Discounting Human Wealth:

Unemployment Risk Or Employment Insurance?

Job Market Paper

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Abstract

This paper relates the riskiness of human capital to uncertainty in the labour market and documents a role for unemployment as a determinant of human wealth. Starting from the labour market equilibrium outcome, I derive two unemployment-adjusted measures of labour income and rely on U.S. micro-level data to quantify their dynamics over time. Comparing representative workers who differ in their endowment of human capital, I find that the riskiness of human capital is inversely related to human capital holdings. My findings point to inequality in human wealth, the discounted value of future labour income, being worse than the well documented inequality in labour income. Sorting U.S. industry-level portfolios by differential exposure to unemployment risk yields a novel cross-section of average excess returns. I interpret the high risk-premia are compensation for less-constrained highly educated workers willing to take financial risk beyond hedging their labour income risk.

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1 Introduction

Empirical studies find that human wealth, the presented discounted value of future labour income, accounts for about 90% of total wealth of U.S. households (Lustig and Verdelhan, 2013). Despite the importance of embedding this component in both empirical and theoretical asset pricing work has been recognised since Mayers (1972) and Roll (1977), the literature has focused mainly on financial rather than human wealth over time. A major challenge is posed by human capital being a non-tradable asset. This makes the treatment of human wealth cumbersome, as cash-flows are observable (wages), but discount rates are not. To the best of my knowledge, researchers have taken two approaches to address this issue over time. This paper proposes an alternate perspective: It sheds lights on the riskiness of human capital by empirically pinning down its determinants in the labour market.

Early empirical asset pricing work imposes ad-hoc restrictions on human capital discount rates (Campbell, 1996; Shiller, 1995; Jagannathan and Wang, 1996). Recent work adopts VAR techniques to recover the human capital discount rate from aggregate consumption data conditioning on a set of standard predictors for consumption growth and stock returns. Under this approach, earlier measures are shown to be inconsistent with the data (Lustig and van Nieuwerburgh, 2008), and reliable economic inference depends on appropriately incorporating a measure of macroeconomic uncertainty (Bansal et al., 2014).

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1 The conditional expected human return is assumed to be constant (Shiller, 1995), equal to the conditional expected return on financial wealth (Campbell, 1996), constant and labour income growth as unforecastable (Jagannathan and Wang, 1996).

2 A separate strand of literature in finance focuses on the consumption-wealth ratio (Campbell and Mankiw (1989); Lettau and Ludvigson (2001), Lustig et al. (2013)). Santos et al. (2006) develop a general equilibrium model that can rationalize the predictability of stock returns by the labour income to consumption ratio. Most recently, Palacios (2014) incorporates investment in human capital in a general equilibrium model and derive a three-factor asset pricing model that depends on the human investment.
This paper presents a new approach based on the idea that human capital is a risky asset, owned by workers and invested in the labour market. Under these premises, human capital risk can be mapped into labour market risk and empirically measured. My starting point is a straightforward insight from labour macroeconomics: At each point in time the labour market equilibrium outcome is jointly determined by wage and unemployment dynamics. I derive a simple measure of human capital that accounts for both macro-variables and use U.S. micro-level data to quantify this measure at aggregate level. I work with representative agents who differ in their endowment of human capital.

Abstracting from governmental transfers, the measure I construct adjusts the growth rate of wages by the unemployment risk borne by employed workers over the same horizon. This measure can also be interpreted as growth in unemployment-(U-) adjusted labour income. To the best of my knowledge, existent work in asset pricing accounts for wages (human capital cash-flows), but ignores unemployment dynamics. This paper contributes to the literature on human wealth by documenting a key role for the unemployment channel beyond the more traditional wage channel. I interpret unemployment as the bad state of the world faced by any employed worker and unemployment risk as the downside risk he bears. I take the probability of being unemployed as a proxy of the worker’s exposure to unemployment risk, and propose the unemployment rate as an empirical proxy for this probability at aggregate level.

Figure 1 compares the cumulated quarterly growth in U-adjusted labour income experienced by a representative diploma holder (in blue) and a representative post-college holder (in green) in the United States over the period 1979 to 2014. Both measures are computed using micro-level (CPS) survey data and generalised to the U.S. population via population sampling weights. To improve precision of estimates, I adopt quasi-experimental methods (propensity score weighting) to estimate their wage-related component. For each agent, the graph compares a pure wage-based measure
(dashed line) with its U-adjusted counterpart (solid line).

The graph shows that highly educated workers historically experience a less severe drop in U-adjusted labour income in bad times than low educated workers. By definition, a risky asset pays-off poorly in bad times. Since labour income is the pay-off of the human capital asset, the graph points to human capital being historically riskier for low educated agents than highly educated ones. Accounting for unemployment is key to draw this conclusion: Wages are sticky, while unemployment captures a deterioration of labour market conditions in real time. In the graph, the unemployment-adjustment visibly crashes in recessions (shaded areas). This figure is also consistent with the well documented fact that highly educated agents earn historically higher wages than low educated ones on average. Taken together, these findings have implications for human wealth, the presented discounted value of future labour income. This evidence points to inequality in human wealth being worse than the well established inequality in labour income. In other words, accounting properly for the riskiness of human capital magnifies inequality in human capital cash-flows and reveals even worse inequality in human capital prices.

I argue that these findings should imply heterogeneous financial investment behaviour. Agents who face high exposure to changes in labour market conditions (low educated) should invest in financial markets mainly to hedge their labour income risk — investing in assets that perform well when they are more likely to lose their jobs — while agents who face mild exposure (highly educated) should be willing to bear the risk of a poor performance of their financial assets in bad labour market states — investing in risky financial assets — but demand a premium for bearing it.

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3Work on trends in the wage structure points to a sharp rise in income inequality in the United States (Piketty and Saez, 2003). See Autor et al. (2008) for a review of the debate on the forces driving income inequality and weak evidence in support of the fall in the real value of the minimum wage as one-time driver (“revisionists” view (Card and Dinardo, 2002)).
Figure 1
Cumulated Human Capital Measures

This figure compares the time-series of cumulated quarterly growth in a pure wage-based measure of human capital ($r_c^W$, dashed line) with its unemployment-adjusted counterpart ($r_c^{W+Emp}$, solid line). Measures are computed for two U.S. representative human capital holders $c$: A diploma holder (blue line) and a post college (green line) holder. The unemployment-adjusted measure is obtained as the sum of growth in wages and growth in employment shares. Measures are in percentage. Shaded areas denote NBER recessions. Data are from monthly samples of the CPS Outgoing Rotation Group. The sample period is 1979:Q1-2014:Q4.
To this extent, I build a macroeconomic factor that captures differential exposure to unemployment risk in the United States as the difference between the growth in quarterly employment rates of highly educated workers (post college holders) and low educated workers (diploma holders). I show that sorting industry-level portfolios by their time-varying loadings on this factor — controlling for aggregate market risk — yields a novel cross-section of average excess returns. A standard long-short strategy, long in high-\(\hat{\beta}^{Emp}\) industries and short in low-\(\hat{\beta}^{Emp}\) industries, has yielded on average a statistically significant premium of about 4% over the last 35 years. Risk premia are driven by bad labour market states. In these quarters unemployment risk is systematic risk, as all types of agents face a higher probability of being unemployed. I show that these risk premia are consistent with heterogeneous financial investment behavior. Finally, I provide some preliminary evidence about the relationship between this novel risk premium and the well-known value premium. Sorting the same set of test assets by time-varying exposure to the HML factor reveals that the two sources of risk are closely related, though they do not fully overlap.

The paper is organised as follows. In the next section I derive a novel unemployment-adjusted measure of human capital and extend it to a related measure of returns to education. In Section 3 I present data and the propensity score methodology. In Section 4, I document patterns in unemployment probabilities of heterogeneous agents and discuss empirical results from U.S. labour and financial markets. Section 5 concludes highlighting avenues for further research.

2 Unemployment-Adjusted Human Capital Measures

I derive a novel unemployment-adjusted measure of human capital from the outcome equilibrium in the labour market and extend it to obtain a related measure of returns to education.
Unemployment-adjusted labour income - $R^e_{t+1}$. Workers in the economy differ in their endowment of educational capital $e$. The investment in education is made prior to entering the labour market: Subject to their preferences, workers study up to a diploma, college or post college degree. At any point in time, the labour force amounts to the set of all full-time employed (E) and unemployed (U) workers in the economy endowed with one of these degrees. The population $P$ is restricted to the labour force, that is $P_t = \sum_{e=1}^{3}(E^e_t + U^e_t)$.

Wages $W_t$ and the employment rate $\Theta_t$, where $\Theta_t = \frac{E_t}{E_t + U_t}$, are determined each period by bargaining between firms and workers subject to the realisation of labour market shocks. Any worker is characterised by educational capital $e$, a labour market status (employed/unemployed) and a pay-off.

The labour market outcome equilibrium is the aggregate payoff for the labour market - the sum of payoffs of employed and unemployed workers - at a given point in time. Under the assumption that pay-offs are earned by a representative investor, the labour market outcome equilibrium is obtained as the sum of the share of employed workers times their aggregate payoff and the share of unemployed workers times their aggregate payoff. Abstracting for governmental transfers, I attach a zero pay-off to any unemployed worker and an aggregate wage to the representative worker\(^4\). Figure 2 - Panel A provides a graphical description of this setup.

\(^4\)Abstracting for governmental transfers is an over-simplifying assumption that I plan to address in future work. Households in the ORG are not asked to disclose unemployment benefits.
Figure 2
Human Capital Measures

This figure presents a graphical representation of the set up presented in the main text that provides foundation for two novel human capital measures derived from the outcome equilibrium in the labour market. These measures are defined in Equation (1) and Equation (4) in the main text and are reported at the top of each panel, respectively. Panel B presents also two existent measures of returns to education, namely the “skill premium” and its risk-adjusted version examined by Palacios-Huerta (2003). $E_t$: Full-time employed workers at time $t$; $U_t$: Full-time unemployed workers at time $t$; $W$: Wage; $\Theta^e_t = \frac{E^e_t}{E^e_t + U^e_t}$: employment rate of workers with educational attainment $e$ at time $t$.

Panel A

$$R^e_{t+1} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{t+1}}{W^e_t}$$

Panel B

$$R^e_{t+1} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{t+1}}{W^e_t} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{e-1}}{W^e_t} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{e-1}}{W^e_t} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{e-1}}{W^e_t} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{e-1}}{W^e_t} = \frac{\Theta^e_{t+1}}{\Theta^e_t} \frac{W^e_{e-1}}{W^e_t}$$
There are three representative workers (i.e., $e$-types) in the economy: A diploma holder, a college holder and a post-college holder. I define growth in unemployment-adjusted labour income as the ratio of labour market outcome equilibria at two different points in time. For any given representative worker $e$, this measure is equal to:

$$R_{t+1}^e = \frac{\Theta_{t+1}^e \times W_{t+1}^e + (1 - \Theta_{t+1}^e) \times 0}{\Theta_t^e \times W_t^e + (1 - \Theta_t^e) \times 0} = \frac{\Theta_{t+1}^e}{\Theta_t^e} \times \frac{W_{t+1}^e}{W_t^e},$$ (1)

where $\Theta_t^e$ denotes the share of workers with endowment $e$ who are employed at time $t$ and $W_t^e$ is the wage of the representative worker $e$ in the same period. In log form (lowercase):

$$r_{t+1}^e = (\theta_{t+1}^e - \theta_t^e) + (w_{t+1}^e - w_t^e).$$ (2)

This human capital measure adjusts the growth rate of wages of worker $e$ (second term) by the growth rate of his employment probability (first term). I interpret the probability of being unemployed as the worker’s exposure to unemployment risk and the unemployment rate as an empirical proxy for this probability. At individual level the unemployment probability is subjective, and likely to depend on the own past history of the worker as well. Under the assumption that past histories of workers are idiosyncratic and average out in the aggregate, the unemployment probability of the representative investor $e$ approximates to $1 - \Theta^e$, the unemployment rate conditional on being endowed with educational human capital $e$.

I interpret unemployment risk as the downside risk faced by any employed worker to become unemployed. Unemployment is the bad state for any human capital holder, as the human capital asset does not pay a full dividend and its price crashes. Intuitively, the longer the time spent in the unemployment state, the less attractive the worker becomes for firms and and the more his bargaining position weakens. In turn, the “price” at which he can sell themselves in the labour market decreases and the value of his human capital asset falls.
Since the unemployment rate is always positive, unemployment risk matters for everyone. The human capital measure in Equation (2) accounts for this phenomenon by adjusting the growth rate of human capital cash-flows over a period by the exposure to unemployment risk borne by the investor over the same horizon. When the unemployment rate of worker $e$ increases, the employment share $\theta^e$ decreases. Adverse changes in labour market conditions are captured by the unemployment-adjustment term $(\theta^e_{t+1} - \theta^e_t)$ being negative.

The human capital measure in Equation (2) can be interpreted as a key-state variable for human capital, as it contains the two main determinants of human wealth, wages and unemployment. The unemployment-adjustment term empirically captures the unemployment channel, that is unemployment having an impact on marginal utility that goes beyond the lost-wage impact. Accounting for unemployment is important, as wage-earners are by definition employed workers. This means that the second term in Equation (2) only captures fluctuations in actual wages in the labour market. But, unemployment, not wages, is a key indicator of labour market conditions. Unemployment probabilities capture the share of the labour force that is in the bad human capital state and can therefore be interpreted as an indirect way to measure empirically changes in the price of human capital in the economy.

**Return to education - $R^e_{t+1}$**. The set up above can be extended to explore the relative gains in the economy by comparing payoffs of agents who differ in their human capital endowment. The return to an additional unit of educational human capital earned by worker $e$ is:

\[
R^e_{t+1} = \frac{\Theta^e_{t+1} \times W^e_{t+1} + (1 - \Theta^e_{t+1}) \times 0}{\Theta^e_{t-1} \times W^e_{t-1} + (1 - \Theta^e_{t-1}) \times 0} = \frac{\Theta^e_{t+1}}{\Theta^e_{t-1}} \times \frac{W^e_{t+1}}{W^e_{t-1}},
\]

(3)

where $e$ and $e-1$ denote two educational endowment - say post-college and college degree - and the star differentiates returns to education from those defined in Equation (2).
Multiplying and dividing the first term in Equation (3) by $\Theta^e_t$ and the second term by $W^e_t$ yield:

$$R_{t+1}^e = \frac{\Theta^e_t}{\Theta^e_{t-1}} \times \frac{W^e_{t+1}}{W^e_{t-1}} \times \frac{W^e_t}{W^e_{t-1}} = R_{t+1}^e \times \frac{\Theta^e_t}{\Theta^e_{t-1}} \times \frac{W^e_t}{W^e_{t-1}}.$$  \hspace{0.5cm} (4)

Terms (b) and (d) are again $R_{t+1}^e$ and are driven by changes in the labour market conditions over time. Terms (a) and (c) quantify relative gains between workers who differ in their educational human capital at a given point in time.

Term (c) is the traditional object of study in the economics literature on the returns to education and is well known as the “skill premium”. It is a “premium”, as wages are found to be increasing in the educational attainment, but also a poor measure of returns in financial terms. First, because it does not account for fluctuations in cash-flows over time. Second, because it does not discount cash-flows by the risk borne by the investor.

Terms (c) and (d) jointly address the first issue, as the “skill premium” is adjusted for earnings risk. The risk properties of these two terms are jointly studied in Palacios-Huerta (2003a).\textsuperscript{5} Henceforth, I refer to this measure as a cash-flow measure of return to human capital (i.e., cash-flow risk-adjusted measure).

Equation (4) is an extension of this measure that addresses also the second issue, as pointed out above. It is an enriched measure of returns to education, as it accounts for two extra terms. Term (a) refers to gains/losses attributable to differences in the exposure to unemployment risk due to a distinct endowment of educational human capital. Term (b) adjusts this quantity to account for the change in the exposure to unemployed risk experienced by the worker who owns the additional human capital unit

\textsuperscript{5}In evaluating the robustness of the conditional CAPM by Jagannathan and Wang (1996), Palacios-Huerta (2003b) finds that an aggregate version of the return measure examined in Palacios-Huerta (2003a) explains about 70\% of the cross-sectional variation in 100 beta-size portfolios of U.S. stocks.
over the period. Figure 2 - Panel B graphically summarises these return measures by extending the setup presented in Panel A.

As per the other return measure, a second important departure from previous contributions in this area is that returns are derived taking into account the entire labour force, rather than being conditional on wage earners (i.e., full-time employed workers).

The following equation (in log form) summarises both the notation and the semantic used henceforth:

\[
    r_{t+1}^e = \left( \theta_t^e - \theta_{t-1}^e \right) + \left( \theta_{t+1}^e - \theta_t^e \right) + \left( w_t^e - w_{t-1}^e \right) + \left( w_{t+1}^e - w_t^e \right). 
\]

(5)

3 Data and Methodology

Labour market data are from the Earner Study, also known as the CPS (Current Population Survey) Outgoing Rotation Group (ORG). The CPS is the major source of labour market statistics in the United States: This survey covers about 60,000 households (approximately 110,000 individuals) conducted monthly by the Bureau of Labor Statistics (BLS) since 1979.\(^6\) The ORG is the monthly subset of these households (about one-fourth) asked to report details about earnings in addition to employment status and demographics.\(^7\) All monthly micro-level extracts used in this paper are from the NBER website and cover the period from 1979 to 2014.\(^8\)

For the purpose of this paper, this dataset is ideal as data on both wages and labour market status are collected jointly at the monthly frequency along with demographics

\(^6\)The annual March CPS survey was initiated in 1964. Only monthly data are used in this paper, as point-in-time data are needed to infer human capital returns from labour market equilibria at the business cycle frequency.

\(^7\)Each CPS household is interviewed for four consecutive months, ignored for the following eight months and interviewed again for other four consecutive months. The ORG comprises all CPS households in either their fourth or sixteenth month.

\(^8\)Monthly micro-level data are available at: http://www.nber.org/data/morg.html.
and educational attainment. I adopt CPS population sampling weights to generalize survey data to the U.S. labour force and recover a proxy of the U.S. labour market outcome equilibrium at any point in time.

The set of employed workers in my dataset is the one traditionally examined in labour market studies on the wage premia. For data cleanings, I follow Katz and Murphy (1992). I retain individuals who declare themselves as full-time employed workers with potential work experience ranging from 0-40 years. The actual number of years of work experience ($\text{Exp}$) is not available in the CPS dataset. Consistent with previous work, I construct this variable combining age and schooling years: $\text{Exp} = \min \{\text{age} - \text{years of schooling} - 7, \text{age} - 17\}$. $\text{Exp}$ is a proxy and does not account for periods spent unemployed. Full time or part time students, self-employed workers, workers without pay and workers with missing weekly earnings are excluded.

Nominal wages are defined as earnings per week (in dollars) and are converted into real terms (2009 dollars) using the Personal Consumption Expenditure (PCE) deflator published by the Bureau of Economic Analysis. CPS nominal wages are top-coded to protect the privacy of respondents and top-coding has been revised twice by BLS over time. I follow Morgan and Cha (2002) and impose the lowest top-code in real terms on all months. To deal with outliers at the bottom of the wage distribution, I remove all individuals that declare nominal weekly earnings below 50 dollars.

I extend this standard dataset to also include unemployed workers, that is, all individuals declaring to be full time unemployed and match the requirements above.

Each individual in the final dataset is characterised by the following set of variables: race (white/black/other), sex (male/female), age, potential years of work experience, labour market status (employed/unemployed), education, industry, geographical area,

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CPS sampling weights (population-based and earnings-based weights) and a real weekly wage (if employed).

Education is measured in schooling years (0-18). It is well known that this classification is not fully consistent over time due to two major changes in the CPS survey questions (in 1992 and 1998, respectively). Before 1992, I define the educational attainment as the highest grade attended and completed. Since 1992, I follow the two classifications proposed by Jaegert (1997, 2002) who map the highest degree received into schooling years. I define diploma, college and post college holders as workers with 12, 16 or more than 16 years of schooling, respectively.

I map CPS industries into 10 divisions using SIC (NAICS)-based codes before (after) 2002. I map Census state codes into nine divisions using the first digit of state code as the division code. Details about these two classifications are provided in the Online Appendix.

Macroeconomic variables, namely the U.S. aggregate unemployment rate and the U.S. industrial production index, are from the BLS and FRED Louis websites, respectively.

Financial variables, namely 30 U.S. industry portfolios, the risk-free rate and the excess return on the aggregate U.S. stock market, are from Kenneth French website. These series are monthly and are compounded at the quarterly frequency.

I identify good and bad times in the labour market using the the monthly job posting index compiled by Barnichon (2010), who accounts for both help-wanted advertisements appeared in major newspapers (i.e., “print” measure of vacancies) and those posted over the internet (i.e., “online” measure of vacancies). The latter component ensures the indicator is representative of the recent past. The number of job openings, or vacancies, is a standard pro-cyclical indicator of labour market conditions: Good times are periods in which firms actively search for new workers by posting vacancies at a high rate. I construct a quarterly series taking the last month of each quarter.
define bad (good) states as quarters in which this series is below (above or equal to) its standardized mean. There are 144 quarters and five NBER recessions in the sample, 66 quarters fall in the bad states and 23 of these quarters are recession periods.

Finally, I define human capital as an asset that is not tradeable but fluctuates in value over time. Human capital holdings are jointly determined by innate abilities (unobservable), educational attainment and years of work experience. I assume that individuals invest in education in the early stages of their life according to their preferences and then enter the labour market endowed with educational human capital. The compensation they get in the labour market each period (if employed) is a joint reward for both the educational investment they have made and their work experience.

I build a cross-section of workers sorting along two characteristics, education and work experience. I restrict the U.S. labour force to workers holding a diploma, a college degree or a post-college degree. These workers are classified as having 1-5, 6-15 or 16-40 experience years. Table 1 shows that the combination of these characteristics results in nine education-experience cells, or equivalently, a cross-section of nine representative human capital holders:

Workers with the lowest human capital endowment in the labour force have a diploma degree and few years of work experience (1-5); workers with the highest human capital endowment in the labour force have a post-college degree and many years of work experience (16-40). I examine human capital returns either at this level of aggregation or by sorting by education only.

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10Labour market studies on the wage premia usually adopt a finer classification by accounting for demographics (i.e., gender-race-education-experience groups). Palacio-Huerta (2003) studies the risk properties of cash-flow risk adjusted returns by allocating workers into 90 gender-race-education-experience groups.
Table 1
Human Capital Endowment Matrix

<table>
<thead>
<tr>
<th>Education</th>
<th>Working Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(years)</td>
</tr>
<tr>
<td></td>
<td>L</td>
</tr>
<tr>
<td>Diploma Holders</td>
<td>L-L</td>
</tr>
<tr>
<td>College Holders</td>
<td>M-L</td>
</tr>
<tr>
<td>Post College Holders</td>
<td>H-L</td>
</tr>
</tbody>
</table>

3.1 Propensity Score Approach to Wage Premia

A leading approach to estimate the “skill premium” (Equation 5, Terms c) is the Mincer (1958)-Becker (1964) approach that quantifies the average internal rate of human return via panel regressions. The approach closer to this paper is the times-series approach. The traditional procedure is to compute differences in average log wages, where averages are obtained by bundling together agents with similar demographic characteristics. In each period, (i) agents are allocated to different sex-race-education-experience subgroups,¹¹ (ii) mean log real weekly wages are computed for each of these subgroups, and (iii) mean wages for broader groups are obtained by taking fixed-weighted averages of the means computed in step (ii). Adjusted wage premia are then studied at this level of aggregation.

There are at least two limitations in using this aggregation procedure: (i) All workers are treated as homogeneous within each sub-group; (ii) the sorting scheme depends on a small set of characteristics due to the standard curse-of-dimensionality problem.

I overcome these two issues by treating the estimation of these quantities as an evaluation problem. For a given educational attainment \( e \), I define the treatment group \( T \) as the set of full-time employed workers in the dataset at time \( t+1 \), \( T = E^e_{t+1} \), and the

treatment variable as their educational attainment $e$. The counterfactual of $T$ is $E_t^{e-1}$, that is the same set of workers of group $T$ but holding lower educational human capital, $e-1$ rather than $e$, in the previous period. This counterfactual is not observable, hence the evaluation problem. I define a control group $C$ as a proxy for this counterfactual, where $C$ is the set of full-time employed workers in the dataset at time $t$, declaring educational attainment $e-1$.

In each quarter, I estimate wage premia and log wage changes, separately, as the average treatment effect on the treated (ATT) using the propensity score methodology (Rosenbaum and Rubin, 1983). This technique is a two-step procedure that uses the propensity scores as weights to create a balanced sample of treated and control observations. The propensity score is the conditional probability of receiving the treatment conditional on a set of observable characteristics. The advantages of this methodology are twofold: (i) It mitigates the curse of dimensionality allowing a larger set of characteristics to be accounted for and (ii) treats all individuals as heterogeneous by assigning individual weights.

The first step of the procedure involves the estimation of a propensity score for each individual in the sample by running a logistic regression conditioning on a set of observable characteristics. I define the following set of predictors: Years of working experience, sex, race (Whites/Blacks), industry dummies, geographical dummies, dummies for broad working experience groups, an interaction term for years of working experience and sex, an interaction term for sex and “Whites”, CPS earnings-based sampling weights.

In the second step of the procedure, wage premia/log wage changes are estimated as the average difference in outcomes between the treatment and the control group.
Controls are weighted by the inverse of the probability of receiving treatment, that is

\[
\hat{\delta}_{ATT} = \frac{1}{N_T} \sum_{i:d_i=1} y_i - \frac{\sum_{i:d_i=0} \hat{r}_i y_i}{\sum_{i:d_i=0} \hat{r}_i},
\]

where \( i \) denotes an agent, \( y \) is the outcome variable (i.e. the log wage), \( d \) is a treatment indicator taking value of 1 if \( i \) is treated and 0 otherwise, \( N_T \) denotes the number of treated individuals and \( \hat{r}_i = \frac{\hat{p}_i}{1-\hat{p}_i} \), where \( \hat{p}_i \) is the estimated propensity score of \( i \) from the first step. This estimator is unbiased and efficient (Imbens et al., 2003).

Following DuGoff et al. (2014) I combine the propensity score method and the CPS sampling weights to obtain unbiased treatment effects that are generalizable to the original survey target population. In the first step, I include the CPS earnings-based sampling weights as a predictor in the propensity score model. In the second step, I weight both treated and controls by their CPS population-based sampling weights. For controls, I create combined weights by multiplying their propensity score-based weights by their CPS weights.

Estimates are robust to the trimming of all individuals whose propensity score does not fall within a common support (lower/upper bound given by the minimum/maximum propensity score) and also to discarding all individuals whose propensity score falls in the bottom/top 1% of the propensity score distribution.

4 Evidence From Labour and Financial Markets

In this section, I document cross-sectional variation in the exposure to unemployment risk, present time-series evidence on each component of human returns and examine differences between cash-flow and risk-adjusted measures. I then derive a macroeconomic factor that captures time-varying heterogeneity in the exposure to unemployment risk in the U.S. labour market. I rely on this factor to examine the risk-return trade
off faced by heterogenous and constrained human capital holders when investing in financial markets.

4.1 Downside Risk to Human Capital

I interpret unemployment risk as the downside risk faced by any employed worker and the unemployment rate as an aggregate proxy of the probability of being unemployed. In this section, I examine if and the extent to which there is cross-sectional variation in the exposure to this risk in the U.S. economy by computing conditional unemployment rates. Percentage quarterly averages are reported in Table 2. Unemployment rates are obtained by conditioning jointly on a human capital endowment (education in Panel I and education and work experience in Panel II) and a labour market state. Cross-sectional patterns are in rows, time-series patterns are in columns. Quarterly series are obtained as the last month of each quarter.

Not surprisingly, all rates are positive and statistically different from zero at the 1% level confirming that at any point in time any representative human capital holder faces the risk to end up in the bad state of the world. More interestingly, Column 1 documents cross-sectional variation in the exposure to this risk: i) Full-sample unemployment probabilities are a decreasing function of the educational attainment (Panel I), ii) these monotonic differences are statistically different from each other (Table 3 - Panel A), and (iii) this pattern is robust when controlling for work experience (Panel II). Over the 1979-2014 period, the average U.S. unemployment rate is 7.2% for diploma holders, about 3.2% for college holders and 2.4% for post-college holders. The average cross-sectional spread in the economy - the difference between junior diploma holders and the most experienced post-college holders - is about 10%.

Bad times in the economy are periods in which labour market condition deteriorates: Firms post less vacancies and aggregate unemployment raises, as predicted by the Bev-
Table 2
Average Conditional Unemployment Rates

This table reports average unemployment rates (in percentage) conditioning on states (all periods/bad/good; Columns 1-3) and human capital endowment (education in Panel I; education and work experience in Panel II). Education is measured as Diploma, College or Post College degree. Working experience is measured in years: 1-5 years, 6-15 years or 16-40 years. The last two columns report time-series mean difference tests for the bad over the good state, that is the mean difference between the two states (Column 4) and the standard error \( \text{s.e.} \) of this difference (Column 5). The unemployment rate is defined as the ratio of the unemployed workers to the labour force. The bad (good) state refers to quarters in which the job posting index by Barnichon (2010) is below (above or equal to) its standardized mean. Data are from monthly samples of the CPS Outgoing Rotation Group. Quarterly series are obtained as the last month of each quarter. The sample period is 1979:Q1-2014:Q4.

<table>
<thead>
<tr>
<th>Cross-Section</th>
<th>Time-Series</th>
<th>All</th>
<th>Bad</th>
<th>Good</th>
<th>Bad–Good</th>
<th>(s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td><strong>Panel I: By Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Diploma</td>
<td></td>
<td>7.13</td>
<td>8.68</td>
<td>5.82</td>
<td>2.86</td>
<td>(0.39)</td>
</tr>
<tr>
<td>College</td>
<td></td>
<td>3.21</td>
<td>4.07</td>
<td>2.49</td>
<td>1.58</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Post college</td>
<td></td>
<td>2.39</td>
<td>2.88</td>
<td>1.98</td>
<td>0.89</td>
<td>(0.16)</td>
</tr>
<tr>
<td><strong>Panel II: By Education And Work Experience</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exp: 1-5 years</td>
<td>Diploma</td>
<td>12.29</td>
<td>14.45</td>
<td>10.46</td>
<td>3.99</td>
<td>(0.76)</td>
</tr>
<tr>
<td></td>
<td>College</td>
<td>3.44</td>
<td>4.39</td>
<td>2.63</td>
<td>1.77</td>
<td>(0.27)</td>
</tr>
<tr>
<td></td>
<td>Post college</td>
<td>2.66</td>
<td>3.19</td>
<td>2.22</td>
<td>0.97</td>
<td>(0.31)</td>
</tr>
<tr>
<td>Exp: 6-15 years</td>
<td>Diploma</td>
<td>8.11</td>
<td>9.90</td>
<td>6.60</td>
<td>3.30</td>
<td>(0.46)</td>
</tr>
<tr>
<td></td>
<td>College</td>
<td>2.95</td>
<td>3.73</td>
<td>2.29</td>
<td>1.44</td>
<td>(0.21)</td>
</tr>
<tr>
<td></td>
<td>Post college</td>
<td>2.27</td>
<td>2.71</td>
<td>1.90</td>
<td>0.81</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Exp: 16-40 years</td>
<td>Diploma</td>
<td>5.46</td>
<td>6.74</td>
<td>4.37</td>
<td>2.37</td>
<td>(0.35)</td>
</tr>
<tr>
<td></td>
<td>College</td>
<td>3.26</td>
<td>4.10</td>
<td>2.55</td>
<td>1.55</td>
<td>(0.25)</td>
</tr>
<tr>
<td></td>
<td>Post college</td>
<td>2.34</td>
<td>2.84</td>
<td>1.93</td>
<td>0.91</td>
<td>(0.21)</td>
</tr>
</tbody>
</table>
ridge curve. Columns 2, 3 and 4 report, respectively, conditional unemployment rates in bad times, good times and their difference. State-spreads are also monotonically decreasing in the educational attainment - about 3% for diploma holders and less than 1% for post-college holders - statistically significant at the 1% level and patterns are robust when controlling for work experience.\textsuperscript{12}

Taken together, this evidence indicates that longer investments in education made before entering the U.S. labour market provide an hedge to workers against unemployment risk. This has twofold implications. On the one hand, at any point in time the human capital holdings of highly educated workers are less risky than those of low educated ones. On the other hand, it is in bad times that highly educated workers gain the most relative to low educated workers, as the increase in the riskiness of human capital they experience is less pronounced.

Table 3 reports cross-sectional mean difference tests, that is tests for differences in means along rows of Table 2. Mean differences are in percentage, associated standard errors are in parenthesis. Panel I tests educational mean spreads conditioning on work experience (Column 1: Diploma versus College; Column 2: College versus Post College); Panel II tests experience mean spreads conditioning on education (Column 1: 1-5 versus 6-15 years; Column 2: 6-15 versus 16-40 years); all tests are conditional on a time-dimension (i.e., bad/good state, all periods). Spreads in Panel I correspond to the “employment premium” (Equation 5, Term a).\textsuperscript{13}

All differences in Panel I except one are statistically significant at the 1% level, indicating that highly educated workers are always better off relative to low educated

\textsuperscript{12}Standard errors of these time-series mean difference tests are reported in parenthesis in Column 5.

\textsuperscript{13}Panel I tests the “employment premium”, as an increase in the unemployment rate of diploma holders relative to college holders is equivalent to an increase in the employment rate of college holders relative to diploma holders, that is $(1 - \theta_{t}^{c-1}) - (1 - \theta_{t}^{c}) = \theta_{t}^{c} - \theta_{t}^{c-1}$.
Table 3  
Average Unemployment Rates: Cross-Sectional Mean Difference Tests

This table reports cross-sectional (along rows) mean ($\mu$) difference tests for average unemployment rates reported in Table 2. For each test, the table shows the difference in means (in percentage) and the standard error of this difference (in parenthesis). Tests in Panel I are for Diploma over College holders (Column 1) and College over Post College holders (Column 2) and are conditional on years of working experience (all years/1-5 years/6-15 years/16-40 years). Tests in Panel II are for workers with 1-5 over 6-15 years of work experience (Column 1) and 6-15 over 16-40 years of working experience (Column 2) and are conditional on the educational attainment (Diploma, College, Post College). The unemployment rate is defined as the ratio of the unemployed workers to the labour force. The bad (good) state refers to quarters in which the job posting index by Barnichon (2010) is below (above or equal to) its standardized mean. Data are from monthly samples of the CPS Outgoing Rotation Group. Quarterly series are obtained as the last month of each quarter. The sample period is 1979:Q1-2014:Q4.

Panel I: Conditioning On Work Experience

<table>
<thead>
<tr>
<th>Work Experience</th>
<th>(1) $\mu_{\text{Diploma}} - \mu_{\text{College}}$</th>
<th>(2) $\mu_{\text{College}} - \mu_{\text{PostCollege}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bad</td>
<td>Good</td>
</tr>
<tr>
<td>All years</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4.61</td>
<td>3.34</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>1-5 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>10.06</td>
<td>7.83</td>
</tr>
<tr>
<td></td>
<td>(0.71)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>6-15 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>6.16</td>
<td>4.30</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>16-40 years</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.64</td>
<td>1.82</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.18)</td>
</tr>
</tbody>
</table>

Panel II: Conditioning on Education

<table>
<thead>
<tr>
<th>Education</th>
<th>(1) $\mu^{(1-5)} - \mu^{(6-15)}$</th>
<th>(2) $\mu^{(6-15)} - \mu^{(16-40)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bad</td>
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</tr>
<tr>
<td>Diploma</td>
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<tr>
<td></td>
<td>4.55</td>
<td>3.86</td>
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<td></td>
<td>(0.78)</td>
<td>(0.44)</td>
</tr>
<tr>
<td>College</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.66</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Post College</td>
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<tr>
<td></td>
<td>0.48</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td>(0.21)</td>
</tr>
</tbody>
</table>
workers with similar work experience. Findings in Panel II depend on the educational attainment of the worker. For workers that enter the labour market with a diploma the exposure to unemployment risk is decreasing in work experience, while for highly educated ones most of the insurance comes from their prior educational investment.

Although the educational spread - the difference between diploma and post-college holders - is diminishing in work experience, the labour market “employment premium” is mainly compensation for holding human capital in the form of education rather than work experience. As Table 2 shows, the average unemployment rate for a worker with high experience and low education is always greater than the average unemployment rate for a worker with low experience and high education.

The take-away of this exercise is twofold. First, U.S. highly educated workers are always less constrained than U.S. low educated workers, as their human capital holdings are less risky. Second, the U.S. labour market rewards educational investments in proportion to the investment made: The longer the time spent in education, the greater the hedge against unemployment risk.

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14 The difference in average unemployment rates between junior diploma and college holder is only marginally significant.
15 For both college and post-college workers the decrease in unemployment probability is very small in magnitude (around 0.5%) when their work experience increase from 1-5 years to 6-15 years, and not statistically significant in their maturity.
4.2 Dissecting Human Returns Over Time

For each representative investor (diploma/college/post college holder), I construct quarterly time-series of the four return components in Equation 5. In the following, I present time-series evidence on each term. I start dissecting the returns to human capital, \( r_{t+1} \).

The first term, log changes in wages (Term d), captures the growth rate of human capital cash-flows over time (Figure 3 - Panel A). The second term, log changes in employment shares (Term b), quantifies the extent to which the unemployment risk associated to those gains varies over time (Figure 3 - Panel B).

**Log changes in wages (d).** Over the last 35 years, the monetary cumulated returns to human capital amount to about 15% for post college holders, 12% for college holders and only 4% for diploma holders. Series are highly correlated to each other - the pairwise correlations is about 0.85 for diploma and post-college holders and above 0.9 for all other workers - indicating that labour market shocks tend to affect all wages simultaneously, regardless the education of the worker. All series show a downward pattern at the beginning of the sample due to negative shocks to wages stemming from the 1980 recession, a steady increase in the ’90s and another downward trend in the final part of the sample, though more pronounced for low educated workers. Cycles reveal that fluctuations have been historically more marked for highly educated workers. This indicates that their wages are higher, but also more volatile.

**Log changes in employment rates (b).** As pointed out by Table 2, swings in the exposure to unemployment risk are more severe the less the worker is educated. Table 4 corroborates this finding by regressing quarterly log changes in educational employment rates on a constant and the log change in either the aggregate U.S. unemployment rate (Panel I) or the U.S. industrial production index (Panel II). A 1% increase in the former is associated to a more than proportional decline in the employment rate of diploma holders (-1.53%), but a less than proportional decline for both college and post-college
Figure 3
Cumulated Log Changes In Wages And Employment Rates By Educational Attainment

This figure shows the time-series of the cumulated percentage growth in wages (left graph) and employment rates (right graph) for diploma (blue line), college (red dashed line) and post-college holders (green circle line). The employment rate is the ratio of employed workers to the labour force conditional on a given educational attainment $e$ and is expressed in log-form. The wage growth is estimated via propensity score weighting at the quarterly frequency. Wages are expressed in real terms. Shaded areas represent NBER recessions. Data are from monthly samples of the CPS Outgoing Rotation Group. Quarterly series for employment rates are obtained as the last month of each quarter. The sample period is 1979:Q1-2014:Q4.

Panel A - Wages
$\sum_{t=1}^{T-1} (w_{t+1}^e - w_t^e)$

Panel B - Employment
$\sum_{t=1}^{T-1} (\theta_{t+1}^e - \theta_t^e)$
holders (-0.60% and -0.44%, respectively). Similarly, a 1% quarterly increase in the latter is associated to a 0.35% (0.11%) increase in the employment rate of diploma (college) holders and a positive but not significant increase for post-college holders (0.06%). Overall, this indicates that highly educated workers have been historically less exposed to business-cycle fluctuations, though Figure 3 points out that in the last two recessions they have also suffered more than in the past.

Table 4
Business Cycle Exposure

This table shows coefficients and associated Newey-West t-statistics obtained by regressing returns to human capital earned by diploma, college and post college holders on a constant and either the log change in the U.S. aggregate unemployment rate (Panel I) or the log change in the U.S. industrial production index (Panel II). Returns are defined as the sum of log changes in employment rates ($\theta_{t+1} - \theta_t$) and log changes in wages ($w_{t+1} - w_t$). These components are examined, separately, in the second and third column. Series are quarterly.

$$r_{t+1}^e = \alpha + \beta X_{t+1} + \epsilon_{t+1}$$

<table>
<thead>
<tr>
<th></th>
<th>$r_{t+1}^e$</th>
<th>$\theta_{t+1} - \theta_t^e$</th>
<th>$w_{t+1} - w_t^e$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha$</td>
<td>$\beta$ t(\alpha) t(\beta)</td>
<td>$\alpha$ $\beta$ t(\alpha) t(\beta)</td>
</tr>
<tr>
<td>Diploma</td>
<td>0.01</td>
<td>-1.59 0.21 -5.55</td>
<td>-0.02 -1.53 -0.41 -4.71</td>
</tr>
<tr>
<td>College</td>
<td>0.09</td>
<td>-0.38 1.12 -1.75</td>
<td>-0.01 -0.60 -0.24 -2.52</td>
</tr>
<tr>
<td>Post College</td>
<td>0.10</td>
<td>-0.13 1.23 -0.34</td>
<td>-0.01 -0.44 -0.19 -3.12</td>
</tr>
<tr>
<td>Diploma</td>
<td>-0.11</td>
<td>0.33 1.10 4.08</td>
<td>-0.16 0.35 -1.89 3.84</td>
</tr>
<tr>
<td>College</td>
<td>0.05</td>
<td>0.11 0.62 1.49</td>
<td>-0.05 0.11 -1.05 2.55</td>
</tr>
<tr>
<td>Post College</td>
<td>0.09</td>
<td>0.03 0.89 0.27</td>
<td>-0.03 0.06 -0.76 1.41</td>
</tr>
</tbody>
</table>

Log changes in the employment rate of diploma holders anticipate those of other workers, but not vice versa. A 1% quarterly increase in the former is followed by a significant 0.2% increase experienced by both college and post-college workers in the next quarter. This points to a structure in the transmission of labour market shocks to employment: Low educated workers are hit at first and shocks subsequently reach the highly educated ones.\(^{16}\)

\(^{16}\)Changes in the employment rate of college holders do not anticipate changes in the employment
I now present evidence on the other two components of the returns to education defined in Equation 5 - employment premia (Term a) and wage premia (Term c) - that capture relative differences between the three representative workers at a given point in time.

**Employment premia (a).** Figure 4 - Panel A shows the time-series of the unemployment rates of diploma, college and post-college holders. The full sample pairwise correlation is 0.86 for diploma-college holders, 0.82 for college-post college holders and 0.73 for diploma-post college holders. Co-movements are stronger in bad than good labour market states indicating that labour market shocks are aggregate shocks in those states.\(^{17}\) Put differently, unemployment risk is aggregate risk in the bad state.

Panels B and C present the time-series of the employment premium for college and post college holders, respectively. The employment premium is the log difference in quarterly employment rates between workers holding a college degree (post college degree) and those holding a diploma (college degree) in a given quarter. Shaded areas represent bad times for the labour market.

Employment premia are time-varying: They widen in bad times and shrink in good times. The college employment premium is about 4% on average - 4.5% in bad times and 3.3% in good times - and positive in all quarters of the sample, indicating that college holders have been systematically better off relative to diploma holders.

The post-college employment premium is smaller, about 0.8% on average - 1.2% in bad times and 0.5% in good times - consistent with the hypothesis of diminishing marginal returns to scale to further education. Like wages, also the employment insurance is an increasing function of the educational attainment, but is decreasing in

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\(^{17}\)Pairwise correlations between diploma-college, college-post college and diploma-post college holders are, respectively, 0.82, 0.81 and 0.69 in the bad labour market state and 0.77, 0.72 and 0.58 in the good state.
Figure 4
College and Post-College Employment Premia

This figure shows the time-series of the educational unemployment rates (Panel A) and the time-series of the employment premia for college and post college holders (Panel B and C, respectively). The educational unemployment rate is the unemployment rate conditional on the educational attainment $e$, that is diploma, college or post-college degree. The employment premium, $\theta^e_t - \theta^{e-1}_t$, is the log difference in employment rates between workers holding a college degree (post college degree) and those holding a diploma (college degree). All series are in percentage. Shaded areas represent NBER recessions in Panel A and bad labour market times in Panels B and C. Bad times for the labour market are periods in which the job posting index by Barnichon (2010) is above its standardized mean. Data are from monthly samples of the CPS Outgoing Rotation Group. Quarterly series are obtained as the last month of each quarter. The sample period is 1979:Q1-2014:Q4.
magnitude at the margin (i.e. for any additional unit of education). Although post-college workers are historically better off relative to diploma workers, the post-college premium is zero or even negative (up to -0.8%) in 14% of the quarters indicating that post-college workers can be worse off relative to college workers. This evidence, however, does not affect the novel informational content of the post-college premium. First, the post-college premium in the good state is statistically different from the post college premium in the bad state and both premia are statistically different from zero (Table 3). Second, 98% of those observations fall in the good labour market state that is quarters in which unemployment risk is not aggregate risk.

Employment premia predict each other. A 1% increase in the college (post college) premium anticipates a 0.25% (0.85%) increase in the post college (college) premium in the next quarter. Both effects are statistically significant (Newey-West standard errors).

**Wage premia (c).** For descriptive purposes, I start defining a representative worker as a median wage earner. Figure 5 - Panel A shows the time-series of median real weekly earnings in U.S. dollars for representative diploma, college and post college holders. As widely documented, wages are historically an increasing function of the educational attainment. Earnings of diploma holders have been relatively stable over time, while those of both college and post college holders have been rising. These gains are not a free lunch, though, as they have come at the cost of greater volatility: Median earnings of post college holders are historically about 3.5 times more volatile than those of diploma holders.\(^{18}\) From an economic perspective, this suggests that labour market shocks transmitted to wages are more severe for workers earning wages at the top rather than

\(^{18}\)The full sample standard deviations of diploma, college and post college holders are 31.55, 78.37 and 113.55 U.S. dollars, respectively.
at the bottom of the wage distribution. In financial terms, this indicates that expected human capital payoffs of highly educated workers are not only higher, but also riskier.

Panel B shows the time-series of the college and post college wage premia estimated via propensity score weighting. As discussed in Section 3.1, this technique accounts for the heterogeneity of the individuals in the sample by assigning individual weights. Both wage premia are positive consistent with the hypothesis of diminishing marginal returns to education. On average, a college (post college) holder has earned 44% (16%) more than a diploma (college) holder over the last 35 years. Overall, both premia steadily increased in the ’80s, dropped in the ’90s and rose again in the next 15 years, though the college premium at a much lower pace than in the past. Trends are very pronounced for college earners - their premium rose from about 35% to about 50% just in the first part of the sample - while swings are moderate for post college earners - their variation is historically bounded between 10% and 20%. Though the contemporaneous correlation in wage premia is moderate, about 0.37, they predict each other: A 1% increase in the college (post-college) premium anticipates a 0.15% (1.15%) increase in the post college (college) premium next period.\textsuperscript{19}

I obtain quarterly time-series of returns to human capital, $r_{t+1}^e$ (Equation 2), and returns to education, $r_{t+1}^{se}$ (Equation 5), by aggregating the time-series of these four components. I discuss evidence in the next section.

\textsuperscript{19}Predictive coefficients are statistically significant at the 1% level (Newey-West standard errors).
This figure shows the time-series of median real weekly earnings (in U.S. dollars) for diploma, college and post college holders (Panel A) and the time-series of the estimated wage premia (i.e., $w_t^c - w_t^{c-1}$, in percentage) for college and post college holders (Panel B). Wage premia, namely log differences in real wages between workers holding a college degree (post college degree) and those holding a diploma (college degree), are estimated via propensity score weighting. Shaded areas represent NBER recessions in Panel A and bad labour market times in Panels B. Bad times for the labour market are periods in which the job posting index by Barnichon (2010) is above its standardized mean. Data are from monthly samples of the CPS Outgoing Rotation Group. All series are computed at the quarterly frequency. The sample period is 1979:Q1-2014:Q4.
4.3 Cash-Flow Versus Risk-Adjusted Return Measures

Figure 6 compares the quarterly time-series of the cumulated returns to human capital earned by the three representative investors. Returns are defined either as the growth rate of wages or by augmenting this term by the growth rate of employment shares. The former is a cash-flow return measure of human capital that captures fluctuations in wages of employed workers. The latter is a risk-adjusted return measure that adjusts those fluctuations by the unemployment risk borne by employed workers over the same horizon. Since employment shares are a decreasing function of the unemployment shares, an increase in unemployment risk translates into a lower return.

Both measures indicate that human capital returns are increasing in the educational attainment, but accounting for risk alters the inference about gains/losses experienced by human capital holders over time. Since wages are sticky, cash-flow return measures account for negative labour market shocks only with a delay. The graph shows that wages have the tendency to fall after recession periods, while a rise in unemployment signals a deterioration of business cycle conditions in real time. Unemployment is key, as the possibility of experiencing a labour income drop in recession is mainly due to risk of losing the job/not finding a job in the near future, rather than being affected by a future change in the wage distribution in the economy (secondary effect).

As revealed by time-series patterns, differences between the risk-adjusted return measure and the cash-flow measure are less pronounced the more the worker is educated and widen in bad times. The correlation between the two measures is negative after recessions as wages are falling while employment is rising relative to the recent past. Since highly educated workers have historically experienced a minimal exposure to business cycle conditions, the spread between their two measures is tiny.

Figure 7 shows the quarterly time-series of returns to education earned by a college (post-college) holder relative to a diploma (college) holder. Cash-flow (dashed line)
Figure 6
Cumulated Human Capital Measures

This figure compares the time-series of cumulated quarterly growth in wages ($r^W_e$, dashed lines) with their unemployment-adjusted counterparts ($r^{W+Emp}_e$, solid line). Both measures are computed for three U.S. representative human capital holders: A diploma holder (blue line), a college holder (red line) and a post college holder (green line). The unemployment-adjusted measure is obtained as the sum of growth in wages and growth in employment shares. Measures are in percentage. Shaded areas denote NBER recessions. Data are from monthly samples of the CPS Outgoing Rotation Group. The sample period is 1979:Q1-2014:Q4.
and risk-adjusted (solid line) return measures are compared as above. Human capital return measures indicate that all workers are worse off in bad times relative to good time, as higher exposure to unemployment risk translates into a drop in returns. Return to education measures point out that there are relative gains in the economy at any point in time, as highly educated workers are always better off relative to low educated ones.

In the United States, education provides benefits through two channels: Higher cash-flows (wages) and lower risk (unemployment probability). This implies that the traditional economic measure of human capital returns, the wage premia, underestimates the overall gains in the U.S. economy, regardless the estimation technique used to quantify it. From an economic perspective, the traditional definition of “skill premium” should also be richer in content, as benefits come from two major sources. From a financial perspective, the take-away is that agents should invest in education not only to maximize their expected human wealth, but also to minimize their unemployment risk. The former is a cash-flow story for an educational investment, the latter is a discount rate one. When educational human capital is invested in the U.S. labour market, investing in education is like shopping for hedging instruments. The longer the time spent in education, the more expensive the instrument, but the greater the insurance provided by the labour market.

In the next section, I investigate the implications of these findings for asset prices by relating differential exposure to unemployment risk to heterogeneous financial investment behaviour.

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20Mean difference tests reported in the Online Appendix indicate that cash-flow and risk-adjusted return measures are statistically different from each other confirming that the employment premium has informational content even after adjusting for log changes in employment shares.
Figure 7
Cash-Flow Versus Risk-Adjusted Measures Of Returns To Education

This figure compares the time-series of cash-flow (dashed line) and risk-adjusted (solid line) measures of returns to education earned by a college holder relative to a diploma holder (top graph) and by a post-college holder relative to a college holder (bottom graph). The cash-flow measure is growth rate of relative wages. The risk-adjusted measure is sum of growth rate of relative wages and growth rate of relative employment shares. Shaded areas represent NBER recessions. Returns are quarterly and in percentage. The sample period is 1979:Q1-2014:Q4.
4.4 Unemployment Risk And Industry-Level Asset Prices

The evidence discussed in the previous section points to human capital being riskier for low educated workers than highly educated ones due to a more pronounced drop in labour income in bad times. The riskiness of human capital, at least at aggregate level, is mainly attributable to the unemployment component of U-adjusted labour income rather than the wage component. These findings have at least two implications for financial assets.

First, if unemployment is a source of systematic risk, this risk should be priced in financial markets.

Second, differential exposure to unemployment risk points to heterogeneous financial investment behaviour. Agents who are highly exposed to changes in labour market conditions should primarily invest in financial markets to hedge their exposure to labour income risk, that is picking assets that perform well when they are more likely to lose their jobs. Agents facing mild exposure to labour market cycles, instead, should be willing to invest beyond hedging purpose, bearing the risk of a poor performance of their financial assets in bad labour market states. Using the terminology by Bodie et al. (1992), human capital holders are income-constrained financial investors. Since agents cannot sell their human capital in bad times, exposure to labour income risk "constrains" their financial investment decisions. The evidence discussed above points to low (highly) educated workers being "highly" ("weakly") income-constrained financial investors and intuitively closer to the former (latter) type of financial investment behaviour.

I investigate the extent to which these two implications hold empirically.

Employment factor, $F_{t, \text{Emp}}$. As a first step, I define a macroeconomic factor that captures time-varying heterogeneity in the exposure to unemployment risk in the U.S. labour market. I build this factor in a standard "high-minus-low" fashion by taking
the difference in the unemployment component of U-adjusted labour income growth experienced by the two extreme types of workers in the economy. At each time $t+1$, the employment factor $F_{t+1}^{Emp}$ is given by:

$$F_{t+1}^{Emp} = (\theta_{t+1}^{PC} - \theta_t^{PC}) - (\theta_{t+1}^{D} - \theta_t^{D}),$$

where $\theta_{t+1}^{e} - \theta_t^{e}$ denotes the growth rate in the employment probability of $e$-type worker and PC and D denote a representative post-college and diploma holder, respectively. $F_{t+1}^{Emp}$ captures relative changes in the exposure to “downside risk” experienced by heterogeneous agents in the U.S. labour market. An increase in $F_{t+1}^{Emp}$ can be interpreted as the low educated worker being more exposed to downside risk than the low educated worker over the quarter, having experienced a higher probability of being unemployed. Equivalently, the highly-educated worker being better off relative to the low educated worker over the quarter, having experienced a lower probability of being unemployed.

The time-series of $F_{t+1}^{Emp}$ is well behaved and tends to be positive at the beginning of each NBER recession and negative afterwards consistent with the evidence discussed in the previous section. A simple variance decomposition attributes 27% of its variation to the first term (highly educated worker) and 70% to the second term (low educated worker).

**Industry-level risk-premia.** As a second step in relating heterogeneous exposure to unemployment risk to asset prices, I use $F_{t+1}^{Emp}$ in standard asset pricing exercises. Test assets are 30 Fama-French U.S. industry portfolios, a challenging set of test assets, but also a natural place to start when macroeconomic uncertainty is the source of systematic risk to price.

As a preliminary exercise, I estimate a single factor model on each test asset using either the excess return on the aggregate U.S. stock market or $F_{t+1}^{Emp}$ as risk factor. Figure 8 reports the average excess return on each test asset (y-axis, in percentage) against its unconditional employment-beta, $\hat{\beta}^{Emp}$, in the top panel and the CAPM-beta,
in the bottom panel. The relationship between employment-betas and average excess returns is positive and the spread in unconditional employment-betas is large ranging from about -1.3 to 0.5. The spread in unconditional market betas, instead, is bounded between 0.5 and less than 1.4. Consistent with standard asset pricing theory, industries that have low exposure to \( F_{t+1}^{Emp} \) earn low risk premia on average and industries that have high exposure to \( F_{t+1}^{Emp} \) earn high risk premia on average. Taken together, these two panels indicate that \( F_{t+1}^{Emp} \) captures a source of risk other than pure aggregate market risk.

As a more formal exercise, I sort test assets into portfolios based on their time-varying \( \hat{\beta}_{t}^{Emp} \)-exposure, controlling for the market factor. The goal of this exercise is twofold. On the one hand, this is a test for unemployment risk being a source of systematic risk. Under the null, the sorted portfolios should reveal a significant risk premium. On the other hand, this is a way to investigate whether there exists a combination of industry-level traded assets that can replicate differential exposure to unemployment risk. This boils down to build a factor mimicking portfolio for the macroeconomic factor \( F_{t+1}^{Emp} \).

At each time \( t \) and for each test asset \( i \), I estimate the following regression over a rolling window of 20 quarters (about 5 years):

\[
r_{i}^{t} = \alpha_{i}^{t} + \beta_{Mkt}^{i} Mkt_{t} + \beta_{Emp}^{i} F_{t+1}^{Emp} + \epsilon_{i}^{t},
\]

where \( r_{i}^{t} \) denotes the excess return on industry-\( i \) between time \( t-1 \) and time \( t \), \( \alpha \) is a constant, \( Mkt_{t} \) is the Fama-French U.S. market factor and \( F_{t+1}^{Emp} \) is the employment factor. All variables are quarterly and defined over the same investment horizon.

In each window, I allocate test assets into 4 portfolios according to their estimated exposure to \( F_{t+1}^{Emp} \) (henceforth \( \hat{\beta}_{t}^{Emp} \)). Low-\( \hat{\beta}_{t}^{Emp} \) industries fall in Portfolio 1, high-\( \hat{\beta}_{t}^{Emp} \) industries fall in Portfolio 4. In assigning industries to portfolios, I use the quartiles of the distribution of \( \hat{\beta}_{t}^{Emp} \).
Figure 8
Unemployment Risk vs Aggregate Market Risk

This figure plots industry-level average excess returns (in percentage) against their unconditional market betas in the top graph and their unconditional employment betas in the bottom graph. Risk exposure is measured by estimating a one-factor model, that is by regressing the excess return on industry- on a constant and either the Fama-French U.S. market factor or the employment factor . Test assets are U.S. industry portfolios from Kenneth French’s website. is growth in quarterly employment rates of post college holders minus growth in quarterly employment rates of diploma holders. (i.e., ). The sample period is 1979Q1-2014Q4.
Figure 9 - Panel A plots average excess returns on these four sorted portfolios (annualized and in percentage terms) against their average time-varying employment betas. Returns do monotonically line up with their risk exposure. From Portfolio 1 to Portfolio 4, average betas vary from -1.05 to 1.22 and annualized average excess returns monotonically increase from 4.83% to 8.89%. High-$\hat{\beta}_{Emp}$ industries – industries that covary positively with $F_{t}^{Emp}$ – earn high risk-premia on average, and low-$\hat{\beta}_{Emp}$ industries – industries that covary negatively with $F_{t}^{Emp}$ – earn low risk-premia on average. Differential exposure to unemployment risk is priced at industry level. A standard long-short strategy, long in high-$\hat{\beta}_{Emp}$ industries and short in low-$\hat{\beta}_{Emp}$ industries, has yielded on average a statistically significant premium of about 4% over the last 35 years.

Figure 9 - Panel B shows that aggregate market risk is not priced at industry-level. When sorting test assets by their time-varying market betas $\hat{\beta}_{t}^{Mkt}$ estimated via Equation (8), the spread in average betas is minimal - bounded between 0.54 and 1.44 - and the resulting cross-section of average excess returns is almost flat and does not command any risk-premium. These findings corroborate the evidence in Figure 8 and confirm $F_{t}^{Emp}$ captures a source of systematic risk beyond aggregate market risk.

Table 5 reports risk-premia and average time-varying employment betas conditioning on subsamples. For completeness, Panel A shows descriptive statistics for the full sample period. Panel B and Panel C jointly reveal that risk-premia are driven by bad labour market states. Returns do monotonically line up with their risk exposure in both states, but the average return-spread is only 2% and is not statistically significant in the good state, while it widens up to 6.7% in the bad state. In bad times, low-$\hat{\beta}_{Emp}$ industries earn on average about 3%, while high-$\hat{\beta}_{Emp}$ industries earn on average about 9.6%. As documented in Table 2, in these quarters all types of agents face a higher probability of being unemployed. Unemployment risk is thus systematic risk and this risk exposure is priced in the U.S. equity market at industry level. Panel D shows that NBER recessions, a subsample of the bad labour market state, are not the key
Figure 9
Industry-Level Sorted Portfolios
This figure plots the cross-section of average excess returns on industry-level sorted portfolio against their average betas. Time-varying loadings are estimated by regressing industry-i excess returns on a constant, the Fama-French U.S. market factor and $F_{t}^{Emp}$ over rolling windows of 20 quarters. In each window, test assets are sorted into four portfolios by their time-varying exposure to either the employment factor $F_{t}^{Emp}$ (Panel A) or the Fama-French U.S. market factor (Panel B). Test assets are 30 U.S. industry portfolios from Kenneth French’s website. $F_{t}^{Emp}$ is growth in quarterly employment rates of post college holders minus growth in quarterly employment rates of diploma holders. (i.e., $F_{t+1}^{Emp} = (\theta_{t+1}^{PC} - \theta_{t}^{PC}) - (\theta_{t+1}^{D} - \theta_{t}^{D})$). The sample period is 1979Q1-2014Q4.

Panel A: $\hat{\beta}_{t}^{Emp}$-sorted portfolios

Panel B: $\hat{\beta}_{t}^{Mkt}$-sorted portfolios
driver. In these quarters, average excess returns on all sorted-portfolios are negative. Finally, Panel E shows that the return-spread between the top and the bottom portfolio increases up to 11% in the post-2007 period, but average returns on the four sorted portfolios do not monotonically line up. This indicates that the risk-premia are not merely compensation for the risk exposure borne by workers over the recent Great Recession. Interestingly, a simple comparison of the distribution of average $\hat{\beta}^{Emp}$ loadings across panels confirm that risk-exposure is time-varying.

**Low-$\hat{\beta}^{Emp}$ vs. high-$\hat{\beta}^{Emp}$ industries.** Is there any clear mapping between industries and sorted portfolios? Figure 10 addresses this question by reporting details about industry turnover rates, that is the percentage of quarters (out of 123) any industry falls in a given portfolio. Industries are ranked from top to bottom according to their likelihood of being low-$\hat{\beta}^{Emp}$ industries. Turnover rates are high, as any industry spans all four sorted portfolios over the sample period. This points again to pronounced time-variation in $\hat{\beta}^{Emp}$-exposure over time. Patterns do emerge, though. Coal, Telecommunication, Oil and Utilities are typical low-$\hat{\beta}^{Emp}$ industries falling about 50% of the quarters in Portfolio 1, while Smoke, Clothes and Beer are typical high-$\hat{\beta}^{Emp}$ industries falling about 50% of the quarters in Portfolio 4. Consumer Goods, Meals, Food and Construction resemble more high-$\hat{\beta}^{Emp}$ industries than low-$\hat{\beta}^{Emp}$ industries, falling more than 60% of the quarters in the two top portfolios, while the opposite conclusion holds for Financials, Wholesale and Other industries.

One potential explanation for these patterns is that time-variation in the employment-betas is driven by labour market states. To test whether industries are more likely to fall in a given portfolio in bad than good times, I run paired t-tests conditioning on any given sorted-portfolio. For each industry $i$, I first compute the probability that $i$ falls in portfolio $j$ conditioning on the economy being in either good ($p_{i}^{Good}$) or bad ($p_{i}^{Bad}$) labour market states and then test the average difference between these two probabilities across industries. Under the null, turnover rates are not driven by labour market
Table 5  
Industry-Level Risk-Premia By States

This table reports means ($\mu$), t-statistics (in brackets) and average exposure ($\bar{\beta}^{Emp}_t$) of four portfolios of industry-level stocks sorted by their time-varying exposure to the employment factor $F^{Emp}_{t+1}$. Descriptive statistics in Panel A refer to the full sample period, results in Panels B to E are obtained conditioning on: The bad and good labour market state, NBER recessions and the post-2007 sample. The number of quarters $T$ in each subsample is reported at the top of each panel. The last column refers to an investor that goes long Portfolio 4 (P4) and short Portfolio 1 (P1). For each test asset, time-varying loadings are estimated by regressing industry-$i$ excess returns on a constant, the Fama-French U.S. market factor and $F^{Emp}_{t+1}$ over rolling windows of 20 quarters. Test assets are 30 U.S. industry portfolios from Kenneth French’s website. $F^{Emp}_{t+1}$ is growth in quarterly employment rates of post college holders minus growth in quarterly employment rates of diploma holders. (i.e., $F^{Emp}_{t+1} = (\theta^{PC}_{t+1} - \theta^{PC}_{t}) - (\theta^{D}_{t+1} - \theta^{D}_{t})$). The sample period is 1979Q1-2014Q4.

<table>
<thead>
<tr>
<th>Portfolios</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P4-P1</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Full sample (T=123)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>4.83</td>
<td>6.18</td>
<td>7.25</td>
<td>8.73</td>
<td>3.90</td>
</tr>
<tr>
<td>[1.33]</td>
<td>[1.82]</td>
<td>[2.25]</td>
<td>[2.85]</td>
<td>[1.98]</td>
<td></td>
</tr>
<tr>
<td>$\bar{\beta}^{Emp}_t$</td>
<td>-1.05</td>
<td>-0.10</td>
<td>0.45</td>
<td>1.33</td>
<td></td>
</tr>
<tr>
<td>B: Bad state (T=50)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>2.91</td>
<td>5.79</td>
<td>6.76</td>
<td>9.57</td>
<td>6.66</td>
</tr>
<tr>
<td>[0.42]</td>
<td>[0.88]</td>
<td>[1.18]</td>
<td>[1.68]</td>
<td>[2.03]</td>
<td></td>
</tr>
<tr>
<td>$\bar{\beta}^{Emp}_t$</td>
<td>-1.15</td>
<td>-0.13</td>
<td>0.49</td>
<td>1.48</td>
<td></td>
</tr>
<tr>
<td>C: Good state (T=73)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>6.15</td>
<td>6.45</td>
<td>7.59</td>
<td>8.16</td>
<td>2.01</td>
</tr>
<tr>
<td>[1.58]</td>
<td>[1.81]</td>
<td>[2.01]</td>
<td>[2.40]</td>
<td>[0.83]</td>
<td></td>
</tr>
<tr>
<td>$\bar{\beta}^{Emp}_t$</td>
<td>-0.97</td>
<td>-0.08</td>
<td>0.42</td>
<td>1.23</td>
<td></td>
</tr>
<tr>
<td>D: NBER recessions (T=14)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>-24.49</td>
<td>-16.57</td>
<td>-16.40</td>
<td>-13.24</td>
<td>11.26</td>
</tr>
<tr>
<td>[-1.35]</td>
<td>[-1.02]</td>
<td>[-1.09]</td>
<td>[-0.96]</td>
<td>[1.31]</td>
<td></td>
</tr>
<tr>
<td>$\bar{\beta}^{Emp}_t$</td>
<td>-1.52</td>
<td>-0.37</td>
<td>0.23</td>
<td>1.25</td>
<td></td>
</tr>
<tr>
<td>E: Post-2007 (T=32)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu$</td>
<td>-0.39</td>
<td>8.60</td>
<td>5.75</td>
<td>10.72</td>
<td>11.11</td>
</tr>
<tr>
<td>[-0.04]</td>
<td>[1.10]</td>
<td>[0.75]</td>
<td>[1.65]</td>
<td>[2.27]</td>
<td></td>
</tr>
<tr>
<td>$\bar{\beta}^{Emp}_t$</td>
<td>-1.03</td>
<td>-0.25</td>
<td>0.19</td>
<td>0.89</td>
<td></td>
</tr>
</tbody>
</table>
cycles, that is $H_0: \bar{p}_i^{BAD} - \bar{p}_i^{GOOD} = 0$.

Results are reported in Table 6. Overall, there is weak support in favour of the null hypothesis. The difference in state probabilities is not statistically significant in Portfolio 1, and it is significant, but small in magnitude in all other sorted portfolios. On average, industries have about a 60% (40%) chance to fall in portfolios other than 1 in good (bad) times, thus implying a minimal state-spread of about 20%.

Figure 10

Low-$\hat{\beta}^{Emp}$ vs. High-$\hat{\beta}^{Emp}$ industries: Turnover Rates

This figure shows industry turnover rates for $\hat{\beta}^{Emp}$-sorted portfolios, that is the percentage of quarters (out of 123) each industry falls in any of the four $\hat{\beta}^{Emp}$-sorted portfolios. Industries are ranked from top to bottom according to their likelihood of being low-$\hat{\beta}^{Emp}$ industries (Portfolio 1). Test assets are 30 U.S. industry portfolios from Kenneth French’s website. $\hat{\beta}^{Emp}$ measures exposure to the employment factor $F_{t}^{Emp}$, that is growth in quarterly employment rates of post college holders minus growth in quarterly employment rates of diploma holders. (i.e., $F_{t+1}^{Emp} = (\theta_{t+1}^{PC} - \theta_{t}^{PC}) - (\theta_{t+1}^{D} - \theta_{t}^{D})$). The sample period is 1979Q1-2014Q4.
Interpreting industry-level risk-premia. On average, industries that covary positively with the employment factor earn high risk-premia, while industries that co-vary negatively with $F_{t}^{Emp}$ earn low risk-premia. Given the nature of the risk factor underlying this novel cross-section of sorted portfolios, hiring/firing decisions taken by firms should play a major role in explaining their return differentials. The explanation I bring to the table takes the perspective of the supply side of the labour market (workers), rather than the demand side (firms). More precisely, I start from the premise that agents are income-constrained financial investors: Workers take hiring/firing decisions as given and invest in financial markets, accordingly. Under this assumption, differential exposure to unemployment risk/changes in labour market conditions should translate into heterogeneous financial investment behaviour. “Highly”-income constrained financial investors (low-educated workers) should invest in financial markets mainly for hedging purposes, while “Weakly”-income constrained financial investors (highly-educated workers) should be willing to take exposure to labour income risk and demand a premium for bearing it.

<table>
<thead>
<tr>
<th>Port 1</th>
<th>Port 2</th>
<th>Port 3</th>
<th>Port 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{p}_i^{BAD}$</td>
<td>0.43</td>
<td>0.40</td>
<td>0.42</td>
</tr>
<tr>
<td>$\bar{p}_i^{GOOD}$</td>
<td>0.57</td>
<td>0.60</td>
<td>0.58</td>
</tr>
<tr>
<td>$\bar{p}_i^{BAD} - \bar{p}_i^{GOOD}$</td>
<td>-0.14</td>
<td>-0.20</td>
<td>-0.17</td>
</tr>
</tbody>
</table>

To investigate whether industry-level risk-premia reflect this behaviour, I combine two relationships, namely the employment factor $F_{t}^{Emp}$ and the average exposure of
β̂Emp-sorted portfolios 𝑗, that is \( \betâ_t^{\text{Emp},j} = Cov(r^j_t, F_t^{\text{Emp}}) \). Table 7 reveals the trade-off faced by two heterogeneous agents, H (highly-educated worker) and L (low-educated worker), who own both human and financial wealth, when investing in either High- or Low-\( \betâ\text{Emp} \) industries. For each agent, the table discriminates assets providing an hedge to labour income risk from those providing full labour income risk exposure (on average). At each point in time, hedging industries are those performing well when the agent is more likely to lose his job. Markers “+” and “-” denote good and poor asset performance, respectively. The table is filled under the assumption of an increase in \( F_t^{\text{Emp}} \), that is good performance for human wealth of H (less likely to lose his job) and poor performance for human wealth of L (more likely to lose his job).

### Table 7
Financial Versus Human Wealth

This table identifies \( \hat{\beta}^{\text{Emp}} \)-sorted portfolio of industries providing either an hedge to labour income risk or full labour income risk exposure to two representative heterogeneous workers. Worker H is highly educated (post-college degree), worker L is low educated (diploma holder). \( F_{t+1}^{\text{Emp}} \) is growth in quarterly employment rates of H minus growth in quarterly employment rates of L. An increase in \( F_t^{\text{Emp}} \) indicates good performance for human wealth of H (less likely to lose his job) and poor performance for human wealth of L (more likely to lose his job). \( j \) denotes a \( \hat{\beta}^{\text{Emp}} \)-sorted portfolio of industries.

<table>
<thead>
<tr>
<th>Worker</th>
<th>( j: ) High-( \hat{\beta}^{\text{Emp}} ) ( \text{Cov}(r^j_{t+1}, F_{t+1}^{\text{Emp}}) &gt; 0 )</th>
<th>( j: ) Low-( \hat{\beta}^{\text{Emp}} ) ( \text{Cov}(r^j_{t+1}, F_{t+1}^{\text{Emp}}) &lt; 0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>Stocks: +</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>HC: +</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>( j ) is risky</td>
<td>( j ) provides insurance</td>
</tr>
<tr>
<td>L</td>
<td>Stocks: +</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>HC: -</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>( j ) provides insurance</td>
<td>( j ) is risky</td>
</tr>
</tbody>
</table>

Table 7 reveals that High-\( \hat{\beta}^{\text{Emp}} \) industries are hedging instruments for L, as on average they perform well \( (r^j_t \uparrow) \) when he is more likely to lose his job \( (F_t^{\text{Emp}} \uparrow) \). Low-\( \hat{\beta}^{\text{Emp}} \) industries, instead, are hedging instruments for H due to a negative covariance between
returns and $F_t^{Emp}$. Both investors should not require a premium to invest in these industries, being both financial instruments providing insurance to them. Standard asset pricing theory requires risky assets to command a premium (high risk premia on average) to compensate the investor for bearing the risk of a poor performance of the financial asset in bad times. Nobody should be willing to invest in risky assets, otherwise. Contrary to this reasoning, Table 7 reveals that worker L earns a premium on average when investing for hedging purposes − high-$\hat{\beta}^{Emp}$ industries outperform on average − while worker H does not.

I argue that differences in the exposure to unemployment risk can provide a rational explanation for this evidence. Agent H is typically wealthy (Mankiw and Zeldes, (1989,1991)) and historically faces a mild exposure to unemployment risk. This agent is willing to bear the risk of a poor performance of financial assets in periods in which he is more likely to lose his job, but expects to be compensated for investing in risky assets. Despite the unemployment state is historically a low probability event for this agent, the income loss he experiences in the unemployment state is severe. For this reason, H demands a premium for bearing exposure to labour income risk. Agent L, instead, is historically highly exposed to unemployment risk. This agent is a “highly”-income constrained financial investor and invests in financial markets primarily for hedging purposes. Taken together, high-$\hat{\beta}^{Emp}$ industries earn high risk premia on average driven by the demand of risky assets of agent H, while low-$\hat{\beta}^{Emp}$ industries earn low risk premia on average, being simply insurance provider for H. This reasoning is consistent with the well documented fact that stock market participation is typically higher for H-type than L-type workers (Campbell, 2006).

$F_t^{Emp}$ vs. HML factor. The value premium, value stocks outperforming growth stocks on average, is a well documented fact in financial markets. Though the HML factor − the traded factor delivering this premium − is commonly used as a control variable in asset pricing tests since its discovery (Fama and French, 1992), the economic
mechanism underlying the success of this trading strategy is still controversial. Since labour income hedging is a recurrent theme, I run a simple exercise to investigate the extent to which my novel $\hat{\beta}_{Emp}$-based trading strategy and a standard HML strategy relate to each other.

I build an industry-level HML factor by re-estimating Equation 8. At each time $t$, I sort industry-level portfolios by their exposure to the Fama-French HML factor rather than the $F_{tEmp}$ factor. Figure 11 - Panel A compares the cumulated returns earned by an investor going long (short) industries with high (low) average exposure to the HML factor (dash-dot line) with the cumulated performance of going long (short) industries with high (low) average exposure to the employment factor $F_{tEmp}$ (solid line). Panel B shows the cumulated performance of each portfolio of industries involved in these two trading strategies.

Panel A reveals that the value-premium historically outperforms the differential-employment premium. The two premia visibly diverge in three instances: Around 1985, 1992 and 2000. In all these cases, the HML-strategy shows an upward trend, earning positive returns, while the $F_{tEmp}$-strategy is on a downward trend, yielding a loss to the investor. Panel B sheds lights on these patterns. Historically, value portfolios tend to outperform high-$\hat{\beta}_{Emp}$ portfolios, but low-$\hat{\beta}_{Emp}$ portfolios tend to outperform growth portfolios thus implying the value premium to be more pronounced than the differential-employment premium. The two trading strategies visibly share similar patterns as well. Except for the period 2000-2008, low-$\hat{\beta}_{Emp}$ portfolios and growth portfolios map each other pretty well, while high-$\hat{\beta}_{Emp}$ portfolios and value portfolios share similar trends but the former always outperforms the latter. Taken together, these two graphs indicate that the HML factor and the $F_{tEmp}$ factor capture similar, but not identical, sources of systematic risk that are priced in equity markets.
Figure 11
Industry-Level Trading Strategies: $\hat{\beta}_t^{Emp}$ Vs. $\hat{\beta}_t^{HML}$ Exposure

The left graph of this figure compares the cumulated performance of going long (short) industries with high (low) average exposure to the HML factor with the cumulated performance of going long (short) industries with high (low) average exposure to the employment factor $F_t^{Emp}$. For each test asset, exposure is estimated over rolling windows of 20 quarters controlling for aggregate market risk. In each window, test assets are sorted into four portfolios, from low to high exposure to $F_t^{Emp}$. The right graph shows the cumulated performance of each portfolio of industries involved in these two trading strategies. Test assets are 30 U.S. industry portfolios from Kenneth French’s website. $F_t^{Emp}$ is growth in quarterly employment rates of post college holders minus growth in quarterly employment rates of diploma holders. The sample period is 1979Q1-2014Q4.
5 Conclusion

This paper pins down the determinants of human wealth in the labour market starting from the simple observation that agents are human capital holder who invest their human capital in the labour market. I bring to the table a set of empirical facts suggesting that unemployment may be the main source of the human capital risk premium and may have an impact on marginal utility that goes beyond its lost-wage impact. I show that the human capital of low educated workers should be riskier than the human capital of the highly educated ones, as they experience a more severe drop in unemployment-adjusted labour income in bad times. Accounting for unemployment is key, as wages are sticky, while unemployment captures a deterioration of labour market conditions in real time. To the best of my knowledge, the role of unemployment beyond a pure cash-flow effect (wage loss) has not been explored in existent empirical asset pricing work.

My findings point to unemployment being a key driver of human capital discount rates and suggest that human capital discount rates are heterogeneous and decreasing in the endowment of human capital. These findings require theoretical foundations that I plan to provide in future work.

The evidence I provide also points to heterogeneous financial investment behaviour. Agents who are highly exposed to changes in labour marker conditions should invest in financial markets mainly for labour income hedging purposes, while agents who face mild exposure should be willing to bear the risk of a poor performance of financial assets in bad labour market states, but demand a premium for bearing it.

I document that differential exposure to unemployment risk in the U.S. labour market is priced in U.S. equity markets at industry-level. To this extent, I build a macroeconomic factor and uncover an average annualized premium of about 4% earned over the last 35 years going short industries with low exposure to my novel employment
factor and long industries with high exposure to it. These risk-premia are consistent with heterogeneous financial investment behaviour and are driven by bad labour market states, that is quarters in which unemployment risk is systematic risk, as all types of agents are more likely to lose their jobs. I provide preliminary evidence that the differential employment premium is related to the well known value-premium. I plan to investigate these patterns in detail in future work.

Overall, this set of empirical findings contributes to our understanding of human wealth and opens the door to further research on this topic.

References


