worked on performance pay and different interactions with demographic variables. Controls (common throughout) include: marital status, a quadratic in age, and family size. Income is deflated by the 2010 personal consumption expenditure index. Standard errors are clustered at the individual-level.

Table 12: Differences in Consumption among Performance Pay and Fixed Wage Workers

Dep. var. =	ln(non-durables)		ln(housing consumption)		(ln(car price)	
	(1)	(2)	(3)	(4)	(5)	(6)
performance pay	0.05***	0.03**	0.09***	0.10***	0.11**	0.07*
	[0.02]	[0.01]	[0.02]	[0.03]	[0.04]	[0.04]
R-squared	0.28	0.35	0.15	0.40	0.14	0.24
Sample Size	16467	16286	20984	44870	7720	7614
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

Notes.–Sources: Panel Study of Income Dynamics, 1970-2014. The table reports the coefficients associated with regressions of logged consumption (non-durables measured following Attanasio and Browning (1995), rental expenditures following Flavin and Yamashita (2002) to impute rent for homeowners using their self-reported property values, and car purchases) on an indicator for performance pay, conditional on controls and fixed effects. Controls include: a quadratic in age, education, indicators on race, male, marital status, and number of children. Standard errors are clustered by person and observations are weighted by the sample weights.

A5. Reduced Form Analysis

Figure 21 documents these facts. Beginning in 1980, the performance pay premium was roughly zero, whereas the college premium was 40%. By 2010, the earnings premium for all performance pay workers was 20%, whereas the premium for the set of performance pay workers who are neither union nor hourly was 42%. Given that performance pay is highly heterogeneous—with investment bankers earning large bonuses and production workers earning much smaller ones—separating out non-union and non-hourly performance pay workers from the rest helps point out the increasing heterogeneity in skill even among the set of performance pay jobs over this period.

As a point of comparison, Figure 21 also plots the college premium, which has grown from 40% to 60% over the same 1980 to 2010 period in the PSID sample.[45] The interesting fact is that the performance pay premium—although lower in the overall level, relative to the college premium—has grown over twice as fast as the college premium of this time period. The fact that they differ also illustrates that performance pay is not simply capturing college attainment. When the sample is further restricted to the set of performance pay and college degree workers, they earn roughly 80-100% more than their purely fixed wage worker counterparts, highlighting complementarity between college and performance pay.

[45]Different samples produce different premia based on the composition of workers. While the annual time series here is produced using PSID sample weights, the Appendix documents a larger college premium using the CPS.

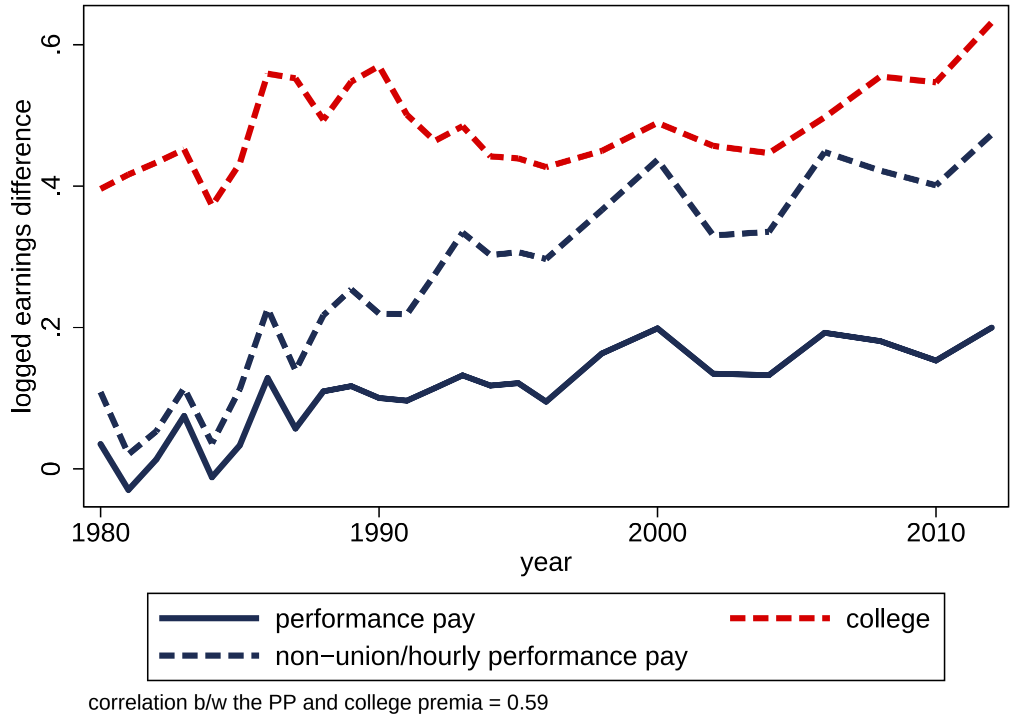


Figure 21: Performance Pay and College Earnings Premia

Notes.–Sources: Panel Study of Income Dynamics (PSID). The figure plots the logged earnings premia for performance pay (relative to fixed wage) workers, college degree (relative to non-college) workers, and performance pay and college degree (relative to fixed wage) workers. The sample is restricted to those at least 20 years old and full-time workers. Observations are weighted by the corresponding sample weights.

A5.1. Supplemental Evidence on Human Capital Investments

Evidence from Occupational Task Concentrations: The Occupational Task Network ("O*NET") provides measures of the importance of different personal characteristics for each detailed six-digit occupation. While human capital is an inherently latent variable, there is general agreement about the integral role that deliberate practice plays in the production of skill (Ericsson et al., 2006). I focus on four measures of personal characteristics from O*NET, namely: how much the job requires establishing and maintaining personally challenging achievement goals and exerting effort towards mastering tasks ("achievement/effort"), how much the job requires persistence in the face of obstacles ("persistence"), how much the job requires a willingness to take on responsibilities and challenges ("initiative"), and how much the job requires a willingness to lead, take charge, and offer opinions and directions ("leadership").

Using the NCS micro-data, I classify occupations as performance pay and fixed wage on the basis of their share of performance pay workers; those with over 50% of the labor force on performance pay contracts are classified as performance pay, fixed wage otherwise. Under this classification scheme, Figure 22 plots the corresponding distribubution of worker habit z-scores across three-digit occupations. Performance pay jobs require an overwhelmingly amount of effort, persistence, initiative, and leadership, relative to fixed wage jobs. In the Appendix, I also use O*NET data between 2004-2016 to plot the change in the share of performance pay with the change in each of these worker habit intensity indices at a four-digit occupation level. The data suggest that increases in the growth of performance pay are associated with increases in the growth of effort, persistence, initiative, and leadership.

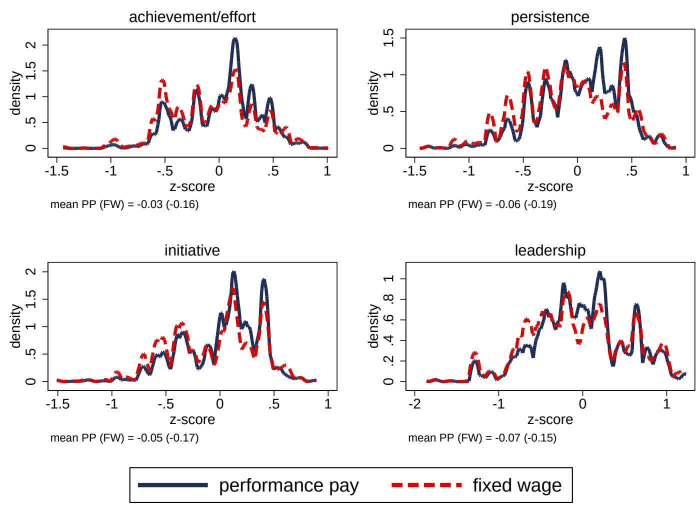


Figure 22: Worker Habits in Performance Pay and Fixed Wage Jobs
Notes.–Source: National Compensation Survey and O*NET. The figure plots the distribution of different worker values at the six-digit occupation level across performance pay and fixed wage jobs. Performance pay jobs are those with incentive pay or non-production bonuses.

I also implement several additional exercises. First, I plot the distribution of z-scores for measures of required education, training, and skills. These results are consistent with those from MacLeod and Parent (2014) who merge the Dictionary of Occupational Titles (DOT) and the PSID between 1977 and 1984, finding that there is positive selection into complex jobs that have some bonus compensation. Second, I report scatter plots of the fraction of performance pay with the occupation's corresponding z-score of worker habits. If, for example, one is concerned that the binary classification scheme in Figure 22 is not detecting true performance pay, then keeping the measure in its continuous form should produce an attenuated result; that is not the case.

Evidence from Complements in the Production of Human Capital: An important component of the learning process is the presence of informal training among peers and/or supervisors. Fortunately, however, the NLSY-79 provides measures of informal training for 1996, 1998, and 2000, which I exploit using probit regressions of informal training on performance pay, conditional on controls.[46] Figure 23 plots the estimated coefficients separately by major occupation. While performance pay workers are uniformly more likely to receive informal training, there is significant heterogeneity across occupations. For example, informal training is highest in management, business, and technical occupations, but almost non-existent in low skill occupations.[47] As a reference point, college educated workers are 17% more likely to receive informal training (p-value = 0.00).

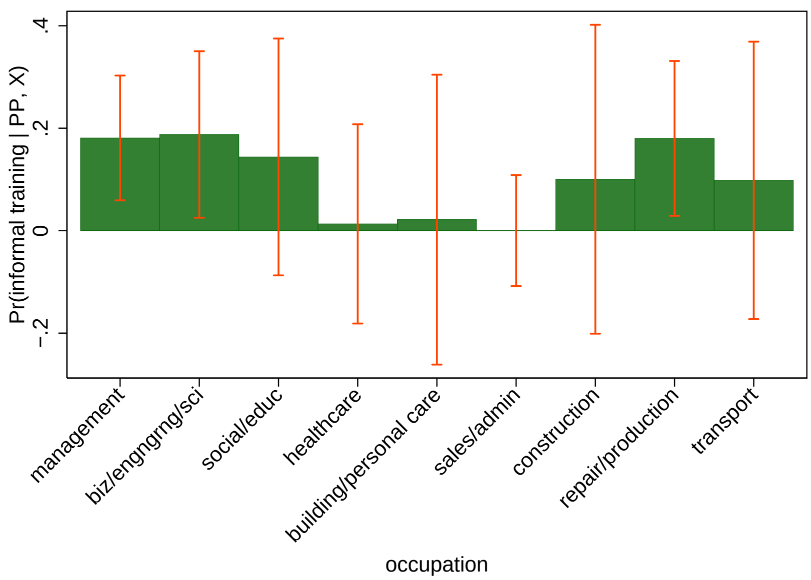


Figure 23: Informal Training and Performance Pay, by Occupation
Notes.–Source: NLSY. The figure plots the coefficients estimated from a probit regression of informal training on an indicator for performance pay, conditional on a quadratic in age and education, gender, marital status, family size, and race (black and white). Performance pay workers are those who receive bonus, tip, or commission at least once with the same employer. Observations are weighted by the NLSY sample weights and standard errors are clustered at the person-level.

These measures of informal training, however, generally capture short-term supervision and learning opportunities on the extensive margin. They do not, for example, capture the under-

[46]The question is worded as follws: "(Besides the schooling and training programs we've just talked about,) During the last 4 weeks while working at [Name of employer], did you receive any informal on-the-job training from your supervisor, coworker(s), or both?"

[47]The only exceptions are production (which has high informal training) and healthcare (which has low informal training). The fact that production has high informal training, however, is consistent with evidence from personnel economics; see, for example, Shaw and Lazear (2008) and Ichniowski et al. (1997). The fact that healthcare has low informal training is likely due to licensing laws and high educational attainment requirements behaving as barriers to entry.

lying organizational characteristics within firms that promote collaboration, learning, and mentorship. To better address these limitations, I turn towards data from PayScale (see Makridis (2016)). Figure 24 plots the distribution of (standardized) ratings on senior leadership, career opportunities, compensation & benefits, and culture across firms in performance pay and fixed wage jobs. The starkest differences emerge with compensation & benefits and career opportunities, but individuals also tend to report higher ratings of senior leadership and culture in performance pay jobs. These results provide motivating evidence on the complementarity between human resource and management practices discussed by Ichniowski and Shaw (1999) and Bloom and Van Reenen (2007), respectively.

Figure 24: Organizational Amenities in Performance Pay and Fixed Wage Jobs

Notes.–Source: PayScale. The figure plots four measures of non-pecuniary amenities in performance pay and fixed wage jobs across firms. The sample is restricted to firms with over 500 observed employees providing ratings information. Ratings of pay transparency, communication, development/training opportunities, and management quality are on an index of one to five and subsequently standardized to a mean of zero and standard deviation of one. Performance pay workers are those who have bonus, commission, stock options, or profit sharing as part of their pay.

Evidence on Career Concerns and Explicit Incentives: One concern is that the presence of career concerns accounts for these differences in hours worked. I now show that, while career concerns may always exist, explicit incentives are also present and are associated with increases in hours worked. Before turning towards the explicit tests, I begin by examining whether the NLSY data is consistent with the theoretical prediction from Gibbons and Murphy (1992) that explicit incentives should grow in importance over the life cycle. Regressing logged performance pay compensation, which is available for a select set of years starting in 2000, on age, conditional on controls (education, male, married, family size, and race), produces a coefficient of 0.012 with a p-value of 0.049. I also regress hours worked on logged performance pay, separately by age bracket, and find an increasing gradient over the life cycle.

Evidence from Industry Labor Productivity: While the ideal empirical setting is to have information on individual productivity and labor supply over time, examining whether lagged levels of labor supply are correlated with increases in future productivity, I approximate it by working at the three-digit industry level. I specifically use three-digit industry GDP data deflated by current prices (2009 base year) normalized by employment as a measure of labor productivity. I subsequently consider regressions of the form

$$\Delta y_{it}^{j} = \beta^{j}\Delta X_{it} + \gamma^{j}\Delta l_{it}^{j} + \epsilon_{it}^{j}, \quad \forall j \in \{PP, FW\}$$

where Δ denotes the growth rates operator (i.e., $\Delta x_t = (x_t - x_{t-1})/x_{t-1}$), X denotes a vector of demographic covariates, l denotes annual hours worked, and PP is an indicator for whether the industry is performance pay (classified using Ward's algorithm on the share of workers with a performance pay contract). Finding that $\gamma > 0$ is consistent with models of human capital formation and finding $\gamma^{PP} > \gamma^{FW}$ is consistent with a model where performance pay provides greater incentives for learning.

Figure 25 plots the two growth rates, together with the estimated gradients in the notes under the plot. Importantly, while a one percentage point rise in the growth rate of hours worked in industries with low performance pay is associated with a statistically imprecise 0.22pp (p-value = 0.317) rise in the growth rate of labor productivity, whereas a comparable increase in hours worked is associated with a 0.74pp (p-value = 0.017) rise in labor productivity in industries with high shares of performance pay. In this sense, increases in labor supply are associated with increases in productivity, which could be due to learning effects. One obvious concern is the presence of unobserved product market shocks, which raise demand and, therefore, the number of hours individuals need to work. However, if anything, this should reduce the gradient given that the estimates are obtained over the period of the Great Recession when product demand fell.

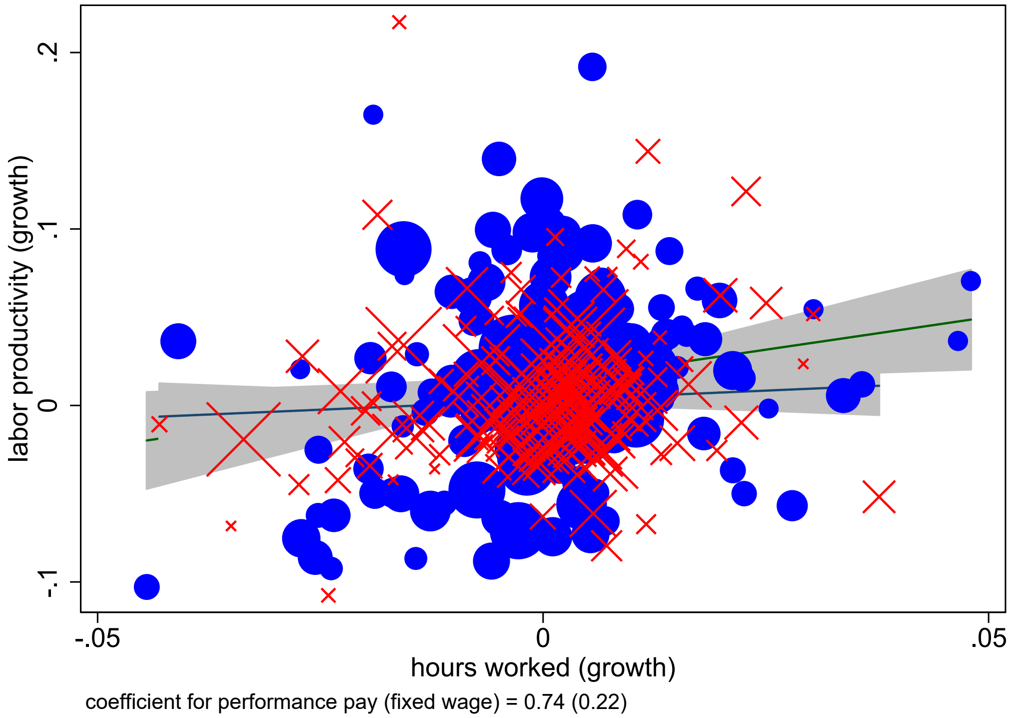


Figure 25: Labor Productivity and Hours Worked Growth Rates
Notes.–Source: Bureau of Economic Analysis, Current Employment Statistics, American Community Survey, and National Compensation Survey, 2006-2015. The figure plots the growth in labor productivity with the growth in hours worked across three-digit industries weighted by their employment. Labor productivity is measured using gross output deflated by industry-specific price indices (2009 base year) and normalized by employment. Hours worked is measured as the product of weeks worked and usual weekly hours worked. Performance pay sectors are classified using Ward's algorith; the share of performance pay ranges from 45% to 95% (mean = 0.54) in high performance pay sectors, whereas it ranges from 14% to 42% (mean = 0.33) in low performance pay sectors.

A6. Quasi-experimental Evidence of Performance Pay and Inequality

The main text presents quantitative results that the rising share of performance pay workers actually contributes to a decline in inequality when human capital accumulation is allowed. The result is counterintuitive in light of the result from Lemieux et al. (2009) that the rise of performance pay accounts for roughly 20% of the rise in earnings inequality from a static variance decomposition perspective. However, when dynamics are allowed, individuals exhibit greater returns to human capital accumulation, which allow workers to self-insure against labor market risk. This section provides microeconomic evidence behind the main result that performance pay is associated with declines in inequality by using the NCS between 2004 and 2015 at the metropolitan-by-year level

$$INEQ_{mt} = f(X_{mt}, \beta) + \gamma PP_{mt} + \phi_m + \lambda_t + \epsilon_{mt} \tag{14}$$

where m denotes metropolitan area, t denotes time, $INEQ$ denotes the logged 90-10 hourly wage difference, X denotes a vector of demographic controls, PP denotes the share of performance pay, and ϕ and λ denote metro and year fixed effects. To control for differences in the underlying composition of a metropolitan's labor market, I use the American Community Survey (ACS), accessed through SocialExplorer, and construct detailed age bracket bins, educational attainment bins, and the shares of males and married families. To measure inequality, I use the Occupation Employment Statistics (OES) tables, which provides the most comprehensive data on earnings across metropolitan areas.

There are, however, potential issues with the estimation of Equation 14. First, areas with greater inequality might also have more performance pay since the labor force is more heterogeneous. While the inclusion of metro fixed effects helps assuage this concern, the second possible problem is the reflection problem (Manski, 1993). When the labor force becomes more heterogeneous (i.e., a rise in the dispersion of earnings), then the returns to performance pay also rise (Lazear, 2000b). Since performance pay is designed to offer tailored incentives based on the individual's disutility of effort, it will naturally be used more in environments that are more diverse.

Although the inclusion of semi-parametric time-varying demographic controls helps reduce the potential endogeneity problems, I turn towards two sources of plausibly exogenous variation. The first leverages heterogeneity in the effects of the Great Recession. Given that the financial crisis behaves as an unanticipated shock, I can leverage the fact that the occupations that were most vulnerable were those that contained performance pay contracts (e.g., finance). In particular, I contruct a Bartik-like measure by interacting the metropolitan employment share in finance for a base period with the occupation-level employment growth in the country

$$Z_{mt} = \sum_{o} (FIN_{m,2003} \Delta e_{o,t})$$

where $FIN_{m,2003}$ denotes the employment share in the financial sector in 2003 for a given metropolitan area. Of course, one major concern with this approach is that the financial crisis affects metropolitan inequality in other ways besides performance pay. For example, if exposure to the financial sector led to greater housing price declines and/or foreclosures, then the estimates may be biased. While these considerations are clearly important, changes in the wage-setting mechanism is an important channel through which labor markets re-equilibrated during the Great Recession (Gittleman and Makridis, 2017).

Given the obvious concerns with this approach, I also exploit an additional source of variation, namely the 2000 share of IT workers at a metropolitan level using a measure from companion work (Gallipoli and Makridis, 2017). The intuition arises from the fact that areas with more IT workers will tend to have output that is more easily observed since IT reduces monitoring costs and, therefore, raises the returns to performance pay contracts (Lazear, 1986). While the identifying assumption here is that the share of IT workers in 2000 is uncorrelated with other contemporaneous shocks between 2004 and 2015, one way to mitigate these concerns is by controlling for other factors from 2000, like the share of college degree workers.

Table 13 documents these results. Consistent with the concern about omitted variables bias, the unconditional and conditional correlations in columns 1 and 2 suggest a positive association between performance pay and inequality. However, once metro and year fixed effects are introduced, the gradient turns negative. Even more surprising is the fact that the gradient remains negative and similar in magnitude under both IV strategies.

Dependent variable =	ln(90-10 earnings gap)			growth in 90-10 gap	
performance pay, share	0.04	0.05***	-0.03***		
	0.03	0.02	0.01		
performance pay, growth				-0.04*	-0.05**
				0.02	0.02
R-squared	0.01	0.52	0.93	N/A	N/A
Sample Size	1635	1635	1621	1109	1110
Controls	No	Yes	Yes	Yes	Yes
Metro FE	No	No	Yes	No	No
Year FE	No	No	Yes	No	No
Bartik IV?	No	No	No	Yes	No
IT share IV?	No	No	No	No	Yes

Table 13: Performance Pay and Inequality during the Great Recession

Notes.–Sources: National Compensation Survey and Occupation Employment Statistics, 2004-2015. The table reports the coefficients of the logged 90-10 hourly wage difference on the share of performance pay workers at the metropolitan level, conditional on demographic controls. Controls include: the share of males, married, white, black, the age distribution (bins), and the education distribution (bins). Standard errors are clustered at the metro level and observations are weighted by the number of observations per metro area in the NCS.

A7. Relationship with Skill-biased Technical Change

Recent literature, however, has also emphasized the importance of skill-biased technical change (SBTC); see, for example, Autor et al. (2006), Autor et al. (2008), and Autor and Dorn (2013). Given that the returns to using performance pay are larger in occupations with greater heterogeneity (Lazear, 1986), then the rise of performance pay should also accelerate SBTC. Using micro-data from the Census Bureau to measure inequality and college attainment, together with the NLSY to measure performance pay, at the three-digit occupation level based on 2010

SOC codes, I run regressions of the form

$$INEQ_{o,t} = \beta f(X_{o,t}) + \gamma PP_{o,t} + \pi 1[\Delta C_{o,t} > \Delta \overline{C}_t] + \delta(PP_{o,t} \times 1[\Delta C_{o,t} > \Delta \overline{C}_t]) + \epsilon_{o,t} \quad (15)$$

where $INEQ$ is the logged 90-10 earnings difference, X is a set of demographic controls, PP denotes the share of performance pay workers, $1[\Delta C > \Delta \overline{C}]$ denotes an indicator for whether the change in the share of college degree workers in an occupation o is above a specified (e.g., mean) constant ($\overline{C}$) growth rate in period t.[48]

Table 14 documents these results with and without the inclusion of demographic controls. While the estimates are noisy, the coefficients are consistent with the theoretical prediction that increases in performance pay should amplify inequality driven by SBTC. Focusing on the interaction between increases in the growth rate of college attainment and performance pay, the coefficients are positive: a 10% rise in the share of performance pay workers in occupations that experienced above average growth in college attainment tend to have a 4.4% rise in the 90-50 earnings gap without controls and a 1.7% rise with controls. The interaction is robust to the weighting scheme (e.g., not weighting by employment), to estimating Equation 15 in first-differences ($\hat{\delta} = 0.045$ [p-value = 0.90] and $\hat{\delta} = 0.03$ [p-value = 0.94] with and without controls), and to using the logged 90-10 earnings gap instead as a measure of inequality.

These results, however, are static—they do not provide a glimpse of the acceleration of SBTC over time. Figure 26 examines the relationship further by plotting the *residualized* logged earnings premium between performance pay and fixed wage workers (in navy blue), together with the premium obtained by restricting the sample to performance pay workers with a college degree (in red). Although the gap between the two is already large in 1985 (about 0.20 log points), it widens considerably after 1995 to a maximum of 0.50 log points by 2004. The relative growth of the premium associated with being both a college and performance pay worker is consistent with the canonical model of skill-biased technological change and job polarization (Autor and Dorn, 2013).

[48]The NLSY is a better alternative to the NCS for this application since it contains a sufficiently large sample to produce averages at a three-digit occupation level, in addition to going back far enough in time since the bulk of the rise in inequality took place before 2004. A limitation is that the NLSY does not cover workers later in their careers. To ensure that these correlations are not driven by differences in the composition of workers used to construct the inequality and performance pay measures, I restrict the sample to those between ages 20 and 40.

Table 14: The Rise of Performance Pay and Skill Biased Technical Change

Dep. var. =	logged 90-50 earnings gap	
	(1)	(2)
$1[\Delta \text{ C} > \Delta \overline{C}]$	.04	.04
	[.08]	[.10]
performance pay, pct	.44*	.17
	[.24]	[.27]
$\times$ $1[\Delta \text{ C} > \Delta \overline{C}]$	.22	.29
	[.21]	[.36]
R-squared	.26	.40
Sample Size	128	128
Controls	No	Yes

Notes.–Sources: IPUMS Census (1970-2010) and NLSY. The table reports the coefficients associated with regressions of the logged 90-50 earnings gap at a three-digit occupation (SOC) level on an indicator for whether growth in the occupation-year was above average, the share of performance pay workers in that occupation-year, and the interaction between the two, conditional on controls. Controls include: the fraction of workers between ages 20-35 and 36-45 (normalized to above age brackets), the fraction of workers who are white and black, the fraction who are male, and the fraction who are married. Observations are weighted by employment at a three-digit occupation level and standard errors are clustered at the occupation-level.

Table 15: The Rise of Performance Pay and Skill Biased Technical Change (NCS)

	ln(performance pay premium)		
	(1)	(2)	(3)
performance pay	.02	.21	-.22***
	[.10]	[.16]	[.08]
1[high college]	-.20**	-.08	-.24**
	[.09]	[.09]	[.11]
$\times$ performance pay	.49**	.37*	.31
	[.23]	[.22]	[.19]
R-squared	.13	.25	.87
Sample Size	1014	1014	1014
Controls	No	Yes	Yes
Occupation FE	No	No	Yes
Year FE	No	No	Yes

Notes.–Sources:

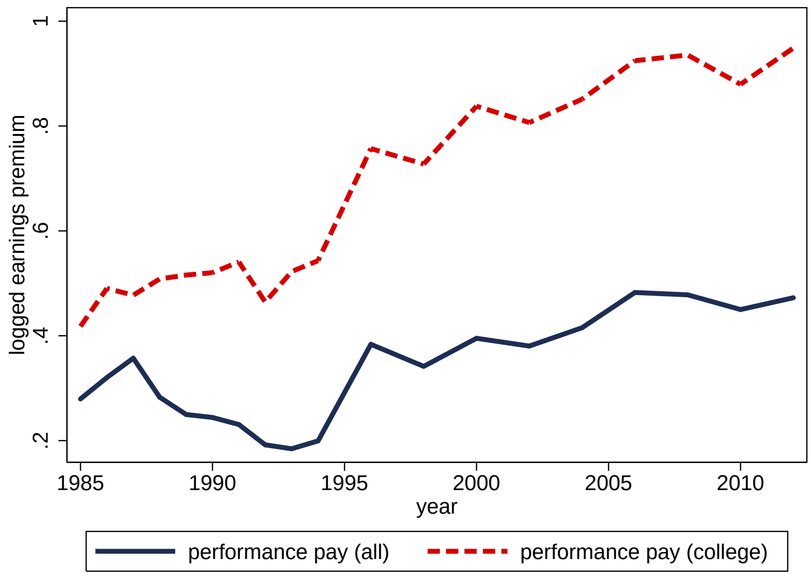


Figure 26: Acceleration of the Performance Pay Premium, 1985-2012

Notes.–Sources: The figure plots the residualized logged earnings premium between all performance pay workers (relative to all fixed wage workers) and performance pay workers with a college degree (relative to all fixed wage workers). Logged earnings is demeaned of a quadratic in age, race, gender, marital status, and family size.

A8. Computational Supplement

A8.1. Earnings Decomposition

Given the following income process

$$y_t = p_t + \varepsilon_t$$

$$p_t = \rho p_{t-1} + \eta_t$$

where $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$, $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, and $p_0 \sim \mathcal{N}(0, \sigma_0^2)$, then the autocovariance matrix is given by

	t	$t+1$	$t+2$	$t+3$	$t+4$
t	$E(y_t, y_t)$				
$t+1$	$E(y_t, y_{t+1})$	$E(y_{t+1}, y_{t+1})$			
$t+2$	$E(y_t, y_{t+2})$	$E(y_{t+1}, y_{t+2})$	$E(y_{t+2}, y_{t+2})$		
$t+3$	$E(y_t, y_{t+3})$	$E(y_{t+1}, y_{t+3})$	$E(y_{t+2}, y_{t+4})$	$E(y_{t+3}, y_{t+3})$	
$t+4$	$E(y_t, y_{t+4})$	$E(y_{t+1}, y_{t+4})$	$E(y_{t+2}, y_{t+4})$	$E(y_{t+3}, y_{t+4})$	$E(y_{t+4}, y_{t+4})$

where the exponent s on the persistence parameter ρ in the covariance terms is defined based on the difference between the $t+s$ term and the t term

$$E(y_t, y_t) = E(p_t, p_t) + \sigma_\varepsilon^2$$

$$E(y_t, y_{t+s}) = \rho^s E(p_t, p_t)$$

where

$$E(p_t, p_t) = \rho^{2t}\sigma_0^2 + \sum_{s=0}^{t-1} \rho^{2s}\sigma_\eta^2 = \rho^{2t}\sigma_o^2 + \frac{1-\rho^{2t}}{1-\rho^2}\sigma_\eta^2 \text{ if } \rho < 1$$

	t	$t+1$	$t+2$	$t+3$	$t+4$
t	$E(p_t, p_t) + \sigma_\varepsilon^2$				
$t+1$	$\rho E(p_t, p_t)$	$E(p_{t+1}, p_{t+1}) + \sigma_\varepsilon^2$			
$t+2$	$\rho^2 E(p_t, p_t)$	$\rho E(p_{t+1}, p_{t+1})$	$E(p_{t+2}, p_{t+2}) + \sigma_\varepsilon^2$		
$t+3$	$\rho^3 E(p_t, p_t)$	$\rho^2 E(p_{t+1}, p_{t+1})$	$\rho E(p_{t+2}, p_{t+2})$	$E(p_{t+3}, p_{t+3}) + \sigma_\varepsilon^2$	
$t+4$	$\rho^4 E(p_t, p_t)$	$\rho^3 E(p_{t+1}, p_{t+1})$	$\rho^2 E(p_{t+2}, p_{t+2})$	$\rho E(p_{t+3}, p_{t+3})$	$E(p_{t+4}, p_{t+4}) + \sigma_\varepsilon^2$

A8.2. Why Endogenous Grid Points Does Not Work

Consider the following dynamic program with simplified notation

$$V(h, a) = u(c, l) + \beta V(h', a')$$

subject to

$$c + a' = W(h, l)(1 - \tau) + a(1 + r) + T$$

$$W = \exp(\alpha_0 + \alpha PP + \sum \zeta^j d^j + \gamma_1 l + \gamma_2 h_{t-1} + \gamma_3 (h_{t-1} \times PP) + \xi o + z)$$

The first-order conditions are

$$c: \quad \chi c^{-\sigma} + \lambda = 0$$

$$l: \quad -(1 - \chi) l^{\psi} - \lambda \gamma_1 \exp(\cdot) = 0$$

$$a': \quad \lambda = \beta \lambda' (1 + r)$$

In this sense, while the intertemporal Euler can be easily solved

$$\chi c_t^{-\sigma} = \beta E[\chi c_{t+1}^{-\sigma}(1 + r)]$$

the intratemporal Euler is more complex

$$(1 - \chi) l^{\psi} = \chi c^{-\sigma} W(h, l)$$

In particular, the intratemporal Euler cannot be manipulated so that labor supply can be written in terms of consumption and assets—due to earnings being a function of cumulative and contemporaneous hours worked.

A8.3. Calibration

To initialize the dynamic program, I estimate the earnings equation using OLS setting the normalized job level dummies relative to the first job group as the baseline. These results are reported for different sample restrictions in Table 16. Beginning with the pooled sample, performance pay workers accept 19% lower earnings today, but experience higher earnings in the future as a result of working longer hours. In particular, a 10% rise in cumulative hours is associated with a 0.2% rise in earnings in the cross-section, but it is associated with an additional 0.3% rise in earnings among performance pay workers. The fact that the interaction is even larger than the direct effect of cumulative hours highlights the heterogeneity in returns to human capital formation that the workers face.

Column 2 subsequently restricts the sample to college degree workers. Interestingly, these workers accept even lower earnings in exchange for higher future earnings due to greater cumulative hours worked. In addition, the gradient on the interaction between performance pay and lagged cumulative hours worked is also twice as large as the gradient for non-college workers, suggesting a potential complementarity between innate ability and work ethic. Interestingly, there are only minor differences in the estimated coefficients between whites and blacks, but large differences among the three groups that are created based on "observed" heterogeneity. For example, the interaction effect is statistically insignificant for these workers, suggesting that they have weak human capital motives.

A8.4. Dealing with Unobserved Heterogeneity

The presence of permanent and unobserved differences among workers is central to understanding the returns to and incidence of performance pay. Put simply, since more productive workers will tend to prefer performance pay jobs , firms offer performance pay as a way to influence the selection of candidates who apply (Lazear, 1986). In this sense, the selection effects of performance pay are integral to understanding the dispersion of earnings and preference parameters that underpin the observed career choices of workers.

The standard approach in this literature is to assume that there are M types of individual who consist of π_m share of the population (Heckman and Singer, 1984). These are time-invariant types that remain throughout all periods. Individuals know their type and preference parameters are allowed to vary by type, in addition to allowing earnings to vary by type. Denote $\theta_1 = (\chi_m, \psi_m)$ as the vector of utility parameters and $\theta_2 = (\alpha, \zeta^j, \gamma_1, \gamma_2, \phi, \xi)$ the set of earnings parameters. The log likelihood function for a dataset with N observations is given by

$$L(\theta) = \sum_{i=1}^{N} \ln \left(\sum_{m=1}^{M} \pi_m \mathcal{L}_{1im} \mathcal{L}_{2im} \right)$$

Table 16: Initial Parameterization for Earnings Equation, by Group

	ln(labor income)							
	all	college	non-college	white	non-white	group1	group2	group3
performance pay	-.19***	-.28***	-.14***	-.20***	-.12*	-.20**	-.23***	-.10
	[.04]	[.10]	[.05]	[.05]	[.07]	[.09]	[.07]	[.06]
job dummy 2	.02	.03	.04**	.01	.07***	.06*	.03	-.03
	[.02]	[.02]	[.02]	[.02]	[.02]	[.03]	[.02]	[.03]
job dummy 3	-.05**	-.07*	.02	-.06**	.00	-.02	-.05*	-.09***
	[.02]	[.04]	[.02]	[.02]	[.03]	[.04]	[.03]	[.03]
job dummy 4	-.03	.01	.01	-.03	-.00	.00	-.04	-.04
	[.02]	[.04]	[.03]	[.03]	[.03]	[.06]	[.03]	[.03]
job dummy 5	.01	.02	.05***	-.00	.06***	.04	.01	-.05*
	[.02]	[.02]	[.02]	[.02]	[.02]	[.03]	[.02]	[.03]
job dummy 6	-.03**	-.03	.04**	-.04**	.01	.00	-.04**	-.07**
	[.02]	[.03]	[.02]	[.02]	[.02]	[.03]	[.02]	[.03]
job dummy 7	-.10***	-.07**	-.06***	-.11***	-.07***	-.08**	-.10***	-.15***
	[.02]	[.04]	[.02]	[.02]	[.03]	[.04]	[.02]	[.04]
job dummy 8	-.05***	-.05*	-.00	-.05***	-.02	-.02	-.06***	-.08***
	[.02]	[.03]	[.02]	[.02]	[.02]	[.03]	[.02]	[.03]
job dummy 9	-.08***	-.14***	-.01	-.09***	-.04	-.02	-.10***	-.12***
	[.02]	[.05]	[.02]	[.02]	[.02]	[.03]	[.02]	[.03]
ln(current hours)	.33***	.32***	.34***	.33***	.35***	.33***	.37***	.26***
	[.01]	[.03]	[.01]	[.01]	[.02]	[.02]	[.02]	[.02]
ln(cumulative hours)$^{t-1}$	-.01***	-.01	-.00	-.01***	.01	-.00	-.01*	-.01*
	[.00]	[.01]	[.00]	[.01]	[.01]	[.01]	[.01]	[.01]
$\times$ pp	.03***	.04***	.02***	.03***	.02**	.03***	.03***	.02**
	[.00]	[.01]	[.01]	[.01]	[.01]	[.01]	[.01]	[.01]
1[switch occupation]	-.04***	-.04***	-.03***	-.04***	-.03***	-.04***	-.04***	-.01*
	[.00]	[.01]	[.01]	[.01]	[.01]	[.01]	[.01]	[.01]
ln(earnings)$^{t-1}$	.79***	.80***	.75***	.80***	.74***	.74***	.73***	.85***
	[.01]	[.02]	[.01]	[.01]	[.01]	[.02]	[.01]	[.01]
Constant	-.22**	-.13	-.02	-.21**	-.04	.12	.16	-.24*
	[.09]	[.21]	[.10]	[.10]	[.14]	[.17]	[.14]	[.14]
R-squared	.75	.74	.70	.75	.67	.70	.67	.78
Sample Size	40278	7727	32551	23989	16289	10883	17332	12063

Notes.–Sources: National Longitudinal Survey of Youth (NLSY79). The table reports the coefficients associated with regressions of logged annual earnings on an indicator for performance pay status, eight job dummies (industry-by-occupation) normalized to the highest paying job cell (management and business), logged annual hours worked, logged lagged cumulative hours worked, its interaction with performance pay, an indicator for whether an individual switched occupations, and lagged logged earnings. Standard errors are clustered at the person-level and observations are weighted by NLSY sample weights.

where $\mathcal{L}_{1im}$ and $\mathcal{L}_{2im}$ denote the likelihood contributions for the preference and earnings parameters, respectively. However, since the log likelihood is not additively separable under unobserved heterogeneity, I use the expectation-maximization (EM) algorithm from Dempster et al. (1977) to effectively return to additive separability. In particular, the conditional probability of being a particular type is given by

$$P_i(m|X_i, \theta, \pi) = \frac{\pi_m \mathcal{L}_{1im} \mathcal{L}_{2im}}{\sum_{m=1}^{M} \pi_m \mathcal{L}_{1im} \mathcal{L}_{2im}}$$

where X denotes a vector summarizing all the decisions and characteristics of the individual. In the first step, I calculate the log likelihood function given the conditional probabilities at the current parameter estimates. In the second step, I maximize the expected likelihood function holding the conditional probabilities fixed. The process is repeated until convergence. Importantly, Arcidiacono and Jones (2003) show that writing the log likelihood in this additively separable form produces large computational savings

$$\sum_{i=1}^{N} \sum_{m=1}^{M} P_i(m|X_i, \theta, \pi)(L_{1im}(\theta_1) + L_{2im}(\theta_2))$$