The Performance Pay Premium, Human Capital, and Inequality: Evidence from Over Forty Years of Microdata

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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 (PSID) and National Longitudinal Survey of Youth (NLSY), I document several stylized facts: (i) the share of performance pay workers grew from 15% in 1970 to nearly 50% by 2000, (ii) performance pay workers experience higher earnings levels and growth rates, work longer hours, and invest more in human capital, and (iii) performance pay workers face lower (higher) permanent (transitory) income shocks, relative to their fixed wage worker counterparts. Second, using the National Compensation Survey (NCS), I show that increases in performance pay are associated with increases in inequality at the micro-level and accelerate the rate of skill-biased technical change. Third, I structurally model the rise of performance pay contracts by solving a dynamic model with unobserved person-specific heterogeneity, discrete sector-occupation job choices, time-varying sector-occupation probabilities of performance pay, and human capital accumulation. The model is estimated using simulated method of moments. Fourth, I use the model to characterize the contribution of performance pay to aggregate inequality and examine the counterfactual effects of making the U.S. marginal tax code as progressive as the one in France.

JEL: H2, J21, J22, J31.

Keywords: Human capital, skill premium, earnings inequality, on the job learning, pay for performance.

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1. Introduction

Earnings inequality in the United States soared over four decades, more so than other OECD economies (Forster and Levy, 2014).[1] These changes are largely explained through changes in permanent income (Kopczuk et al., 2010). A voluminous literature has emerged to explain these trends using models of skill-biased technical change (Acemoglu, 1998; Katz and Murphy, 1992; Acemoglu, 2002; Autor et al., 2006, 2008). These models distinguish between skilled and unskilled workers—typically measured through binary measures of college attainment—and more recently have allowed for heterogeneity in the relationship between skills and tasks (Autor et al., 1998, 2003; Autor and Dorn, 2013).

While these models have been successful in understanding many features of the U.S. labor market, they fall short of explaining several key dimensions, such as the changing nature of wage inequality (Lemieux, 2008; Card and DiNardo, 2002) and cross-country trends in inequality (Freeman and Katz, 1995).[2] Since these models of skill-biased technical change rely on the assumption of perfectly competitive labor markets, they omit heterogeneity in employer-employee contracting. The two main types of employment contracts that have prevailed in the United States labor market are based on performance pay (PP) and fixed wage (FW) compensation schemes. The former links compensation with output; the latter tends to compensate employees through a seniority-based or hourly pay system. Performance pay contracts are used to encourage higher productivity and influence the selection of employees into the firm (Lazear, 1986).[3]

The fraction of performance pay worker grew from nearly 10% of the labor force in 1970 to 50% by the early 2000s. While the share has exhibited a small decline since the early 2000s, many workers in the labor market are compensated with some form of performance pay contract. Remarkably, a reduced-form regression of the logged 90/50 earnings difference on the fraction of performance pay produces an R-squared of 0.71 (see Figure 1). The primary contributions of this paper are to structurally model the effects of changing labor market institutions (through the rise of performance pay contracts) on the labor market. My model provides an economic mechanism linking wage-setting institutions with the private returns to on-the-job skill accumulation through the equilibrium set of contracts.[4],[5]

The economic mechanism is as follows. Policies and wage-setting institutions, such as marginal tax rates and unions, affect firms' demand for labor services by introducing a wedge between the employee's marginal product and compensation. Lower wedges raise firms' demand for labor services by making it less costly for them to compensate employees. These wedges are dynamic since the way employees allocate their time

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

[2] 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.

[3] Individuals also sort into these contracts based on their risk aversion (Holmstrom and Milgrom, 1987; Holmstrom, 1979) and an array of other behavioral characteristics, like over confidence (Dohmen and Falk, 2011).

[4] Studying on-the-job human capital accumulation (a form of learning-by-doing) is crucial given that over half of the variation in individuals' life time earnings arises from uncertainty after the decision to go to college. See Cunha et al. (2005) and Storesletten et al. (2004) (about 50%), Kahn and Lange (2014) (about 66%), and Huggett et al. (2011) (about 40%). Altonji et al. (2013) find that (under more general proxies for) human capital accounts for most of the growth in earnings over a career.

[5] Rising wage inequality is been linked with the decline in unionization over the past 40 years (Champagne and Kurmann, 2013; Acikgoz and Kaymak, 2014). Rising wage volatility is not driven by compositional effects (Comin et al., 2009), but rather a rise in the volatility of sales in larger companies, consistent with evidence from Song et al. (2015) that cross-sectional, rather than within-firm, variation in earnings accounts for the bulk of the rise in inequality.

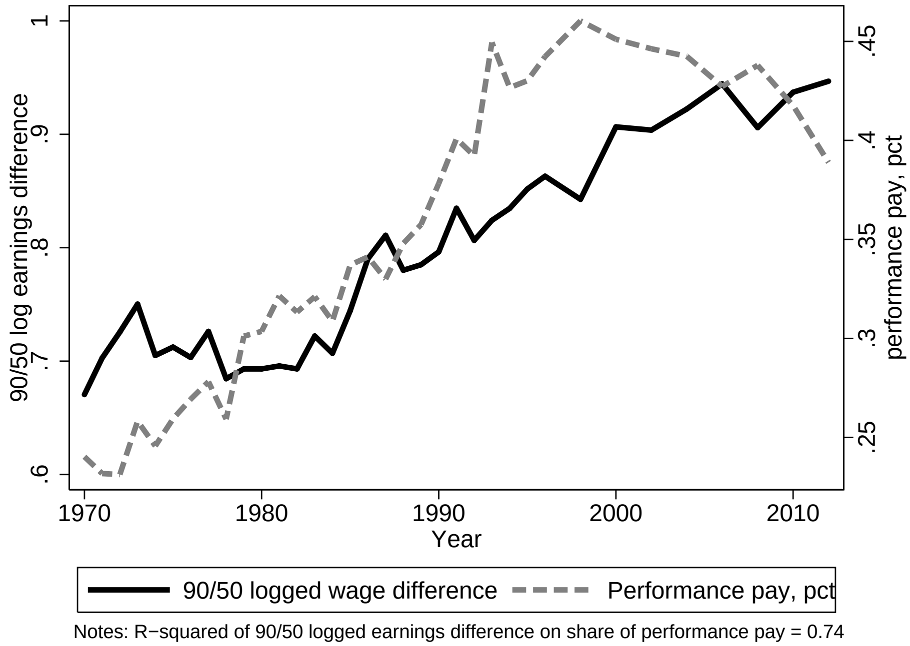

Figure 1: Motivating Evidence on Performance Pay and Inequality

Notes.–Source: Panel Study of Income Dynamics (PSID). The figure plots the logged 90/50 earnings difference with the fraction of performance pay workers between 1970 and 2012. The sample is restricted to full-time workers with over $5,000 in annual labor income. While the measurement of performance pay workers is documented and validated in Section 2.2., the classification tags workers as performance pay if they receive a bonus, tip, or commission at least once with the same employer.

affects their rate of human capital accumulation. Declines in these wedges, therefore, raise the returns to human capital accumulation both directly and indirectly: (i) directly by raising individuals' returns to labor supply, which is a prediction from neoclassical growth models, and (ii) indirectly by altering both their hours and effort in response to stronger incentive contracts that firms are only willing to offer in a policy regime with low labor market distortions. However, the indirect incentives to accumulate human capital are muted in fixed wage jobs where there is little link between on-the-job performance and compensation, generating a difference in skill prices between the two groups of workers. Policy, therefore, shapes the path of inequality by affecting the returns to skill accumulation for individuals not only directly through the labor supply decision, but also indirectly through the selection of contracts.

The first section of the paper begins by using data from the Panel Study of Income Dynamics (PSID, 1970-2012), National Longitudinal Survey of Youth (NLSY, 1980-2012), and restricted data from the National Compensation Survey (NCS, 2004-2016) to document several stylized facts. Performance pay workers are those who receive bonus, tip, or commission at least once with the same employer (Lemieux et al., 2009). After validating that my baseline measure of performance pay in the PSID and NLSY with the true measure of performance pay in the NCS, I document the rise of performance across industries and occupations. On average, it grew from 15% of the labor force to 50% between 1970 and 2000.[6]

Using variation in job-to-job switches, I find that performance pay workers earn 10% more than their

[6]While information technology may have complemented the rise of performance pay, it is not associated with performance pay after controlling for labor market distortions (e.g., union density). These results are also robust to changes in demographic composition.

fixed wage worker counterparts, experience a 3% greater earnings growth rate, and allocate 6% more time towards work. Using measures of formal and informal job training, I also find that they invest more in human capital accumulation. While the longitudinal variation allows me to isolate selection effects, a broad theme throughout the results is the fact that incentive effects also dominate between 30-60% of the effects depending on the outcomevariable, complementing an already burgeoning literature on the incentive effects of performance pay.[7] I also decompose earnings into permanent and transity shocks, finding that fixed wage workers tend to have greater permanent shocks, whereas performance pay workers have greater transitory shocks. These facts are consistent with companion evidence that fixed wage, relative to performance pay, workers are more likely to be laid off, which explains the mechanism behind their greater permanent shocks.[8]

Motivated by these stark differences in individual behavior between performance pay and fixed wage workers, I use the NCS to examine whether changes in performance pay are associated with changes in earnings inequality at the metro-level. To address the potential endogeneity of performance pay, I construct a new measure of local information technology (IT) intensity from O*NET as an instrument, controlling for the share of college degree workers to mitigate concerns about IT deepening inequality through SBTC (Autor et al., 1998). My results are consistent with case-study evidence from Bandiera et al. (2007) who found that the transition to performance pay widened earnings dispersion. I also provide evidence that increases in performance pay deepen SBTC since performance pay raises the productivity of college degree workers more than their non-college counterparts.

The second section of the paper develops a structural labor model in the tradition of Keane and Wolpin (1997) and Lee and Wolpin (2006) using recent innovations with two-step estimators from Arcidiacono and Miller (2011). The model contains four core features: human capital accumulation, heterogeneous preferences, discrete sector-occupation job choices, and time-varying probabilities of receiving performance pay compensation based on the sector-occupation choice. Importantly, I allow for the loss of occupation-specific human capital when individuals switch jobs, which is important for characterizing earnings dynamics.[9],[10] Individuals decide whether to work and, conditional on working, which of nine different sector-by-occupation

[7]See, for example, Paarsch and Shearer (1999), Paarsch and Shearer (2000), and Shearer (2004) for evidence from a field experiment with tree planters transitioning compensation scheme, Lazear (2000a) for evidence from a blue-collar work environment, and Lavy (2009); Muralidharan and Sundararaman (2011); Adams et al. (2009) for evidence in the education sector.

[8]See Jacobson et al. (1993) for early evidence and Jarosch (2016) for a model consistent with these facts.

[9]See, for example, Kambourov and Manovskii (2009a) and Kambourov and Manovskii (2009b) for evidence on occupation-specific human capital, and Neal (1995) industry-specific human capital. More recent contributions have emphasized that Second, Poletaev and Robinson (2008) human capital is skill-specific—tied to a limited number of basic skills—and Yamaguchi (2012) who implements a similar experiment. Mouw and Kalleberg (2010) find that occupational differences in wages helps explain increasing wage differences over the past 15 years; in particular, they argue that between-occupation changes explain 66% of the increase in inequality from 1992/1994 - 2007/2008.

[10]While the bulk of the literature has emphasized skill accumulation arising from educational attainment, my mechanism embeds insights from the psychology literature about the role of deliberate practice in accumulating new skills (Lemov et al., 2012; Duckworth et al., 2015). Schooling is only a small subset of aggregate skill. For example, Khan (2015) studies the British industrial revolution between 1750-1930 and finds that important discoveries were largely achieved by individuals exercising commonplace skills and entrepreneurial abilities. Specialized educational institutions may play a smaller role in fostering creativity and problem solving than the underlying on the job incentives for learning and skill accumulation. There are also different ways of modeling on the job learning—learning by doing versus Ben-Porath (Ben-Porath, 1967)—the specification of the production function for learning is important (Trostel, 1993). 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).

pairs of jobs to take. When an individual joins a job (a unique sector-by-occupation), he receives a probability of receiving performance pay based on the concentration of performance pay recovered from the micro-data. Following Murphy and Topel (2016), an important feature of the model is the extensive margin choice to enter sectors and occupations that provide more opportunities to accumulate human capital. After making their discrete choice, individuals decide how much to work and how hard to work. Firms hire labor services. Performance pay and fixed wage workers are imperfect substitutes and are compensated differently. The parameters are calibrated using simulated method of moments.

The third section of the paper uses the structural model to quantitatively examine the importance of wage-setting institutions and their relative contribution to aggregate inequality over the past 40 years. Whereas Lemieux et al. (2009) focused on the static effects of performance pay through an earnings decomposition, my structural model allows for dynamics—that is, the effect of performance pay on human capital, which is capitalized into wages. After illustrating that the model matches core features of the labor market, I simulate a counterfactual economy holding fixed the probability of receiving performance pay based on 1970 levels. Comparing the baseline and counterfactual economies suggests that X% of the observed rise in inequality is driven by the rise of performance pay. The results show that, while inequality subsides in first decade, inequality grows three decades after the change. Individuals with high ability grow rich, whereas those with lower ability do not invest as much in human capital, relative to the baseline. Since performance pay and fixed wage workers tend to perform different sets of tasks, these results complement emerging literature on the extended SBTC model that introduces heterogeneity in tasks and technology to explain growing job polarization (Autor et al., 2006; Autor and Dorn, 2013). The fact that performance pay workers accumulate more human capital is also related to the literature on partial insurance (Blundell et al., 2008; Heathcote et al., 2014). I subsequently examine the counterfactual effect of raising the progressivity of the U.S. marginal tax rate schedule to French levels. These results are also consistent with neoclassical macroeconomic models of taxation, which show a strong association between marginal tax rates and labor supply (Prescott, 2004; Ohanian et al., 2008; Rogerson, 2006) and structural transformation (Rogerson, 2008).[11]

This framework suggests an array of fruitful areas for further research. There has been a preponderance of new incentive mechanisms and non-wage amenities implemented across organizations. 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. 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.[12]

[11]Readers should be aware of two labor supply elasticity surveys in the literature that discuss opposite worldviews, namely Emmanuel Saez and Giertz (2012) and Keane and Rogerson (2012). See Chetty (2012) for establishing micro elasticity bounds and Chetty et al. (2011) for another survey. Aside from Imai and Keane (2004), most papers ignore the role of skill accumulation in estimating the labor supply elasticity. Including human capital identifies the elasticity from the ratio of the slope of the hours to opportunity cost of time curve, whereas traditional approaches take the slope between the hours and the wage curve. Current microeconometric literature typically notions labor supply purely in terms of hours, even though there is an important effort dimension to hours worked that would raise the elasticity much further. Importantly, individual labor supply elasticities are not a sufficient statistic for aggregate labor supply elasticities, as Emmanuel Saez and Giertz (2012) would suggest.

[12]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,

More generally, this paper provides a framework for linking labor market institutions with the human capital accumulation decisions among individuals. All of these features will undoubtedly shape the modeling of optimal taxation.[13]

2. The Empirical Content of Performance Pay

2.1. Data Sources

The ideal dataset for studying the incidence of performance pay would contain matched employee-employer records over a range of individual-level outcomes, ranging from consumption to earnings, that allows me to distinguish performance pay and fixed wage workers. Unfortunately, none of the administrative datasets meet the appropriate criteria.[14] The Panel Study of Income Dynamics (PSID) contains the required longitudinal information at the individual-level. The foundation of my empirical strategy, therefore, leverages each wave of the PSID between 1970 and 2012. Data is collected annual for each year up until 1997 when it subsequently becomes a bi-annual survey. Of course, there are limitations to labor survey data, in particular measurement error.[15],[16] The PSID offers repeated and comparable data on employment, consumption, and, importantly, performance pay status. The sample is restricted to heads of households (nearly 90% of the sample), non-retired (ages 20-65), and able-bodied individuals. Financial variables (earnings and consumption) are deflated by the 2010 consumer price index. All relevant variables (earnings, hours worked, and consumption) are winsorized by year at the first and last percentiles. The Appendix contains all remaining details on the construction of the data and several basic descriptive statistics.

The National Longitudinal Survey of Youth (NLSY) also provides useful information that is not contained in the PSID. The NLSY 1979 and 1997 cohorts are a nationally representative sample of approximately 12,600 and 9,000 youths between the ages of 12 and 16, respectively. In addition to containing detailed measures of performance pay, 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

1990; Jones, 2002) and shaping management practices among firms (Bloom et al., 2012, 2013; Bloom and Van Reenen, 2007).

[13]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)).

[14]For example, the Longitudinal Employer-Household Dynamics (LEHD) does not contain information on bonus compensation and/or performance pay. If it did, the dataset would be ideal since performance pay could be verified with the employer records.

[15]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. Importantly, they suggested that the measurement error obtained from the validation subset of workers was mean reverting—that is, it is 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.)

[16]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.

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.[17] These measurements allow me to provide reduced-form evidence on the different learning technologies between performance pay and fixed wage jobs.

While the measurements of performance pay in the PSID and NLSY are self-reported, the Bureau of Labor Statistics also administers the National Compensation Survey (NCS), a restricted-access dataset contains responses about specific jobs across establishments throughout the U.S. beginning in 1994. The NCS is unique in that it is the only source that contains detailed job-by-establishment data on not only various labor outcomes (e.g., employment and compensation), but also non-pecuniary compensation and the type of contractual arrangement across a subset of sampled jobs within each establishment. The NCS surveys employees in private establishments throughout the United States and all three-digit industries and occupations; establishments in the NCS tend to be in the sample for 20 quarters. 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. While the data is not at the individual-level, which is a necessary data requirement for inferring human capital profiles over the life-cycle, I begin to use it by validating the PSID and NLSY measures of performance pay.[18]

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

Performance pay is a multi-dimensional term used to describe various types of compensation, ranging from profit sharing to bonus payments. These compensation schemes are designed to induce employees to work hard and effectively in the presence of moral hazard problems. While much of the literature on moral hazard has focused on managerial and CEO pay (Edmans et al., 2012), performance pay for the average worker has received less attention. To facilitate a parsimonious empirical analysis of labor market dynamics between performance pay and fixed wage workers, it is vital to accurately measure these workers in the data.

My main measure for performance pay follows along the lines 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. While the PSID (and NLSY) is ideal for these purposes because of its longitudinal structure, unfortunately, self-reported job tenure contains a significant amount of measurement error. The Appendix contains a detailed explanation of my corrections on self-reported tenure and validatoin exercises from the Current Population Survey (CPS) supplements on employee tenure. Given reliable self-reported data on employment versus unemployment, my correctoin takes the maximum tenure within each job spell and iterates backwards in the periods that the individual is employed. The corrected measure of tenure is more similar to that generated in the CPS, relative to the original self-reported version.

[17]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?*

[18]Unfortunately, economists at the BLS in charge of the NCS informed me that the pre-2004 data is not available for various reasons, including comparability.

Since binary misclassification is a source of non-classical measurement error (Aigner, 1973; Bollinger, 1996), it is important to question the accuracy of the constructed performance pay indicator. To my knowledge, this has not been implemented before. However, using restricted access data form the Bureau of Labor Statistic's National Compensation Survey (NCS) between 2004 and 2014, I can compare the incidence of performance pay between the two datasets to validate the measure in the PSID. The first row in Figure 2 plots the share of performance pay workers by approximate two-digit industry and occupation. In the vast majority of cases, the two shares are very similar. In the cases where there exists a gap between the two—for example, leisure and hospitality (by industry) and community, social, and legal (by occupation)—the difference appears to be driven by a small sample size in the PSID.

The second row in Figure 2 plots the share of variable compensation, consisting primarily of bonus income, relative to total labor income by industry and occupation. While there are several instances where the NCS and PSID align relatively closely, on average the PSID systematically underestimate individuals' bonus compensation. For example, whereas the PSID reports that individuals in management and business operations earn about 2% of their total labor income from bonuses, the NCS reports that it is nearly 5%. In this sense, an important theme to keep in mind throughout this paper is that, while the PSID is the best longitudinal data available for the objective, it also will tend to underestimate the underlying phenomena.

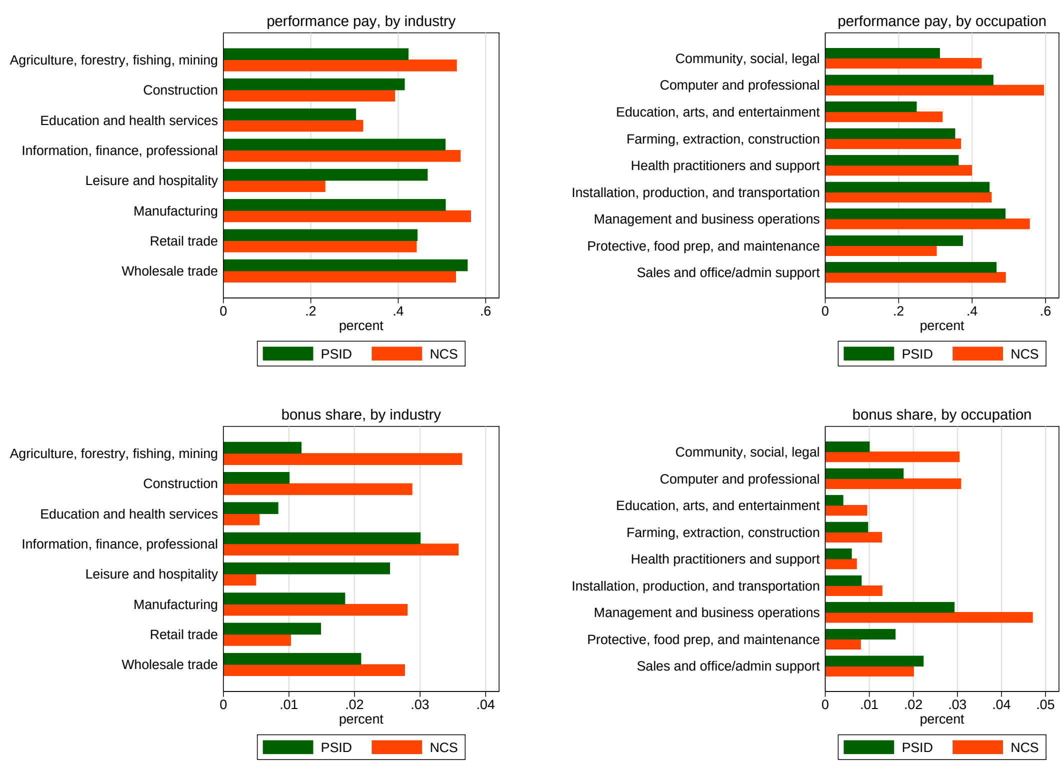

Figure 2: Validating Performance Pay with the National Compensation Survey, 2002-2014

Notes.–Source: Panel Study of Income Dynamics (PSID) and National Compensation Survey (NCS). The figure plots the share of full-time workers in the PSID and the NCS at two-digit industry and occupation level. The PSID share is a weighted average using the PSID sample weights.

Having documented these cross-sectional features about the incidence of performance pay, I now turn towards measuring its evolution over time and validating it with the NCS. Figure 3 plots the total fraction of performance pay workers in the labor force between 1970 and 2012 and a subset consisting of only non-hourly and non-union performance pay workers with the NCS measure of performance pay. The key observation is that performance pay increased dramatically over the past 40 years—moving from approximately 10% of the labor force to nearly half by the 2000s. While the NCS measure of performance pay is only available starting in 1994—although the micro-data from the survey apparently is not accessible until 2004—the correlation between my measure and the true NCS measure is 0.61. The levels are also quite similar, although it appears that the PSID is underestimating the incidence by 2-10% with the 10% wedge occurring in 2004 and the 2% wedge occurring in 2012. Interestingly, the fraction of income arising from performance compensation has a -0.75 correlation with the share of performance pay, which is consistent with companion work on the countercyclicality of performance pay jobs and procyclicality of performance pay compensation (Gittleman and Makridis, 2015; Champagne and Makridis, 2016).[19]

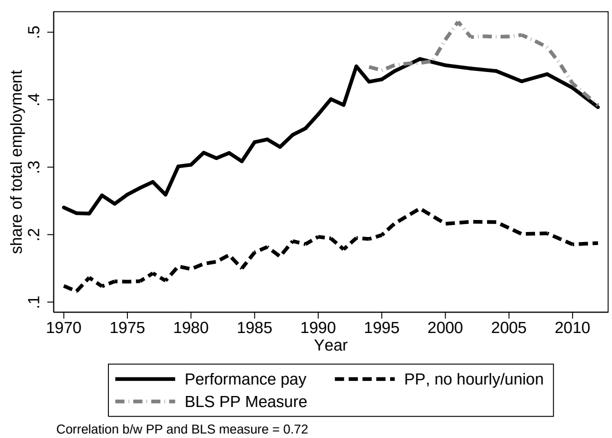

Figure 3: The Evolution of Performance Pay, 1970-2012
Notes.–Source: Panel Study of Income Dynamics (PSID). The figure plots the share of performance pay workers by industry and occupation. Discussed in Section 2.2., performance pay workers are those who receive bonus, tip, or commission at least once with the same employer. Observations are weighted by the PSID sample weights.

Are these trends in performance pay driven by changes in composition? For example, since the share of manufacturing is declining, which tends to be thought of as an industry with more performance pay (although Figure 2 shows it has a share of 55%), it is possible that the rise of performance pay is purely a story about structural transformation or outsourcing. Figure 4 examines this possibility in greater detail by partitioning the evolution of performance pay by four main industry and occupation categories over the past 40 years. Although performance pay is clearly rising more in some industries and occupations over others, it is increasing in each and every one of them.

[19]While the PSID contains a measure of time spent in overtime work starting in 1984, which can be used with information on the wage rate for overtime hours, there is no way to separate between income from true performance pay compensation and overtime pay pre-1984. Moreover, the PSID only began distinguishing between true performance pay income (bonus, tip, commission) from overtime starting in 1992.

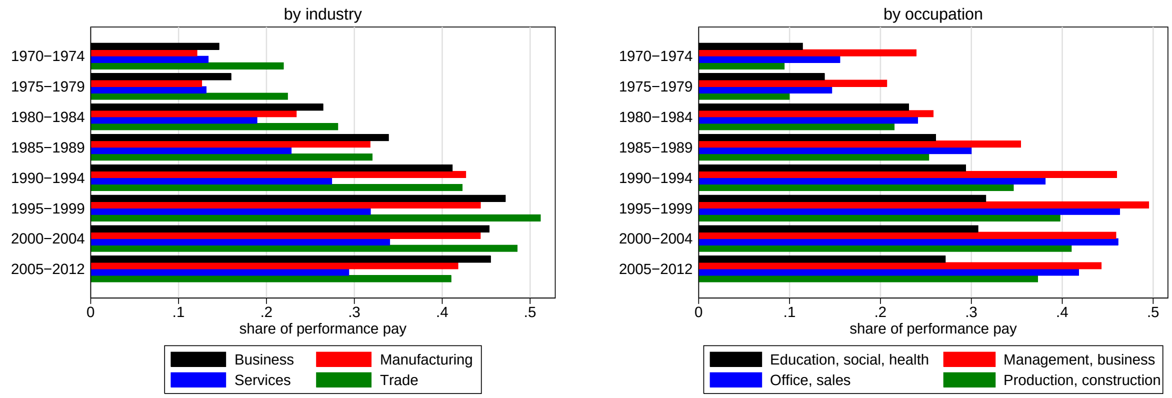

Figure 4: Performance Pay by Industry and Occupation, 1970-2012

Notes.–Source: Panel Study of Income Dynamics (PSID). The figure plots the share of performance pay workers by industry and occupation. Discussed in Section 2.2., 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) education, health and social assistance, leisure and hospitality, food preparation, and other services. Military and public administration 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) education, health practitioners and 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.

2.3. Differences in Earnings and the Time Allocation

Figure 5 compares the difference in logged earnings between performance pay and fixed wage workers ("the performance pay premium") under two classifications: overall performance pay and those performance pay workers who are in neither union contracts nor paid by the hour. These two measures are paired against the college premium over the 1970 and 2012 era. There are two important observations. The first observation is that performance pay workers earn much more than their fixed wage counterparts on average (about 20-30% more). While it oscillates over the past 40 years, it has generally risen about 10 percentage points if the endpoints (1970 and 2012) are directly compared. The second observation is that there is a striking divergence in earnings premia between two types of performance pay workers—those who are in unions or paid by the hour and those who are not. In fact, it is even greater than the college premium ever between 2000 and 2012! Nonetheless, even after omitting those with college degrees, the performance premium for non-college workers rises from approximately 10% to 15% over the 1970 to 2012 era.

Are these earnings differences driven by selection of more productive workers into performance pay jobs? While there is a large literature on the incentive effects of performance pay already (e.g., in manual labor jobs (Paarsch and Shearer, 1999, 2000; Shearer, 2004; Bandiera et al., 2007), blue-collar jobs (Lazear, 2000a), and education (Lavy, 2009), there is not yet much systematic evidence about the premia more generally. I regress logged earnings, hours worked, and home production on performance pay, controlling for various individual covariates. To address the endogeneity arising from selection into performance pay jobs, I consider three empirical specifications: without fixed effects, fixed effects on occupation and year, and fixed effects on person and year. The latter specifications exploit variation emerging from job-to-job changes, which control for the person-specific component of earnings that is potentially correlated with selection into these jobs.

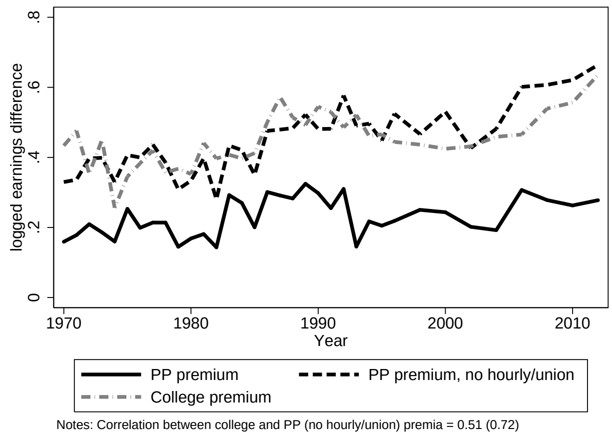

Figure 5: Performance Pay and College Earnings Premia

Notes.–Sources: Panel Study of Income Dynamics. The figure plots the earnings ratio between (i) performance pay and fixed wage workers, (ii) non-hourly / non-union performance pay and fixed wage workers, and (iii) college and non-college workers. The sample is restricted to full-time workers (at least 500 hours/year) between the ages of 20-65. Sample weights are used to produce the annual averages. See Section **??** for the definition of performance pay.

Table 1 documents these results under three definitions of performance pay status: the baseline (bonus, tip, or commission at least once in the same job, see Lemieux et al. (2009)), an alternate definition (received bonus, tip, or commission at least twice in the same job), and performance pay status among non-union and non-hourly workers. The conditional correlations suggest that performance pay workers earn about 16% more than their fixed wage worker counterparts with only the observable controls, which is about half as much as the return on college. Once occupation fixed effects are included, the gap between the college and performance pay premia narrows considerably. These estimates are fairly stable with the alternative definition, but the premium rises considerably when the definition narrows to non-hourly and non-union workers, who tend to be higher skilled. Turning towards hours worked, performance pay workers allocate approximately 5% more time in their jobs, which is more than the coefficient associated with college attainment. Performance pay workers also tend to spend less time in home production, although these estimates are noisy and suffer from attenuation bias because of the measurement error. These coefficients are lower in magnitude than those in my companion paper using the American Time Use Survey (Makridis, 2016b).

The Appendix also considers several additional issues. The first issue is whether binary misclassification is an important source of potential bias in these results. The Appendix documents similar results for earnings and hours worked using a combination of the NLSY between ages 20-35 and the Survey of Consumer Finances (SCF). While the SCF documents an earnings premium that is approximately twice the size in magnitude, making the above estimates in Table **??** conservative. However, while the SCF has the advantage of directly measuring performance pay through a question about whether the job contains bonus and stock options as part of the compensation, the survey contains a wealthier sample of the population and is purely cross-sectional, making the estimates upwards biased.

The second issue is the presence of heterogeneity; see, for example, Heywood and Parent (2012), for evidence on performance pay and the black-white wage gap. While the PSID sample of females is not necessarily representative, the correlation between the performance pay earnings premia for males and females

Table 1: Salary and Hours Differences between Performance Pay and Fixed Wage Workers

	PP=At least1x			PP=At least 2x			PP=No Hourly/Union		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln(Earnings)									
Performance Pay	0.16***	0.13***	0.13***	0.20***	0.17***	0.19***	0.27***	0.19***	0.13***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]
College	0.42***	0.22***	0.14***	0.42***	0.22***	0.14***	0.38***	0.21***	0.14***
	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.02]
R-squared	0.35	0.47	0.78	0.35	0.47	0.78	0.36	0.47	0.78
Sample Size	64116	64116	64116	64116	64116	64116	64116	64116	64116
Ln(Hours Worked)									
Performance Pay	0.06***	0.05***	0.05***	0.07***	0.05***	0.07***	0.09***	0.06***	0.05***
	[0.00]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]
College	0.03***	0.01*	0.04***	0.03***	0.01*	0.04***	0.02***	0.01	0.04***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]
R-squared	0.08	0.14	0.49	0.07	0.14	0.49	0.08	0.14	0.49
Sample Size	64116	64116	64116	64116	64116	64116	64116	64116	64116
Ln(Home Production)									
Performance Pay	-0.02	-0.01	-0.02	0.07***	-0.02	-0.03	0.09***	-0.04	-0.06**
	[0.02]	[0.02]	[0.02]	[0.01]	[0.03]	[0.04]	[0.00]	[0.03]	[0.03]
College	0.04	0.02	0.07	0.03***	0.02	0.07	0.02***	0.03	0.07
	[0.03]	[0.03]	[0.05]	[0.00]	[0.03]	[0.05]	[0.00]	[0.03]	[0.05]
R-squared	0.05	0.09	0.51	0.07	0.09	0.51	0.08	0.09	0.51
Sample Size	60884	60884	60884	64116	60884	60884	64116	60884	60884
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Occupation FE	No	Yes	No	No	Yes	No	No	Yes	No
Person FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes.–Sources: PSID. The table shows the coefficients associated with regressions of log salary and log hours worked on an indicator for performance pay under three definitions and controls. The preferred definition is whether a worker received performance pay at least once within the same job; the second changes the frequency requirement to at least two times; the third excludes hourly and union workers from the definition in columns 1-3. Controls include five measures of occupational skill content (nonroutine cognitive, routine cognitive, nonroutine manual, routine manual, and interpersonal), a quadratic in educational attainment, tenure, experience age, and fixed effects on race, gender, industry, as well as family size, marital status, union status, and the number of children in the family. Standard errors are clustered at the person-level.

is 0.41. However, an important difference is that the premia is very high (approximately 80%) for females in 1970, but declines to 60% by 2012. Since the labor force consisted of a smaller share of women in 1970, there was a much larger premium because supply was more scarce. 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).

The third issue is whether there are any meaningful differences in consumption between performance pay and fixed wage workers. Using the PSID measures of non-durables consumption from 1999 onwards, I find these differences are small. Conditioning on standard observables, performance pay workers consume approximately 4% more (p-value = 0.001). However, once person fixed effects are introduced, the magnitude declines to 2.8% (p-value = 0.137). While it is likely that the noisy estimate is due to a lack of variation in the latter part of the sample (since it is bi-annual from 1999 onwards), the low magnitude is noteworthy since large differences in consumption could prompt concerns about welfare.

While the preceeding results show that performance pay workers earn, work, and learn more than their fixed wage counterparts, they potentially expose themselves to much more risk since a component of their pay is more sensitive to business cycle fluctuations. Motivated by the presence of partial insurance in Blundell et al. (2008), Heathcote et al. (2014) showed that elastic labor supply and preference heterogeneity are essential for accounting for the co-movement between hours worked and consumption. Both of these features are conspicuously present in the selection into performance pay jobs and the incentive effects of performance pay (conditional on being in a job). While the Appendix documents the variance of residual logged earnings between both sets of workers (Juhn et al., 1993)—showing that, surprisingly, performance pay workers have a lower variance—this test is potentially misleading due to the presence of composition effects (Lemieux, 2006) and changes in the magnitude of permanent shocks (Lochner and Shin, 2014).

To address these shortcomings, I now decompose earnings shocks into permanent and transitory components. Following the methodology that is now standard in the literature on earnings decompositions (Heathcote et al., 2010; Meghir and Pistaferri, 2004; Blundell et al., 2008), suppose log earnings, denoted w, contains both a permanent component, P, and a transitory component, v, such that $w_{it} = P_{it} + v_{it}$ where P follows a martingale of the form

$$P_{it} = P_{i,t-1} + \zeta_{it}$$

where ζ_{it} is serially uncorrelated, and the transitory component follows an $MA(q)$ process

$$v_{it} = \sum_{m=0}^{q} \theta_m \varsigma_{i,t-m}$$

with $\theta_0 \equiv 1$ and q will be determined by the data.[20],[21] Figure 6 shows that, while performance pay workers tend to have greater transitory shocks, they have lower permanent shocks, which are the larger of the two types of shocks. This is important since it highlights the fact that performance pay workers tend to sort into jobs that are generally riskier in the short-run, but less risky in the long-run since they accumulate much more human capital. Motivated by Low et al. (2010) who distinguished between productivity and employment risk, the Appendix provides some descriptive evidence that lower permanent income shocks among performance pay workers is driven by greater labor market mobility due to more transferable and versatile human capital. This evidence is consistent with Forstner (2013) who finds that nearly half of the observed increase in residual wage inequality between the mid-1980s to mid-2000s can be explained by changes in job-to-job transitions and mobility.

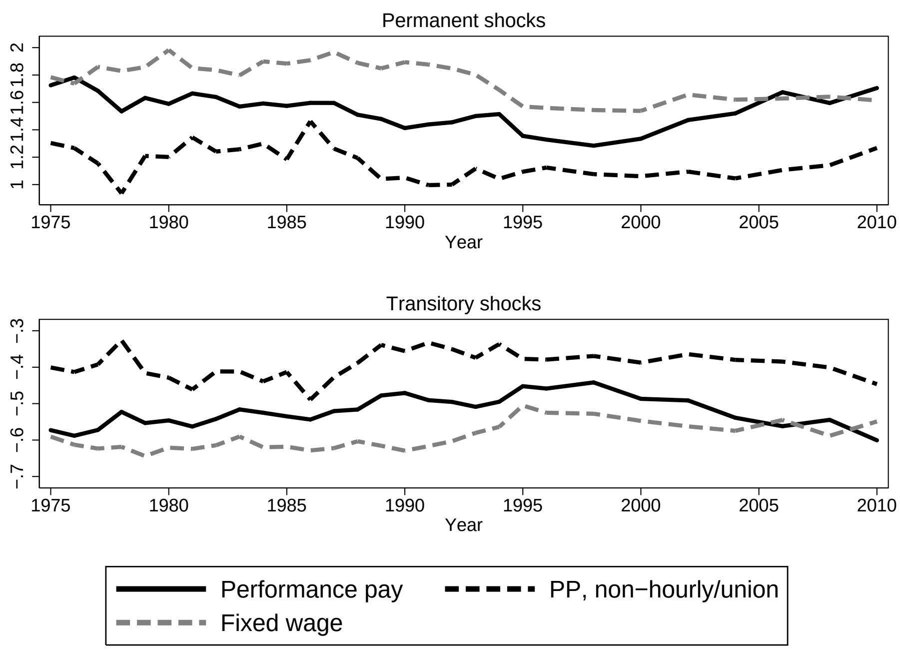

Figure 6: Transitory and Permanent Shocks, Pay for Performance and Fixed Wage

Notes.–Source: PSID. The Figure plots permanent and transitory income shocks for performance pay and fixed wage full time employees between 1968-2010. These shocks are obtained by running a regression of the change in log earnings on controls and person fixed effects. Controls include: educational attainment, experience, age, and inclusive of dummies on one-digit industry, occupational task and skill content, race, marital status, and gender. Using residualized earnings, denoted y, the permanent shocks, ζ, are computed as follows:$Var(\zeta_t) = Cov(\Delta y_t, \Delta y_{t-1} + \Delta y_t + \Delta y_{t+1})$. The transitory shocks, v, are computed as follows: $Var(v_t) = -Cov(\Delta y_t, \Delta y_{t+1})$.

The Appendix contains a number of robustness exercises. First, following Blundell et al. (2008), I use additional moments on consumption in order to separately identify permanent and transitory shocks

[20]While Guvenen (2007) provides evidence of a heterogeneous, rather than restricted, income profile—meaning that individuals are subject large and persistent shocks while facing the same life-cycle income profiles, recent evidence by Hryshko (2012) illustrates that the estimated growth-rate heterogeneity is decreasing in the time dimension of the sample data (e.g., PSID). Because the HIP theory requires that the distribution of the growth-rate heterogeneity should be equal for a fixed cross section of individuals, regardless of time, this pattern suggests is consistent with the RIP theory. As he articulates, the policy ramifications of properly specifying the income process are large; under HIP, the government should *subsidize* human capital investments among the disadvantaged to protection against shocks of moderate persistence, whereas, under RIP, the government should *educate* households about risk-sharing instruments and human capital investments.

[21]Since within-group estimators for dynamic panel data are biased for samples with small T (Nickell, 1981), only workers with 9 or more observations in the PSID are considered as in Meghir and Pistaferri (2004).

without requiring as stringent assumptions about their correlation. These additional data are important for identifying the insurance coefficients. Nonetheless, it is important to keep in mind that these decompositions require a number of assumptions, including: attrition in the sample and measurement error.[22],[23]

2.4. Differences in Human Capital Investments

Although the prior section illustrated that performance pay workers allocate more time towards the market, even after controlling for selection effects, the technology of human capital accumulate while at work is an open question. According to a survey of 2076 employees in the UK conducted by the National Institute of Adult Continuing Education, 82% of the respondents said that doing their job on a regular basis is very or quite helpful in helping them become better at their job. The next highest category (with 62% attesting to it) was learning by showing others how to do certain activities or tasks. Only 54% of the sample said that training courses paid by the employer or themselves were very or quite helpful. While these are anecdotal examples, they motivate a focus on the determinants of on-the-job learning.[24]

Using a combination of training, education, and skill intensities from O*NET, I can provide motivating evidence over several stark differences. Skill categories are compiled by aggregating a subset of specific skills. For example, "technical skills" are those involving programming, quality control analysis, systems analysis, systems evaluation, and technology design, whereas "cognitive skills" are those involving decision making, learning strategies, listening, learning, problem solving, coordination, and critical thinking. Training, education, and skill intensities are subsequently standardized to mean zero and a standard deviation of one.

As a first-pass, I classify three-digit occupations as performance pay or fixed wage based whether the share of workers with performance pay is over 50% (using the NCS micro-data). Figure 7 plots the corresponding distribubution of z-scores across three-digit occupations. There is an overwhelming difference in the concentration of cognitive and technical skills in performance pay jobs, as well as higher average amount of on-the-job-training and required education. 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.

However, in addition to selection effects, O*NET's measure of on-the-job training in Figure 7 omits informal sources of training, such as collaboration and mentoring by supervisors and/or coworkers. For example, in companion work Makridis (2016a), I show that workers in performance pay jobs tend to report higher degrees of managerial and organizational practices. Fortunately, however, the NLSY-79 provides

[22]As Meghir and Pistaferri (2004) point out, the decomposition requires that attrition is not induced by the time varying shocks of interest. Both Lillard and Panis (1998) and Fitzgerald et al. (1998) find that, although there is a lot of attrition, the biases are insignificant and mild. Selection seems to be moderated by regression to the mean effects based on selection arising from transitory shocks that fade over time.

[23]Although the PSID changed its reporting procedures in the early 1990s, which coincides with some of the changes in volatility, my results suggest that the variance of shocks for PPJ workers is strictly lower than those for FWJ workers over all periods. Gouskova et al. (2010) provide a quantitative comparison between the PSID and CPS, suggesting that they exhibit similar time trends and that procedural changes had little effects on these trends. Bound et al. (1994) find that 22% of the variance in earnings growth in the PSID is measurement error.

[24]Thank you to Clive Shepherd for pointing it out to me. http://clive-shepherd.blogspot.com/2007/06/so-how-do-employees-learn-to-do-their.html

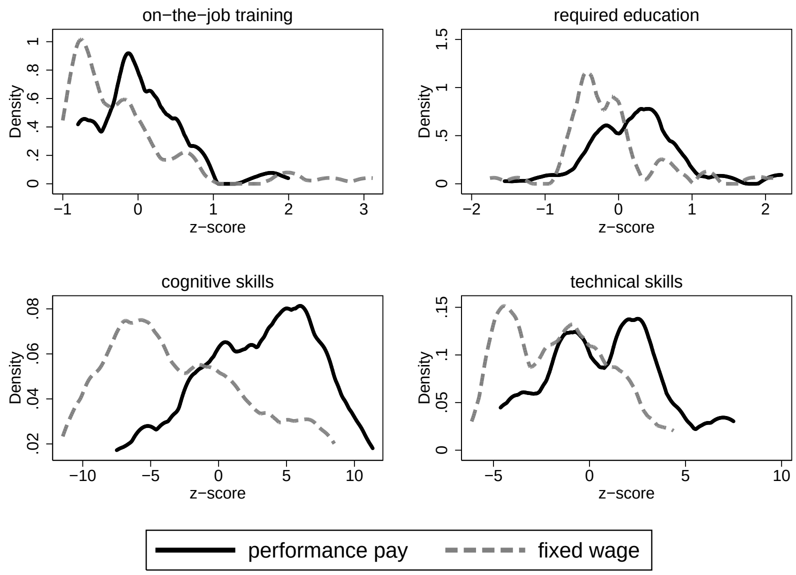

Figure 7: Training, Education, and Skills in Performance Pay and Fixed Wage Jobs
Notes.–Source: O*NET, the Occupation Employment Statistics tables, and the National Compensation Survey. Three-digit occupations are classified into performance pay and fixed wage based on whether at least 50% of the jobs have performance pay (from the NCS). The skill groups are as follows: (1) cognitive skills (decision making, learning strategies, listening, learning, problem solving, coordination, and critical thinking), (2) manual (repairs, equipment maintenance, equipment selection, installation, instruction), (3) technical (programming, quality control analysis, systems analysis, systems evaluation, technology design), (4) social (persuasion, social, speaking, negotiation), (5) service (management of financial resources, of material resources, of personnel resources, monitoring, service, operations control, operations monitoring, operations analysis, troubleshooting), and (5) general (math, writing, time management, reading, science). The ONET skill data is available from 2010-2014 and is made to have a mean zero and variance of 1. All occupations are harmonized to the 2010 SOC codes.

measures of informal training starting in 1994. I can regress the intensity of informal training on an indicator for performance pay status, individual covariates, and person fixed effects, separately by major two-digit occupation. These regressions exploit variation in training intensity for the same person in different jobs, allowing for heterogeneity in the relationship by occupation. Figure 8 documents these results.

[TBD]

Figure 8: Informal Training and Performance Pay, by Occupation
Notes.–Source: NLSY.

3. Performance Pay and Inequality

3.1. Data and Measurement

Shares of performance pay.–Summarizing from earlier, the National Compensation Survey (NCS, 2004-2016) provides direct measurements of performance pay. Here, rather than using the three-digit industry and occupation aggregations, I focus on more narrow metropolitan measures of performance pay. Since the unit of observations is a job within a given establishment, the data allows me to avoid potential binary misclassification in the designation of a job as performance pay.

Inequality ratios.–The Census Bureau's American Community Survey (ACS, 2005-2016), accessed through

SocialExplorer, provides the most comprehensive data on individual earnings. For each metropolitan area, I obtain its Gini coefficient, together with an array of other demographic measurements, including: age bracket bins, educational attainment bins, and the shares of males and married families. The inclusion of these demographic characteristics, in particular the share of college degree workers, will allow me to control for composition effects across metro areas.

Local information technology (IT) intensity.–O*NET provides comprehensive measurements of skills, tasks, and the work environment at a detailed six-digit occupation level. These measurements generally focus on the intensity and utilization of the skill, task, or work environment feature and are updated almost every other year. To construct a measure of IT intensity, I select ten measurements of information technology listed within the O*NET database based on a qualitative read of their survey questionnaires, including the following skill sets: "Operations Analysis", "Technology_Design", "Programming", "Quality_Control_Analysis", "Troubleshooting", "Systems Evaluation", "Computers and Electronics", "Updating and Using Relevant Knowledge", "Interacting with Computers", "Electronic_Mail".[25] These task intensities are all rated with an index, aggregated into a single IT index, and standardized with a mean of zero and standard deviation of one. Using the BLS Occupation Employment Statistics (OES) tables, I recover the employment for each occupation-by-metro-by-year, denoted $E_{o,m,t}$, and metro-by-year, denoted $E_{m,t}$, allowing me to produce a local information technology (LIT) index

$$LIT_{m,t} = \sum_{o} \left(\frac{E_{o,m,t}}{E_{m,t}} \right) IT_{o,t} \tag{1}$$

3.2. Empirical Strategy

Unfortunately, earlier results with the PSID and NLSY were plagued by a combination of potential binary misclassification (which cannot be solved using person fixed effects), a small sample size, and potential endogeneity. This section addresses these limitations using the restricted NCS data. The baseline empirical specification is given by

$$INEQ_{m,t} = \beta f(X_{m,t}) + \gamma PP_{m,t} + \phi_m + \lambda_t + \epsilon_{mt} \tag{2}$$

where $INEQ$ denotes the Gini coefficient, X denotes a vector of demographic controls, PP denotes the share of performance pay, and ϕ and λ denote metro and year fixed effects. There are, however, potential issues with the estimation of Equation 2. 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 fact that increases in inequality raise the returns to performance pay (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.

While the inclusion of demographic controls helps in part to reduce the reverse causality inherent in Equation 2, I also instrument for performance pay using the constructed local IT index in Equation 1.

[25] http://www.onetcenter.org/questionnaires.html

Figure 9 illustrates that there is a strong first-stage relationship between the two, consistent with the fact that IT helps firms better monitor workers, which is an essential ingredient in the provision of performance pay (Prendergast, 2002).

[TBD]

Figure 9: First-stage Results of Performance Pay and Local Information Technology Intensity

3.3. Results

3.4. 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

$$INEQ_{o,t} = \beta f(X_{o,t}) + \gamma PP_{o,t} + \pi 1[\Delta C_{o,t} > \overline{C}_t] + \delta(PP_{o,t} \times 1[\Delta C_{o,t} > \overline{C}_t]) + \epsilon_{o,t} \tag{3}$$

where $INEQ$ is the logged 90-10 earnings difference, X is a set of demographic controls, PP denotes the share of performance pay workers, $1[\Delta C > \overline{C}]$ denotes an indicator for whether the change in the share of college degree workers in an occupation o is above a specified constant ($\overline{C} = 0$) growth rate in period t.[26] Figure 10 plots the estimates of δ in Equation 3 separately for each decade between 1970 and 2010.

[TBD]

Figure 10: The Rise of Performance Pay and Skill-biased Technical Change

4. Quantitative Framework

This section develops a quantitative model for explaining the aforementioned empirical regularities and quantitatively assessing the relative significance of changes in wage-setting institutions as a determinant of inequality and candidate policy solution for existing inequality. The modeling decisions strike a balance between the inherent complexity of incorporating moral hazard into a general equilibrium setting with the importance of including it as an economic mechanism by maintaining other assumptions that are standard in many structural labor models, namely free mobility among sectors and competitive factor markets.

[26] 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.

4.1. Environment

4.1.1. Preferences

Individuals enter the model at the working age 25 and decide every year (until age 65 upon retirement) among mutually exclusive career options, denoted j for either unemployment or one of nine industry-occupation unique combinations, respectively, to maximize their lifetime utility subject to a budget constraint and technology of skill production. The inclusion of different industry-occupation pairs explicitly incorporates the presence of unobserved group-specific heterogeneity as in Heckman and Sedlacek (1985). Conditional on the individual's discrete choice, d, over a sector-occupation pair j, individuals have preferences over their after-tax income, W, and their labor supply (hours worked), n, given by

$$u(W_{it}, l_{it}) = \frac{W_{it}^{1-\iota}}{1-\iota} - \chi_m \frac{n_{it}^{1+\psi_j}}{1+\psi_j} \tag{4}$$

where ι is the intertemporal elasticity of substitution, χ_m denotes the disutility of labor supply for type-m worker and ψ_j denotes the labor supply elasticity for type-j job. Letting w denote logged earnings, $1[PP]$ an indicator for performance pay status, n denote logged hours worked, e denote logged years of labor market experience, TR a government-based transfer (e.g., unemployment insurance), $1[o]$ an indicator for an occupational switch, the earnings process can be represented as follows

$$w_{it} = \alpha 1[PP_{it}] + \gamma_1 n_{it} + \gamma_2 (1[PP_{it}] \times n_{it}) + \delta_1 e_{it} + \delta_2 (1[PP_{it}] \times e_{it}) + \nu TR_{it} + \xi 1[o_{it}] + \mu_k + u_{it} \tag{5}$$

where $u \sim \mathcal{N}(0, \sigma^2)$ is the idiosyncratic shock. When the individual is unemployed, his labor income is zero and only receives governmental transfers (unemployment benefits) that have a replacement rate equal to about 45% (i.e., 45% of past labor income).[27] The fact that individuals working in performance pay jobs learn more tends to underestimate the performance pay versus fixed wage earnings differential. Dating back to at least Rosen (1972), markets for learning imply that individuals are willing to accept lower wages in exchange for greater human capital accumulation since investment in skill is capitalized in future earnings.[28]

Ever since Keane and Wolpin (1997), the importance of unobserved heterogeneity in wages has been a central feature in structural labor models. The first, and most obvious, form of heterogeneity in this model is the fact that each job, j, is a unique combination of an industry—consisting of (i) general services, (ii) information, finance / real estate, and business, (iii) manufacturing, wholesale and retail trade—and an occupation—consisting of (i) management, professional, and specialty / support workers, (ii) general service workers, and (iii) production workers. Each industry-occupation pair has its own unique wage-setting practices, which manifest themselves in heterogeneous labor supply elasticities, ψ_j. The second, and

[27] The Department of Labor estimates this replacement rate on average: http://workforcesecurity.doleta.gov/unemploy/ui_replacement_rates.asp.

[28] See Burdett et al. (2011) with both equilibrium search and learning by doing. They argue that, while younger workers are willing to accept lower wages to accumulate greater skill, wages increase at a decreasing rate because it becomes harder to search for higher paying jobs as an individual ages.

more novel, form of heterogeneity arises through the distinction of performance pay and fixed wage workers. Within each sector-occupation pair, there exist both performance pay and fixed wage workers. When an individual enters a sector-occupation, they have a probability p^j of receiving a performance pay contract and a probability $1 - p^j$ of receiving fixed wage contract, capturing the reality that individuals do not explicitly choose whether to join a performance pay job, but indirectly influence their odds by sorting into a particular sector and occupation. The third, and more standard, form of heterogeneity enters through unobserved type-m specific disutilities of labor supply, χ_m, and learning curvatures, γ_m.

Three remarks are in order. First, the absence of a savings decision for households requires that labor supply affects capital only through changes in the aggregate labor supply, rather than through the distribution of skills. In other words, the assumption restricts changes in household assets affecting firms' capital holdings in ways independent of labor supply. To the extent that there are complementarities between physical and human capital (Krusell et al., 2000), my results will be strengthened; a discussion is included later.[29] Second, while human capital in this model is general, and human capital consists of both general and firm-specific human capital in reality, the assumption here is that general human capital can be separately identified from firm-specific human capital when calibrating the model parameters (e.g., γ). [30] Third, the production function for human capital embeds learning-by-doing (Imai and Keane, 2004; Shaw, 1989; Wallenius, 2011), which contrasts with other representations (e.g., under Ben-Porath where investments in skill trade off with labor supply (Bils and Klenow, 2000). Evidence from psychology largely concludes that deliberate practice (concentrated effort) is a crucial determinant, if not the largest, of human capital accumulation (see Ericsson et al. (2006) for a comprehensive survey).[31],[32]

4.2. Equilibrium and Computation

4.2.1. The Value Function

Let $\Omega_{it} = (e_{it}, h_{it})$ denote the set of state variables (experience and human capital) and $O_{it} = (D_{it}, w_{it}, l_{it})$ denote the set of observed choices (industry-occupation decision, wages, and hours worked). The economy consists of overlapping generations of individuals between the ages of 25-65. In every period t, an individual i solves the following dynamic programming problem

$$V(\Omega_{it}) = \max_{d_{it}^j=1} \left\{ V^j(\Omega_{it}) \right\} \tag{6}$$

where the conditional choice probabilities are given by

[29] Other seminal studies of the labor market also omit savings, e.g., Lee and Wolpin (2006).

[30] Using panel data Loewenstein and Spletzer (1999), find that most of the contributions of on-the-job training to human capital is general. Of course, as they recognize, this does not necessarily make it general human capital, but rather that most employers reward similar types of skills (e.g., team work, leadership, problem solving, etc).

[31] Lazear (2001) provides the inspiration for such a production function, which he uses in the context of educational production. In his context, the analog to effort represents the fraction of time students are behaving in a classroom and he uses the functional form to characterize congestion externalities arising from greater student class sizes.

[32] There is also strong empirical support for the inclusion of effort. Baker et al. (1994) remark (p. 947) that "since observable characteristics seem able to explain only a portion of the serial correlation, the correlation must in large part be due to characteristics that are unobservable at least to us."

$$V^j(\Omega_{it}) = u^j(\Omega_{it}, d_{it}^j) + \varepsilon_{it}^j + \beta\mathbb{E}\left[V(\Omega_{i,t+1})|\Omega_{it}, d_{it}^j = 1\right] dF(h_{i,t+1}|h_{it}) \tag{7}$$

where ε denotes the idiosyncratic job-specific error that follows a Type I extreme value distribution and $F(\cdot|h_{it})$ denotes the law of motion for human capital.[33] The distribution of the error implies that the $\mathbb{E}$max expression from Equation 7 takes the form

$$\mathbb{E}\left[V(\Omega_{i,t+1})|\Omega_{it}, d_{it}^j = 1\right] \equiv \mathbb{E}\left[\max_{j'} V^{j'}(\Omega_{i,t+1}, \varepsilon_{i,t+1})|\Omega_{it}, \varepsilon_{it}, d_{it}^j = 1\right] = \Gamma + \mathbb{E}\left[\ln\left(\sum_{j'} \exp(V^{j'}(\Omega_{i,t+1})\right)|\Omega_{it}, d_{it}^j = 1\right] \tag{8}$$

where Γ is Euler's constant and $V^{j'}(\Omega)$ is the expectation of the alternative j' specific value function given the observed state, Ω, and the current alternative, j. The conditional probability of choosing choice j is given by

$$P(d_{it}^j = 1|\Omega_{it}) = \frac{\exp\left(u^j(\Omega_{it}, d_{it}^j) + \varepsilon_{it}^j + \beta\mathbb{E}\left[V(\Omega_{i,t+1})|\Omega_{it}, d_{it}^j = 1\right]\right)}{\sum_{j'} \exp\left(u^j(\Omega_{it}, d_{it}^j) + \varepsilon_{it}^j + \beta\mathbb{E}\left[V(\Omega_{i,t+1})|\Omega_{it}, d_{it}^j = 1\right]\right)} \tag{9}$$

4.2.2. Dealing with Initial Conditions

The presence of unobserved state variables—in particular, the data lacks complete histories of employment and experience at every point in time for the surveyed individuals—poses an identification problem. Identification would require integrating out all the possible unobserved elements in the state space (Heckman, 1981), which poses computational problems. However, Keane and Wolpin (2001) developed a method that uses the unconditional simulation by introducing (normally distributed and independent) measurement error into the binary and continuous variables.

Letting $P(O^i|\tilde{O}^n)$ denote the probability of observing an outcome history O^i generated by a simulated history $\tilde{O}^n$, then $P(O^i|\tilde{O}^n)$ can be written as the product of classification rates when looking at discrete outcomes and as measurement error densities for continuous variable outcomes. Since $P(O^i|\tilde{O}^n)$ depends only on the outcomes, Keane and Wolpin (2001) bypass the initial conditions problem. Let $\hat{P}_N(O^i) = N^{-1}\sum_{n=1}^{N} P(O^i|\tilde{O}_k^n)\pi_k/\pi_{k0}$ denote the unbiased simulator of outcome histories, where π_{k0} and π_k denote the frequency of type k individual based on the simulation of the model. To guarantee that $\hat{P}_N(O^i)$ is smooth, importance weights can be applied—that is, by holding fixed the simulated outcome histories and reweighting them under different parameter iterations.

[33] Iskhakov et al. (2015) show that introducing "taste shocks" helps smooth the value function by behaving as a homotopy device around the kinks. Iskhakov et al. (2015) found that even when these "shocks" create model mis-specification, they still improve the accuracy of the model as evaluated by the root mean square error of the parameter estimates implied by the numerical approximation.

4.2.3. Accelerating Computation with a Two-step Estimator

If there were no unobserved heterogeneity, Equation 9 could be used to directly compute the likelihood pooling individuals and time periods. However, computing the value function for each iteration is costly. To accelerate computation, the insight from Hotz and Miller (1993) and Arcidiacono and Jones (2003) was that the term inside $\ln(\cdot)$ from Equation 8 is a function of current utility and future conditional choice probabilities such that

$$\ln(\xi^j(\Omega_{i,t+1})) = V^j(\Omega_{i,t+1}) - \ln\left(\sum_j \exp(V^j(\Omega_{i,t+1}))\right) \tag{10}$$

where $\ln(\xi^j(\Omega_{i,t+1}))$ comes from taking the log of both sides in $\xi^j(\Omega_{i,t+1}) = P(d^j_{i,t+1} = 1|\Omega_{i,t+1}) = \exp(V^j(\Omega_{i,t+1}))/\sum_j \exp(V^j(\Omega_{i,t+1}))$. Since $\xi^j(\Omega_{i,t+1})$ can be computed directly from the data by taking the proportion of individuals in state Ω who make choice j. Using the simplification from Equation 10, re-write Equation 8 as

$$\mathbb{E}\left[V(\Omega_{i,t+1})|\Omega_{it}, d^j_{it} = 1\right] = \Gamma + \sum P(h_{it} = h|\Omega_{it}, d^j_{it} = 1)\left(V^j(\Omega_{i,t+1}) - \ln(\xi^j(\Omega_{i,t+1}))\right) \tag{11}$$

where $\sum P(h_{it} = h|\Omega_{it}, d^j_{it} = 1)$ controls the individual's expectation about their career prospects and wage growth arising from human capital accumulation.

Letting $\mathcal{L}(O_{it}|\Omega_{it}, m_i; \theta, \pi, \xi)$ denote the likelihood of observed choices and outcomes for individual i in period t conditional on their state (Ω_{it}, m_i), structural parameters and type probabilities (θ, π), and nuisance parameter (ξ), the likelihood for a given path of outcomes, $O_i = (O_{i1}, ..., O_{iT})$ conditional on an observed sequence of states, $\Omega_i = (\Omega_{i1}, ..., \Omega_{iT})$ and unobserved type k is computed by taking the product over all T period likelihoods

$$\ln \mathcal{L}(\Theta) = \sum_{i=1}^{N} \ln\left(\sum_{m=1}^{M}\prod_{t=1}^{T} \pi_m \mathcal{L}_{imt}(O_{it}|\Omega_{it}, m_i; \theta, \pi, \xi)\right) \tag{12}$$

Rather than maximizing Equation 12 over the structural parameters (θ, π), Arcidiacono and Miller (2011) provide an efficient approach to incorporating unobserved heterogeneity using the expectation-maximization (EM) algorithm. In particular, set initial values for the conditional choice probabilities, $\xi^{(1)}$, the sample proportion for each unobserved type, $\pi^{(1)} = 1/K$, and the structural parameters, $\theta^{(1)}$.[34] Given these initial values for the structural parameters, compute the following for every $k = 1, 2, ..., K$ types, conditional on the observed outcomes and state variables, (O_{it}, Ω_{it})

$$q^{(n+1)}_{im} = \frac{\prod_{t=1}^{T} \pi^{(n)}_m \mathcal{L}_{imt}(O_{it}|\Omega_{it}, m_i; \theta^{(n)}, \pi^{(n)}, \xi^{(n)})}{\sum_{m=1}^{M}\prod_{t=1}^{T} \pi^{(n)}_m \mathcal{L}_{imt}(O_{it}|\Omega_{it}, m_i; \theta^{(n)}, \pi^{(n)}, \xi^{(n)})}$$

where the numerator varies is invariant across time periods and the denominator is invariant across all

[34] Initial values for $\xi^{(1)}$ and $\theta^{(1)}$ can be recovered by estimating the model without unobserved heterogeneity.

time periods and types.[35] Having computed $q_{im}^{(n+1)}$, simply average across all individuals to recover the proportion of type-k individuals in the sample

$$\pi_m^{(n+1)} = \frac{1}{N}\sum_{i=1}^{N} q_{im}^{(n+1)}$$

Given these individual type probabilities, proportions, conditional choice probabilities, and outcomes / state sequences, $(q_{im}^{(n+1)}, \pi^{(n+1)}, \xi^{(n)}, O_i, \Omega_i)$, now maximize the following likelihood equation

$$\ln \mathcal{L}(\Theta) = \sum_{i=1}^{N}\sum_{m=1}^{M}\prod_{t=1}^{T} q_{im}^{(n)} \ln \pi_m \mathcal{L}_{imt}(O_{it}|\Omega_{it}, m_i; \theta, \pi, \xi)$$

to recover an updated set of parameters, $\theta^{(n+1)}$. Next, update the conditional choice probability estimates, $\xi^{(n+1)}$, using the conditional likelihood of observing choice $m = 0$ for a given state (Ω, m) under the new parameters $(\theta^{(n+1)}, \xi^{(n)})$

$$\xi^{(n+1)} = P(d_{it}^m = 1|\Omega_{it}, \theta^{(n+1)}, \xi^{(n)})$$

4.3. Calibration and Estimation

The parameters are estimated in the usual "two-step" fashion. In the first step, some parameters can be calibrated according to external data and/or prior estimates. In the second step, the remaining parameters that are unique to the model are estimated and identified explicitly from the model using simulated method of moments (SMM) and indirect inference (Gourieroux and Monfort, 1996; Gourieroux et al., 1993). The objective in the second step is to find the parameter vector that yields simulated life-cycle decision profiles that best match the data, given a GMM criterion function. Letting Ψ^A denote actual moments in the data, and Ψ^S denote simulated moments from the model, then $\vartheta \in \Theta$ is solved by searching over the parameter space to find a parameter vector minimizing the criterion function[36]

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

The standard in the literature for the optimal weighting matrix has become to take Λ as the inverse of the variance-covariance matrix. The moment conditions used to identify the four parameters are discussed below. The crucial insight in these auxiliary regressions is the mapping between the simulated model moments and those in the data. Auxiliary regressions do not need to deliver consistent estimates on their own to identify the parameter vector in the model; they merely need to provide reduced-form characterizations of the parameters. The discount rate, β, is set to 0.98 to match the fact that each time step is a year. The depreciation rate of human capital, ξ, is set according to Hendricks (2013). The intertemporal risk aversion

[35]By applying Baye's rule, the denominator is the likelihood of observing the sequence of choices and outcomes conditional on the sequence of state variables for a given set of parameters.

[36]When simulating these stocks, I will discard the first $\hat{T}$ simulations to ensure that I begin from an ergodic distribution; I can easily experiment on different values of $\hat{T}$.

coefficient, ι, is set to 0.50, 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.

5. Quantitative Results

5.1. Model Validation

5.2. Decomposing Sources of Inequality

5.3. Counterfactual Tax Simulation

6. Conclusion

References

Acemoglu, D. (1998): "Why do new technologies complement skills? Directed technical change and wage inequality," *Quarterly Journal of Economics*, 113, 1055–1089.

——— (2002): "Directed technical change," *Review of Economic Studies*, 69, 781–809.

Acikgoz, O. T. and B. Kaymak (2014): "The rising skill premium and deunionization," *Journal of Monetary Economics*, 63, 37–50.

Adams, S. J., J. S. Heywood, and R. Rothstein (2009): "Teachers, performance pay, and accountability: What education should learn from other sectors," *Economic Policy Institute*.

Aigner, D. (1973): "Regression with a binary independent variable subject to errors of observations," *Journal of Econometrics*, 1, 49–60.

Albanesi, S. and C. Olivetti (2009): "Home production, market production and the gender wage gap: Incentives and expectations," *Review of Economic Dynamics*, 12, 80–107.

Ales, L., A. Bellofatto, and J. J. Wang (2014): "Taxing Atlas: Using firm data to derive optimal income tax rates," *Working paper*.

Altonji, J. G., A. A. Smith, and I. Vidangos (2013): "Modeling earnings dynamics," *Econometrica*, 81, 1395–1454.

Arcidiacono, P. and J. B. Jones (2003): "Finite mixture distributions, sequential likelihood and the EM algorithm," *Econometrica*, 71, 933–946.

Arcidiacono, P. and R. A. Miller (2011): "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," *Econometrica*, 79, 1823–1867.

Atkinson, A. B., T. Piketty, and E. Saez (2011): "Top incomes in the long run of history," *Journal of Economic Literature*, 49, 3–71.

Autor, D. and D. Dorn (2013): "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review*, 103, 1553–1597.

Autor, D. H., L. F. Katz, and M. S. Kearney (2006): "The Polarization of the U.S. Labor Market," *American Economic Review*, 96, 189–194.

——— (2008): "Trends in U.S. wage inequality: Revising the revisionists," *Review of Economics and Statistics*, 90, 300–323.

Autor, D. H., L. F. Katz, and A. B. Krueger (1998): "Computing inequality: Have computers changed the labor market?" *Quarterly Journal of Economics*, 113, 1169–1213.

Autor, D. H., F. Levy, and R. J. Murnane (2003): "The skill content of recent technological change: An empirical exploration," *Quarterly Journal of Economics*, 118, 1279–1333.

Badel, A. and M. Huggett (2014): "Taxing top earners: A human capital perspective," *Working paper*.

Baker, G., M. Gibbs, and B. Holmstrom (1994): "The wage policy of a firm," *Quarterly Journal of Economics*, 109, 921–955.

Bandiera, O., I. Barankay, and I. Rasul (2007): "Incentives for managers and inequality among workers: Evidence from a firm-level experiment," *Quarterly Journal of Economics*, 122, 729–773.

Ben-Porath, Y. (1967): "The production of human capital and the life cycle of earnings," *Journal of Political Economy*, 75, 352–365.

Best, M. C. and H. J. Kleven (2013): "Optimal income taxation with career effects of work effort," *American Economic Review RR*.

Bils, M. and P. J. Klenow (2000): "Does schooling cause growth?" *American Economic Review*, 90, 1160–1183.

Bloom, N., B. Eifert, D. McKenzie, A. Mahajan, , and J. Roberts (2013): "Does management matter: Evidence from India," *Quarterly Journal of Economics*, 128, 1–51.

Bloom, N., R. Sadun, and J. Van Reenen (2012): "The organization of firms across countries," *Quarterly Journal of Economics*, 127, 1663–1705.

Bloom, N. and J. Van Reenen (2007): "Measuring and explaining management practices across firms and countries," *Quarterly Journal of Economics*, 3, 1560–1689.

Blundell, R., L. Pistaferri, and I. Preston (2008): "Consumption inequality and partial insurance," *American Economic Review*, 98, 1887–1921.

Bohacek, R. and M. Kapicka (2008): "Optimal human capital policies," *Journal of Monetary Economics*, 55, 1–16.

Bollinger, C. (1996): "Bounding mean regressions when a binary regressor is mismeasured," *Journal of Econometrics*, 73, 387–399.

Bound, J., C. Brown, G. J. Duncan, and W. L. Rodgers (1994): "Evidence on the validity of cross sectional and longitudinal labor market data," *Journal of Labor Economics*, 12, 345–368.

Bound, J., C. Brown, and N. Mathiowetz (2001): "Measurement error in survey data," *Handbook of Econometrics*, 5.

Burdett, K., C. Carrillo-Tudela, and M. G. Coles (2011): "Human capital accumulation and labor market equilibrium," *International Economic Review*, 52, 657–677.

Card, D. and J. E. DiNardo (2002): "Skill biased technological change and rising wage inequality: Some problems and puzzles," *Journal of Labor Economics*, 20, 733–783.

Champagne, J. and A. Kurmann (2013): "The great increase in relative wage volatiltiy in the United States," *Journal of Monetary Economics*, 72, 343–366.

Champagne, J. and C. Makridis (2016): "In Search for Amplification in Search Models: On the Importance of Heterogeneity in Wage-setting over the Business Cycle," *Working paper*.

Chen, X., H. Hong, and D. Nekipelov (2011): “Nonlinear models of measurement errors,” *Journal of Economic Literature*, 49, 901–937.

Chetty, R. (2012): “Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply,” *Econometrica*, 80, 969–1018.

Chetty, R., A. Guren, D. Manoli, and A. Weber (2011): “Does Indivisible Labor Explain the Difference between Micro and Macro Elasticities? A Meta-Analysis of Extensive Margin Elasticities,” Harvard University.

Comin, D., E. L. Groshen, and B. Rabin (2009): “Turbulent firms, turbulent wages?” *Journal of Monetary Economics*, 56, 109–133.

Cunha, F., J. J. Heckman, and S. Navarro (2005): “Separating uncertainty from heterogeneity in life cycle earnings,” *Oxford Economic Papers*, 57, 191–261.

Diamond, P. and E. Saez (2011): “The case for a progressive tax: From basic research to policy recommendations,” *Journal of Economic Perspectives*, 25, 165–190.

Dohmen, T. and A. Falk (2011): “Performance pay and multidimensional sorting: Productivity, preferences, and gender,” *American Economic Review*, 101, 556–590.

Duckworth, A., J. Eichstaedt, and L. Ungar (2015): “The mechanics of human achievement,” *Social and Personality Psychology Compass*.

Duncan, G. J. and G. S. Fields (1985): “An investigation of the extent and consequences of measurement error in labor economic survey data,” *Journal of Labor Economics*, 3, 508–532.

Edmans, A., X. Gabaix, T. Sadzik, and Y. Sannikov (2012): “Dynamic CEO compensation,” *Journal of Finance*, 67, 1603–1647.

Emmanuel Saez, J. S. and S. H. Giertz (2012): “The elasticity of taxable income with respect to marginal tax rates: A critical review,” *Journal of Economic Literature*, 50, 3–50.

Ericsson, K. A., N. Charness, P. J. Feltovich, and R. R. Hoffman (2006): “The Cambridge Handbook of Expertise and Expert Performance,” *Cambridge University Press*.

Fitzgerald, J., P. Gottschalk, and R. Moffitt (1998): “An analysis of sample attrition in panel data: The Michigan Panel Study of Income Dynamics,” *Journal of Human Resources*, 33, 251–299.

Forster, M. and H. Levy (2014): “United States: Tackling high inequalities creating opportunities for all,” *OECD, Social Policy Division*.

Forstner, S. (2013): “Job-to-job mobility and wage inequality: A quantitative assessment,” *Working paper*.

Freeman, R. B. and L. Katz (1995): “Differences and changes in wage structures,” *University of Chicago Press*.

Gayle, G.-L. and R. A. Miller (2009): “Has moral hazard become an important factor in managerial compensation?” *American Economic Review*, 99, 1740–1769.

Gittleman, M. and C. Makridis (2015): “Does "Performance Pay" Pay? The Effects of Contract Structure on Firm Dynamics, 2004-2014,” *Working paper*.

Gottschalk, P. and M. Huynh (2010): “Are earnings inequality and mobility overstated? The impact of nonclassical measurement error,” *Review of Economics and Statistics*, 92, 302–315.

Gourieroux, C. and A. Monfort (1996): “Simulated based econometric methods,” *CORE Lectures, Oxford University Press*.

GOURIEROUX, C., A. MONFORT, AND E. RENAULT (1993): “Indirect inference,” *Journal of Applied Econometrics*, 8, 85–118.

GOUSKOVA, E., P. ANDRESKI, AND R. F. SCHOENI (2010): “Comparing estimates of family income in the Panel Study of Income Dynamics and the March Current Population Survey, 1968-2007,” *Survey Research Center, Institute for Social Research University of Michigan*, Technical Series Paper 10-01.

GREENWOOD, J., A. SESHADRI, AND M. YORUKOGLU (2005): “Engines of liberation,” *Review of Economic Studies*, 72, 109–133.

GUVENEN, F. (2007): “Learning your earning: Are labor income shocks really very persistent?” *American Economic Review*, 97, 687–712.

GUVENEN, F., B. KURUSCU, AND S. OZKAN (2014): “Taxation of human capital and wage inequality: A cross country analysis,” *Review of Economic Studies*, 81, 818–850.

HALL, R. E. (2009): “Reconciling Cyclical Movements in the Marginal Value of Time and the Marginal Product of Labor,” *Journal of Political Economy*, 117, 281–323.

HEATHCOTE, J., F. PERRI, AND G. L. VIOLANTE (2010): “Unequal we stand: An empirical analysis of economic inequality in the United States, 1967-2006,” *Review of Economic Dynamics*, 13, 15–51.

HEATHCOTE, J., K. STORESLETTEN, AND G. L. VIOLANTE (2014): “Consumption and labor supply with partial insurance: An analytical framework,” *American Economic Review*, 104, 1–52.

HECKMAN, J. J. (1981): “The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process and some Monte Carlo evidence,” *Structural Analysis of Discrete Data with Econometric Applications*, Cambridge, MA: MIT Press, 179–195.

HECKMAN, J. J., L. LOCHNER, AND R. COSSA (2003): “Learning by doing versus on the job training: Using variation induced by the EITC to distinguish between models of skill formation,” in *Designing Inclusion: Tools to Raise Low-end Pay and Employment in Private Enterprise*, Cambridge University Press.

HECKMAN, J. J. AND G. SEDLACEK (1985): “Heterogeneity, aggregation, and market wage functions: An empirical model of self-selection in the labor market,” *Journal of Political Economy*, 93, 1077–1125.

HENDRICKS, L. (2013): “The Ben-Porath model and age wage profiles,” *Working paper.*

HEYWOOD, J. S. AND D. PARENT (2012): “Performance pay and the white-black wage gap,” *Journal of Labor Economics*, 30, 249–290.

HOLMSTROM, B. (1979): “Moral hazard and observability,” *The Bell Journal of Economics*, 10, 74–91.

HOLMSTROM, B. AND P. MILGROM (1987): “Aggregation and linearity in the provision of intertemporal incentives,” *Econometrica*, 55, 303–328.

HOTZ, J. AND R. MILLER (1993): “Conditional choice probabilities and the estimation of dynamic modles,” *Review of Economic Studies*, 60, 497–529.

HRYSHKO, D. (2012): “Labor income profiles are not heterogeneous,” *Quantitative Economics*, 3, 177–209.

HUGGETT, M., G. VENTURA, AND A. YARON (2011): “Sources of lifetime inequality,” *American Economic Review*, 101, 2923–2954.

IMAI, S. AND M. P. KEANE (2004): “Intertemporal labor supply and human capital accumulation,” *International Economic Review*, 45, 601–641.

ISKHAKOV, F., T. H. JORGENSEN, J. RUST, AND B. SCHJERNING (2015): “Estimating discrete-continuous choice models: The endogenous grid method with taste shocks,” *Working paper.*

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993): “Earnings losses of displaced workers,” *American Economic Review*, 83, 685–709.

Jarosch, G. (2016): “Searching for job security and the consequences of job loss,” *Econometric, Review and Resubmit.*

Jones, B. F. (2014): “The human capital stock: A generalized approach,” *American Economic Review*, 104, 3752–3777.

Jones, C. (2002): “Sources of U.S. economic growth in a world of ideas,” *American Economic Review*, 92, 220–239.

Juhn, C., K. M. Murphy, and B. Pierce (1993): “Wage inequality and the rise in returns to skill,” *Journal of Political Economy*, 101, 410–442.

Kahn, L. B. and F. Lange (2014): “Employer learning, productivity, and the earnings distribution. Evidence from performance measures,” *Review of Economic Studies*, forthcoming.

Kambourov, G. and I. Manovskii (2009a): “Occupational specificity of human capital,” *International Economic Review*, 50, 63–115.

——— (2009b): “Occupational mobility and wage inequality,” *Review of Economic Studies*, 76, 731–759.

Kapteyn, A. and J. Y. Typma (2007): “Meausrement error and misclassification: A comparison of survey and administrative data,” *Journal of Labor Economics*, 25, 513–551.

Katz, L. F. (1994): “Active labor market policies to expand employment and opportunity,” *Proceedings - Economic Policy Symposium - Jackson Hole, Federal Reserve Bank of Kansas City*, 239–322.

Katz, L. F. and K. M. Murphy (1992): “Changes in relative wages, 1963-1987: Supply and demand factors,” *Quarterly Journal of Economics*, 107, 35–78.

Keane, M. and R. Rogerson (2012): “Micro and macro labor supply elasticities: A reassessment of conventional wisdom,” *Journal of Economic Literature*, 50, 464–476.

Keane, M. and K. Wolpin (1997): “The career decisions of young men,” *Journal of Political Economy*, 105, 473–522.

Keane, M. P. and K. I. Wolpin (2001): “The effect of parental transfers and borrowing constraints on educational attainment,” *International Economic Review*, 42, 1051–1103.

Khan, B. Z. (2015): “Knowledge, human capital and economic development: Evidence from the British Industrial Revolution, 1750-1930,” *NBER working paper.*

Kopczuk, W., E. Saez, and J. Song (2010): “Earnings inequality and mobility in the United States: Evidence from Social Security Data since 1937,” *Quarterly Journal of Economics*, 125, 91–128.

Krusell, P., L. Ohanian, J.-V. Rios-Rull, and G. L. Violante (2000): “Capital-skill complementarity and inequality: A macroeconomic analysis,” *Econometrica*, 68, 1029–1053.

Lavy, V. (2009): “Performance pay and teachers’ effort, productivity, and grading ethics,” *American Economic Review*, 99, 1979–2011.

Lazear, E. (2000a): “Performance pay and productivity,” *American Economic Review*, 90, 1346–1361.

Lazear, E. P. (1986): “Salaries and piece rates,” *Journal of Business*, 90, 405–431.

——— (2000b): “The power of incentives,” *American Economic Review*, 90, 410–414.

——— (2001): “Educational production,” *Quarterly Journal of Economics*, CXVI, 777–803.

Lee, D. and K. I. Wolpin (2006): “Intersectoral labor mobility and the growth of the service sector,” *Econometrica*, 74, 1–46.

Lemieux, T. (2006): "Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill?" *American Economic Review*, 96, 461–498.

——— (2008): "The changing nature of wage inequality," *Journal of Population Economics*, 21, 21–48.

Lemieux, T., W. B. MacLeod, and D. Parent (2009): "Performance pay and wage inequality," *Quarterly Journal of Economics*, CXXIV, 1–49.

Lemov, D., E. Woolway, and K. Yezzi (2012): *Perfect practice: 42 rules for getting better at getting better*, Jossey-Bass.

Lillard, L. A. and C. W. A. Panis (1998): "Panel attrition from the Panel Study of Income Dynamics: Household income, marital status, and mortality," *Journal of Human Resources*, 33, 437–457.

Lochner, L. and Y. Shin (2014): "Understanding earnings dynamics: Identifying and estimating the changing roles of unobserved ability, permanent and transitory shocks," *NBER working paper*.

Loewenstein, M. A. and J. R. Spletzer (1999): "General and specific training: Evidence and implications," *Journal of Human Resources*, 34, 710–733.

Low, H., C. Meghir, and L. Pistaferri (2010): "Wage risk and employment risk over the life cycle," *American Economic Review*, 100, 1432–1467.

MacLeod, W. B. and D. Parent (2014): "Transaction costs and the employment contract in the US Economy," *Journal of Law, Economics, and Organization*, 0, 1–37.

Makridis, C. (2016a): "Does Culture Pay? Compensating Differentials, Job Satisfaction, and Organizational Practices," *Working paper*.

——— (2016b): "Time at Work Pays: Evidence from Performance Pay and Fixed Wage Workers," *Working paper*.

Manuelli, R. E. and A. Seshadri (2014): "Human capital and the wealth of nations," *American Economic Review*, forthcoming.

Meghir, C. and L. Pistaferri (2004): "Income variance dynamics and heterogeneity," *Econometrica*, 72, 1–32.

Mouw, T. and A. L. Kalleberg (2010): "Occupations and the structure of wage inequality in the United States, 1980s to 2000s," *American Sociological Review*, 75, 402–430.

Muralidharan, K. and V. Sundararaman (2011): "Teacher performance pay: Experimental evidence from India," *Journal of Political Economy*, 119, 39–77.

Murphy, K. M. and R. H. Topel (2016): "Human capital investment, inequality, and economic growth," *Journal of Labor Economics*, 34, S99–S127.

Neal, D. (1995): "Industry-specific human capital: Evidence from displaced workers," *Journal of Labor Economics*, 13, 653–677.

Nickell, S. (1981): "Biases in dynamic models with fixed effects," *Econometrica*, 49, 1417–1426.

Ohanian, L., A. Raffo, and R. Rogerson (2008): "Long-term changes in labor supply and taxes: Evidence from OECD countries, 1956-2004," *Journal of Monetary Economics*, 55, 1353–1362.

Olivetti, C. (2006): "Change in women's hours of market work: The role of returns to experience," *Review of Economic Dynamics*, 9, 557–587.

Orazio, A. (1999): "Consumption," *Handbook of Macroeconomics*, 1.

Paarsch, H. J. and B. Shearer (2000): "Piece rates, fixed wages, and incentive effects: Statistical evidence from payroll records," *International Economic Review*, 41, 59–92.

Paarsch, H. J. and B. J. Shearer (1999): "The response of worker effort to piece rates: Evidence from the British Columbia tree-planting industry," *Journal of Human Resources*, 34, 643–667.

Piketty, T., E. Saez, and S. Stantcheva (2014): "Optimal taxation of top labor incomes: A tale of three elasticities," *American Economic Journal: Economic Policy*, 6, 230–271.

Poletaev, M. and C. Robinson (2008): "Human capital specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys," *Journal of Labor Economics*, 26, 387–420.

Prendergast, C. (2002): "Uncertainty and incentives," *Journal of Labor Economics*, 20, 115–37.

Prescott, E. (2004): "Why do Americans work so much more than Europeans?" *Minneapolis Quarterly Review*, 28, 2–13.

Rogerson, R. (2006): "Understanding differences in hours worked," *Review of Economic Dynamics*, 9, 365–409.

——— (2008): "Structural transformation and the deterioration of European labor market outcomes," *Journal of Political Economy*, 116, 235–259.

Romer, P. (1990): "Endogenous technological change," *Journal of Political Economy*, 98, S71–S102.

Rosen, S. (1972): "Learning and experience in the labor market," *Journal of Human Resources*, 7, 326–342.

Shaw, K. (1989): "Lifecycle labor supply with human capital accumulation," *International Economic Review*, 30, 431–456.

Shearer, B. (2004): "Piece rates, fixed wages and incentives: Evidence from a field experiment," *Review of Economic Studies*, 71, 513–534.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. von Wachter (2015): "Firming up inequality," *NBER working paper No. 21199*.

Stantcheva, S. (2014): "Optimal taxation and human capital policies over the life cycle," *Econometrica*.

Storesletten, K., C. I. Telmer, and A. Yaron (2004): "Consumption and risk sharing over the life cycle," *Journal of Monetary Economics*, 51, 609–633.

Trostel, P. A. (1993): "The effect of taxation on human capital," *Journal of Political Economy*, 101, 327–335.

Wallenius, J. (2011): "Human capital accumulation and the intertemporal elasticity of substitution: How large is the bias," *Review of Economy Dynamics*, 14, 577–591.

Yamaguchi, S. (2012): "Tasks and heterogeneous human capital," *Journal of Labor Economics*, 30, 1–53.