Internet Appendix for

"Time-varying Risk Premium and Unemployment Risk Across Age Groups"

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Abstract

This document provides additional results for Mitra and Xu (2019). Section A shows the mapping between labor market outcomes in economies with and without idiosyncratic mortality risk. Section B provides additional empirical results.

A Labor Market Equilibrium with Idiosyncratic Mortality Risk

In this section, we compare labor market outcomes for two similar economies, whose only difference is:

- (Economy I.) Workers are subject to idiosyncratic death shocks, which occur with probability $\chi \in (0, 1)$ each period. Conditional on receiving the death shock, a worker permanently exits the workforce and is immediately replaced by newly born workers so

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that the overall worker population remain constant. In addition, an employed worker can (exogenously) separate from their job, but not permanently exit the workforce, with probability $\widetilde{s}$.

- (Economy II.) Workers are not subject to death shocks. Employed workers (exogenously) separate from their jobs with probability s.

We show that under the textbook representative agent setting with perfect household risk sharing and complete asset markets (see, e.g., Shimer (2010)), the aggregate labor market outcome in economies I and II are identical so long as:

$$s = 1 - (1 - \chi)(1 - \widetilde{s}). \tag{IA.1}$$

That is, we could always map an economy subject to mortality risk to an equivalent economy without mortality risk by adjusting the job separation rate according to (IA.1). As the crux of the argument is independent of learning regarding match quality, for ease of exposition, we illustrate this equivalence result in the simpler textbook setting in which there is no match-specific component to output (i.e. output is simply e^z).

We start with Economy I. The representative household maximizes welfare, J_t^{rep}, which is defined over the consumption streams, C_{cit}, of all individuals i in previously born cohorts $c \leq t$,

$$\begin{aligned}
J_t^{rep} &= \max_{\Pi_{t+1}, \{C_{cit}\}} \sum_{c \leq t} \int_0^{L_{c,t}} u\left(C_{cit}\right) \, di + \mathbb{E}_t\left[J_{t+1}^{rep}\right], && \text{(IA.2)}\\
& s.t. \\
\sum_{c \leq t} \int_0^{L_{c,t}} C_{cit} \, di &\leq \Pi_t + T_t + w_t\left[N_t + f_t U_t\right] + b(1 - f_t) U_t - \mathbb{E}_t\left[\Lambda_{t,t+1} \Pi_{t+1}\right], && \text{(IA.3)}\\
N_{t+1} &= (1 - \chi)(1 - \widetilde{s})\left(N_t + f_t U_t\right), && \text{(IA.4)}\\
U_{t+1} &= \left[1 - (1 - \chi)(1 - \widetilde{s})\right] N_t + \left[1 - (1 - \chi)(1 - \widetilde{s}) f_t\right] U_t, && \text{(IA.5)}
\end{aligned}$$

where $u(\cdot)$ is the felicity function and $L_{c,t} = \chi(1 - \chi)^{t-c}$ is the period t population of cohort c. The choice variables in the above problem (IA.2) consists of consumption, C_{cit}, and portfolio choice, which is viewed as a vector of (state dependant) wealth, Π_{t+1}, for the next period $t+1$, and is subject to budget constraint (IA.3). Asset prices, as summarized by the stochastic discount factor (SDF) $\Lambda_{t,t+1}$, lump sum transfers T_t, and labor market variables, including wages w_t and the job finding probability f_t, are all taken as given. In addition, under our timing assumptions, aggregate employment and unemployment respectively obey laws of motion (IA.4) and (IA.5). Perfect household risk sharing equates consumption $C_{cit} = C_t$ across cohorts c and workers i.

The representative firm posts aggregate vacancies V_t to maximize firm value:

$$\begin{aligned} F_t^{rep} &= \max_{N_{t+1}, V_t \geq 0} \left(e^{z_t} - w_t\right)\left(N_t + g_t V_t\right) - \kappa V_t + \mathbb{E}_t\left[\Lambda_{t,t+1} F_{t+1}^{rep}\right], && \text{(IA.6)} \\ & s.t. \\ N_{t+1} &= (1-\chi)(1-\widetilde{s})\left(N_t + g_t V_t\right), && \text{(IA.7)} \end{aligned}$$

where the SDF $\Lambda_{t,t+1}$, labor market variables wages w_t and the vacancy filling probability g_t, as well as the law of motion (IA.7) are taken as given.

The representative firm's value for hiring an additional worker is defined as $F_t \equiv \partial F_t^{rep} / \partial N_t$. The representative household's value of an additional unit of employment, in marginal utility terms, is defined as $J_{e,t} \equiv \left(\partial J_t^{rep} / \partial N_t\right) / \lambda_t$, where λ_t denotes the Lagrange multiplier on the representative household's budget constraint (IA.3). The value of an additional unit of unemployment is defined as $J_{u,t} \equiv \left(\partial J_t^{rep} / \partial U_t\right) / \lambda_t$.

A standard argument shows:

$$\begin{aligned} F_t &= e^{z_t} - w_t + (1-\chi)(1-\widetilde{s})\mathbb{E}_t\left[\Lambda_{t,t+1} F_{t+1}\right], && \text{(IA.8)} \\ J_{e,t} &= w_t + \mathbb{E}_t\left[\Lambda_{t,t+1}\left[(1-\chi)(1-\widetilde{s})J_{e,t+1} + \left[1-(1-\chi)(1-\widetilde{s})\right]J_{u,t+1}\right]\right], && \text{(IA.9)} \\ J_{u,t} &= f_t w_t + (1-f_t)b && \text{(IA.10)} \\ &\quad + \mathbb{E}_t\left[\Lambda_{t,t+1}\left[(1-\chi)(1-\widetilde{s})f_t J_{e,t+1} + \left[1-(1-\chi)(1-\widetilde{s})f_t\right]J_{u,t}\right]\right], \end{aligned}$$

which are the counterparts of equations (7), (11), and (13), of our main paper, respectively. Note that we can write $J_{u,t} = f_t J_{e,t} + (1-f_t)J_{eu,t}$, where

$$J_{eu,t} = b + \mathbb{E}_t\left[\Lambda_{t,t+1} J_{u,t+1}\right] \tag{IA.11}$$

is the analogue to equation Equation (12) in the main paper.

The value functions for Economy II are analogous. It is easy to see that given any set of labor market outcomes (i.e. wages w_t, job finding probability f_t, and vacancy filling probability g_t), the corresponding value functions for economies I and II are all identical when condition (IA.1) is satisfied. Since both economies I and II are also governed by the same set of wage setting and labor market clearing conditions, they will also have the same labor market equilibrium under condition (IA.1).

B Additional Empirical Results

This section contains the following additional robustness results:

1. Controlling for observable differences between workers
2. Analysis for additional age groups.
3. Alternate time trends.
4. Employment rates in the time-series.

Controlling for observable differences between workers. Our learning-based theory focuses on worker selection that results from unobserved differences in productivity across workers. A natural concern is that our findings may instead be driven by observable differences across workers. Geography, gender and race are important observable dimensions along which workers differ.[1] In our paper we showed that our model's cross-sectional predictions hold when we control for the (geographic) state in which the worker was employed. Publicly available data allows us to test our model's predictions in sub-samples of women and men workers, both in the cross-section as well as in the time-series. For the cross-sectional tests, in addition to gender, we can further control for geography. We are also able to test our

[1] Another important observable is the worker's educational attainment level. Unfortunately, the publicly available LEHD data does not allow us to simultaneously control for education and age. In the time-series, the data on unemployment rates for workers of different ages which control for education level starts from 2000. We do not analyze this since the series is short.

model's time-series prediction in sub-samples of workers belonging to three major races.[2] We present these results below.

LEHD data allows us to run our baseline cross-sectional regression (equation (35) in our paper),

$$r_{I,t} = \alpha_I + \delta \times t + a \times GDP_t + b \times \beta_I \times GDP_t + \epsilon_{I,t}, \tag{IA.12}$$

in sub-samples restricted to either women or men employees. Columns (1) through (4) of Table IA.I reports results for regression (IA.12), where panel A is for women and panel B is for men. We see that our model's predictions hold up in these sub-samples. For instance, from Column (1) we see that, in line with our model's prediction, the log-ratio of prime-age to young employed workers increases when GDP declines. Column (2) shows that this increase is higher for industries with higher CAPM beta. This result is both statistically and economically significant. Columns (5) through (8) reports results for the state level regression (equation (36) in our paper),

$$r_{I,s,t} = \alpha_I + \alpha_s + \delta \times t + a \times GDP_t + b \times \beta_I \times GDP_t + \epsilon_{I,s,t}, \tag{IA.13}$$

again in sub-samples for either women or men employees. One model's predictions continue to hold up.

In Table IA.II and Table IA.III, we see that our baseline time-series results reported in Table 8 of main paper remain unchanged when we control for the workers' gender and race, respectively. Table IA.II reports our time-series results restricted to sub-samples of workers who are women (panel A) and men (panel B). Table IA.III shows the result when we restrict our sample to Black or African American (panel A), Hispanic of Latino (panel B), and White (panel C) workers.

Analysis for additional age groups. In our baseline cross-sectional empirical test (see Table 7 of our main paper), we define young (prime-age) workers to be those between the ages of 22—24 (35—44) years. Table IA.IV shows that our results are robust to using three alternate definitions of prime-age workers to construct the log-employment ratio, namely

[2] Unemployment rates for Asian workers are available only from 2000. We do not analyze this since the series is short.

either those between 25—34, or 35—44, or 45—54 years of age. In each of these, we maintain the same definition of young workers as in our baseline, i.e. those between 22—24 years old. The point-estimates show that the results are stronger when the age-difference between young and prime-age is larger.

In Table IA.V we analyze unemployment rates for each CPS defined age bucket between 16—54 years of age. We find our baseline results reported in Table 8 of our main paper to be robust to alternate definitions of young and prime-age workers. Columns (1) through (5) show that the sensitivity of unemployment rates to the credit spread declines monotonically with age. Columns (6) through (8) show that the unemployment rate of young workers (20—24 years old) are more sensitive to variations in the risk premium than the unemployment rate of prime-age workers for three alternate definitions of the latter (either 25—34, or 35—44, or 45—54 years old). We find the difference in sensitivities to be larger when the age gap is bigger.

Alternate time trends. Our baseline cross-sectional regression results of Table 7 of our main paper use a linear time-trend, common across all industries. In Table IA.VI we report results which (a) exclude time-trends (columns (1) through (4)) and (b) include an industry-specific linear time-trend (columns (5) through (8)). We find our model's predictions to hold robustly across these alternate time-trend specifications.

Employment rates in the time-series. In our model, we assume that the population and labor supply are constant. Under this assumption, a prediction about the unemployment rate is equivalently a prediction about the employment to population ratio. For ease of exposition, we will refer to the employment to population ratio as the "employment rate." The unemployment and employment rates are related through the labor force participation rate

$$\text{unemployment rate}_t = 1 - \frac{\text{employment rate}_t}{\text{participation rate}_t}. \tag{IA.14}$$

However, as we show below, over the period 1951Q1—2016Q4, there is a large, non-linear trend in the labor force participation rate, especially for women. This introduces a large, non-linear trend in the employment rate and violates our model's assumption of a constant labor supply.[3] Even so, for completeness, we include results for the sensitivity of the employment rate in Table IA.VIII.

Table IA.VIII shows results for our model's time-series predictions for the employment rates of young and prime-age workers. Panels A, B, and C show results for all workers, Women, and Men, respectively. All three panels use a linear time-trend, as in the main analysis from our paper. Panel A shows that in contrast to unemployment rates, employment rates of the aggregate population do not significantly depend on either labor productivity or the BAA-AAA spread. To better understand this result, we analyze the behavior of unemployment rates separately for women and men.

Panel B of Table IA.VIII shows the result for women workers. Columns (2) and (3) of panel B show that in a specification with a linear time-trend, the one-quarter ahead employment rate of women *increases* when credit spreads increase. To better understand why both the unemployment rate as well as the employment rate of women increase when the BAA-AAA spread increases, it is useful to look at the behavior of the employment rate time-series (for women). This is shown in Figure IA.1. We see from this plot that a linear trend is a very poor approximation for the time-trend in the employment rate for both young and prime-age women, as well as the difference in these two employment rates (lower panel of Figure IA.1). Superposed on the relatively small business cycle fluctuations in the employment rate is a large, non-linear upward trend in the employment rate. Perhaps not surprisingly, therefore, our regression specification which uses a linear trend generates counter-intuitive results indicating an increase in the employment rate of women during times when the BAA-AAA spread is high.

The underlying cause of this non-linear, upward trend in employment rates is the large upward trend in women's participation rates over our sample period. Figure IA.2 shows this large non-linear increase in women's labor force participation from 35% in 1951 to 75% in 2016 (see also the discussion in the review article by Juhn and Potter (2006)). From this figure we see that this large change in the trend swamps out the business cycle variation of the participation rate for women.[4]

Figure IA.3 shows that the employment rate series for Men is much better captured by

[3]Over the shorter sample of our cross-sectional analysis, 1997Q1-2016Q4, a simple linear trend suffices.
[4]We do not pursue non-linear specifications of the time-trend in the employment rate.

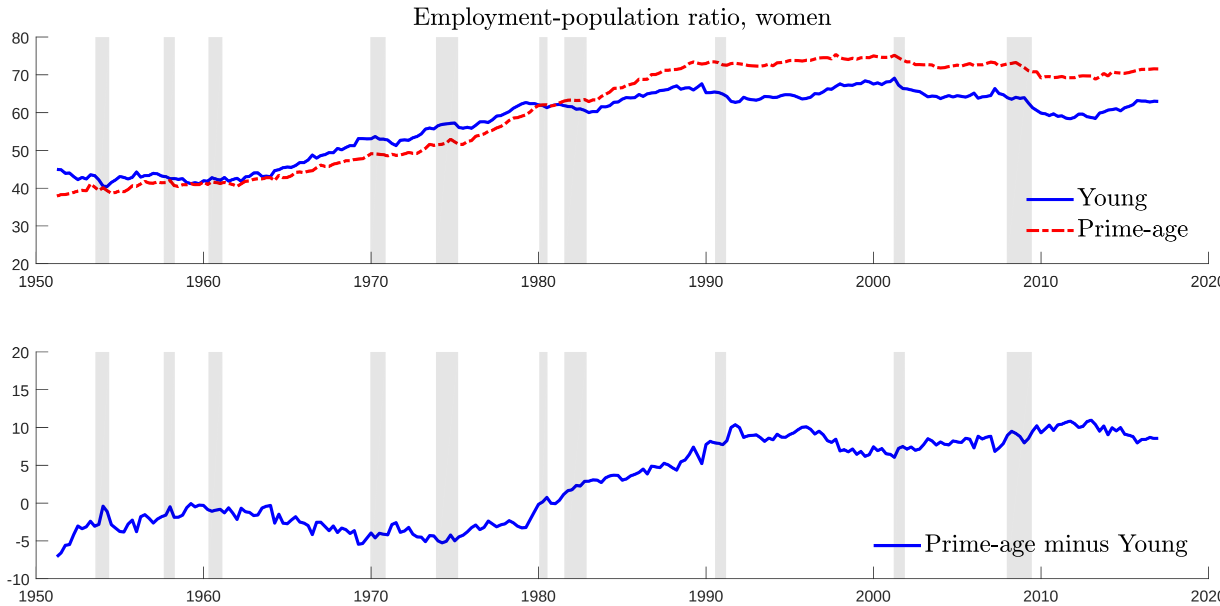

Figure IA.1: Quarterly Employment Rates for Young (20-24 year old) and Prime-age (35-44 year old) Women. We define employment rates to be the employment to population ratio. Quarterly numbers are averages of de-seasonalized monthly numbers. Panel A plots employment rates of young and prime-age workers, Panel B plots the cyclical component of the difference between these two rates (HP filtered with smoothing parameter 1600). The employment rate is defined to be the employment level divided by the size of the civilian labor force. The grey bands are NBER recessions. Data source: series LNU02300038 and LNU02300334 from the Bureau of Labor Statistics.

a linear time-trend. The top panel of this figure shows the employment rates for young (solid, blue line) and prime-age (dot-dash, red line) Men. The bottom panel shows the difference in these two employment rates. Inspecting these figures, we would expect our model's assumption about stable labor force supply to better hold up for men. This, in fact, turns out to be true in the data.

Panel C of Table IA.VIII shows the behavior of the employment rate in a sub-sample of Men workers. In line with our model's predictions, the employment rate of young (column (2)) and prime-age workers (column (5)) both decrease when the BAA-AAA spread increases. Relative to prime-age workers, this decrease is twice as large for young workers as can be seen from the magnitude of the slope coefficients. Therefore, the difference in the employment

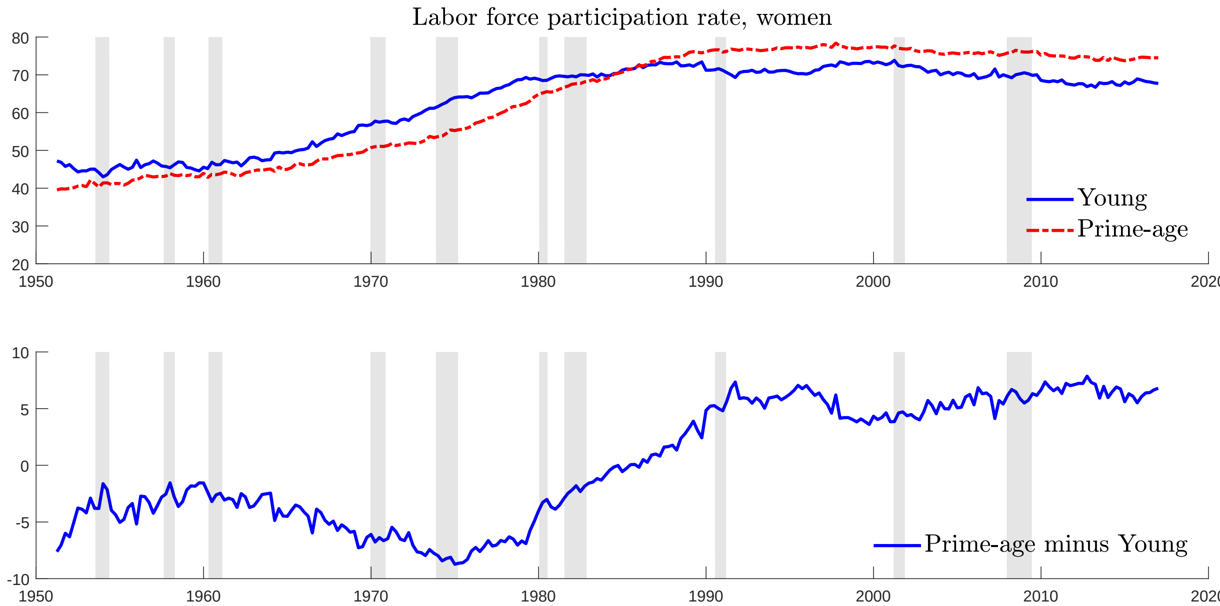

Figure IA.2: Labor Force Participation Rate for Young (20-24 year old) and Prime- age (35-44 year old) Women. Quarterly numbers are averages of de-seasonalized monthly numbers. Panel A plots participation rates of young and prime-age workers, Panel B plots the cyclical component of the difference between these two unemployment rates (HP filtered with smoothing parameter 1600). The grey bands are NBER recessions. Data source: series LNU01300038 and LNU01300334 from the Bureau of Labor Statistics.

rate of prime-age minus young workers increases when the BAA-AAA spread goes up. From column (8) of this table, we see that this increase is statistically significant.

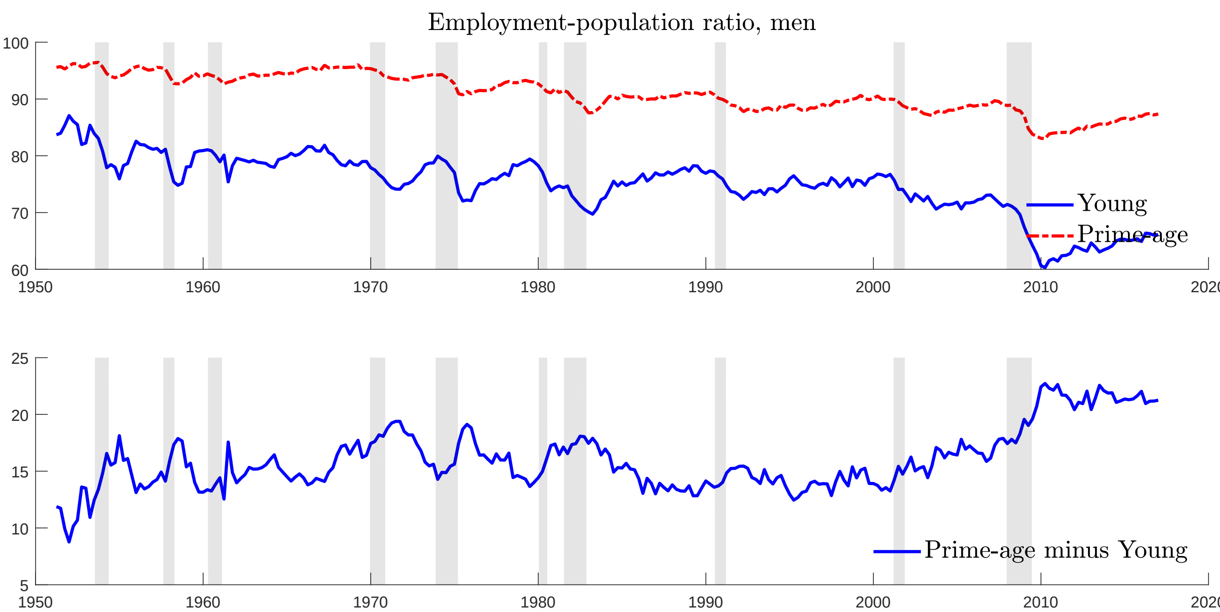

Figure IA.3: Quarterly Employment Rates for Young (20-24 year old) and Prime-age (35-44 year old) Men. We define employment rates to be the employment to population ratio. Quarterly numbers are averages of de-seasonalized monthly numbers. Panel A plots employment rates of young and prime-age workers, Panel B plots the cyclical component of the difference between these two rates (HP filtered with smoothing parameter 1600). The employment rate is defined to be the employment level divided by the size of the civilian labor force. The grey bands are NBER recessions. Data source: series LNU02300037 and LNU02300173 from the Bureau of Labor Statistics.

Table IA.I: Cyclicality of the Log Employment Ratio of Prime-age to Young Workers across industries for Women and Men workers This table reports results for regression equation (35) of our main paper restricted to the sub-sample of female (panel A) and male (panel B) workers. All regression specifications and variable definitions are otherwise identical to Table 7 in our main paper.

A. Women

	Aggregate level regressions				State level regressions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log GDP$ (cycle)	-0.97	3.67	-0.87	3.80	-0.97	1.62	-0.66	1.79
	(-1.68)	(3.50)	(-1.42)	(3.26)	(-1.43)	(1.85)	(-0.93)	(1.37)
$\beta_I^{\mathrm{CAPM}} \times \log GDP$		-4.47		-4.48		-2.40		-2.30
		(-3.78)		(-3.68)		(-2.13)		(-1.70)
$\beta_I^{\mathrm{LP}} \times \log GDP$			-0.23	-0.25			-0.78	-0.72
			(-0.50)	(-0.63)			(-1.28)	(-0.93)
$t \times 10^{-3}$	-1.26	-1.26	-1.26	-1.26	-2.22	-2.22	-2.22	-2.22
	(-0.86)	(-0.86)	(-0.86)	(-0.86)	(-1.13)	(-1.13)	(-1.13)	(-1.13)
Observations	2560	2560	2560	2560	24480	24480	24480	24480
Adjusted R^2	0.92	0.92	0.92	0.92	0.88	0.88	0.88	0.88

B. Men

	Aggregate level regressions				State level regressions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log GDP$ (cycle)	-1.39	4.22	-1.43	4.20	-1.04	2.30	-0.78	2.44
	(-2.36)	(3.64)	(-2.30)	(3.32)	(-1.39)	(2.07)	(-1.04)	(1.60)
$\beta_I^{\mathrm{CAPM}} \times \log GDP$		-5.41		-5.41		-3.10		-3.02
		(-3.77)		(-3.77)		(-2.14)		(-1.86)
$\beta_I^{\mathrm{LP}} \times \log GDP$			0.08	0.05			-0.67	-0.59
			(0.11)	(0.08)			(-0.99)	(-0.68)
$t \times 10^{-3}$	-3.39	-3.39	-3.39	-3.39	-2.39	-2.39	-2.39	-2.39
	(-2.28)	(-2.28)	(-2.28)	(-2.28)	(-2.58)	(-2.58)	(-2.58)	(-2.58)
Observations	2560	2560	2560	2560	24480	24480	24480	24480
Adjusted R^2	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91

Table IA.II: Sensitivity of Young versus Prime-age Workers to risk premium for Women and Men workers This table reports results for the baseline regression in Table 7 of our main paper, but restricted to the sub-sample of female (panel A) and male (panel B) workers. All regression specifications and variable definitions are otherwise identical to Table 8 of our main paper.

A. Women

	u^Y_{t+1}			u^P_{t+1}			$u^Y_{t+1} - u^P_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	-0.13		0.22	-0.10		0.08	-0.03		0.14
	(-0.57)		(1.32)	(-0.77)		(-0.69)	(-0.23)		(1.74)
BAA-AAA		2.86	3.02		1.53	1.59		1.33	1.43
		(6.67)	(7.23)		(8.33)	(8.15)		(4.71)	(5.20)
$t \times 10^{-3}$	0.11	0.06	0.06	0.03	-0.00	-0.00	0.09	0.06	0.06
	(3.22)	(2.04)	(2.01)	(1.20)	(-0.06)	(-0.12)	(5.01)	(4.18)	(4.09)
N	263	263	263	263	263	263	263	263	263
R^2	0.16	0.47	0.48	0.03	0.33	0.33	0.28	0.48	0.49

B. Men

	u^Y_{t+1}			u^P_{t+1}			$u^Y_{t+1} - u^P_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	-0.41		0.07	-0.13		0.08	-0.28		-0.01
	(-1.34)		(0.30)	(-0.76)		(0.55)	(-1.76)		(-0.10)
BAA-AAA		4.23	4.28		1.81	1.87		2.42	2.42
		(9.52)	(9.71)		(7.30)	(6.93)		(6.46)	(6.62)
$t \times 10^{-3}$	0.19	0.12	0.12	0.11	0.07	0.07	0.09	0.04	0.04
	(4.11)	(2.89)	(2.96)	(4.24)	(3.29)	(3.38)	(3.53)	(2.03)	(2.06)
N	263	263	263	263	263	263	263	263	263
Adjusted R^2	0.23	0.55	0.55	0.25	0.48	0.48	0.17	0.49	0.49

Table IA.III: Sensitivity of Young versus Prime-age Workers to risk premium for workers of different races. This table reports results for the baseline regression in Table 8 of our main paper, but restricted to the sub-samples of Black or African American (panel A), Hispanic or Latino (panel B), and White (panel C) workers. The data is quarterly between 1972Q1 to 2016Q4 in panel A, 1977Q1 to 2016Q4 in panel B, and 1954Q1 to 2016Q4 in panel C. All regression specifications and variable definitions are otherwise identical to Table 8 of our main paper.

A. Black or African American

	u^Y_{t+1}			u^P_{t+1}			$u^Y_{t+1} - u^P_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	-0.11		0.80	-0.01		0.47	-0.10		0.33
	(-0.16)		(1.81)	(-0.03)		(1.80)	(-0.31)		(1.52)
BAA-AAA		5.39	6.02		2.81	3.18		2.58	2.84
		(4.69)	(5.51)		(5.06)	(5.81)		(4.02)	(4.69)
$t \times 10^{-3}$	-0.22	-0.14	-0.12	0.06	0.10	0.11	-0.28	-0.24	-0.23
	(-1.62)	(-1.23)	(-1.12)	(0.79)	(1.73)	(1.92)	(-3.77)	(-3.62)	(-3.62)
N	180	180	180	180	180	180	180	180	180
Adjusted R^2	0.06	0.38	0.40	0.01	0.34	0.38	0.27	0.44	0.45

B. Hispanic or Latino

	u^Y_{t+1}			u^P_{t+1}			$u^Y_{t+1} - u^P_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	0.00		0.63	-0.02		0.36	0.02		0.28
	(0.00)		(1.39)	(-0.05)		(1.15)	(0.07)		(1.36)
BAA-AAA		3.36	3.81		2.01	2.26		1.36	1.55
		(5.13)	(5.08)		(4.49)	(4.36)		(4.06)	(4.42)
$t \times 10^{-3}$	-0.12	-0.05	-0.03	-0.12	-0.08	-0.07	0.00	0.03	0.04
	(-1.11)	(-0.60)	(-0.38)	(-1.69)	(-1.37)	(-1.17)	(0.04)	(0.74)	(0.97)
N	163	163	163	163	163	163	163	163	163
Adjusted R^2	0.03	0.31	0.35	0.07	0.28	0.30	-0.01	0.18	0.21

C. White

	u^Y_{t+1}			u^P_{t+1}			$u^Y_{t+1} - u^P_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	-0.33		0.03	-0.13		0.06	-0.20		-0.03
	(-1.40)		(0.17)	(-0.91)		(0.54)	(-1.84)		(-0.36)
BAA-AAA		3.10	3.12		1.61	1.66		1.49	1.47
		(9.61)	(9.56)		(8.88)	(8.21)		(6.34)	(6.36)
$t \times 10^{-3}$	0.08	0.04	0.04	0.06	0.04	0.04	0.02	0.00	0.00
	(2.28)	(1.22)	(1.24)	(2.81)	(1.98)	(2.02)	(1.33)	(0.01)	(0.03)
N	251	251	251	251	251	251	251	251	251
Adjusted R^2	0.11	0.48	0.48	0.14	0.44	0.44	0.06	0.40	0.40

Table IA.IV: Cyclicality of the Log Employment Ratio of Prime-age to Young Workers across industries: Alternate definitions of prime-age. Regression specification in Equation (35) of main paper with three alternate definitions of prime-age workers as shown below. All definitions use the same age range for young workers as in the baseline (22—24 years). The regressions are run with a linear time-trend that is common across industries and with industry-level fixed effects at the 3-digit NAICS code level. Standard errors are clustered at the 2-digit NAICS code level. Numbers in parentheses are t-statistics.

	Prime-age: 25 - 34 years				Prime-age: 35 - 44 years				Prime-age: 45 - 54 years			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\log GDP$ (cycle)	-1.90	2.28	-2.03	2.14	-1.81	5.02	-1.93	4.91	-2.43	4.65	-2.52	4.57
	(-3.97)	(2.67)	(-4.08)	(2.45)	(-2.58)	(4.23)	(-2.49)	(3.92)	(-3.21)	(3.38)	(-3.17)	(3.41)
$\beta_I^{\mathrm{CAPM}} \times \log GDP$		-4.02		-4.01		-6.58		-6.57		-6.82		-6.81
		(-3.69)		(-3.84)		(-4.26)		(-4.32)		(-3.91)		(-3.97)
$\beta_I^{\mathrm{LP}} \times \log GDP$			0.30	0.28			0.27	0.23			0.20	0.16
			(0.64)	(0.69)			(0.32)	(0.36)			(0.21)	(0.21)
$t \times 10^{-3}$	-0.90	-0.90	-0.90	-0.90	-2.85	-2.85	-2.85	-2.85	4.43	4.43	4.43	4.43
	(-2.06)	(-2.06)	(-2.06)	(-2.06)	(-2.15)	(-2.15)	(-2.15)	(-2.15)	(2.51)	(2.51)	(2.51)	(2.51)
Observations	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560	2560
Adjusted R^2	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92

Table IA.V: Time-series results: Alternate definitions of prime-age. Predictive regressions of one-quarter ahead unemployment rates for all CPS age-buckets between 16—54 years. Columns (6)—(8) report results for differences in unemployment rates for three alternate definitions of prime-age ($P1 : 25 - 34$, $P2 : 35 - 44$, or $P3 : 45 - 54$ years old) and our standard definition of young ($Y1 : 20 - 24$ years old). Right hand side variables are the same as in Table 8 of our main paper. The data is quarterly between 1951Q1 to 2016Q4. All variables are de-seasonalized. Standard errors are Newey-West with 4 lags. Numbers in parentheses are t-statistics.

	$Y0$: 16- 19 yrs (1)	$Y1$: 20 - 24 yrs (2)	$P1$: 25 - 34 yrs (3)	$P2$: 35 - 44 yrs (4)	$P3$: 45 - 54 yrs (5)	$u^{Y1}_{t+1} - u^{P1}_{t+1}$ (6)	$u^{Y1}_{t+1} - u^{P2}_{t+1}$ (7)	$u^{Y1}_{t+1} - u^{P3}_{t+1}$ (8)
Labor productivity	0.29	0.13	0.15	0.08	0.10	-0.02	0.05	0.03
	(1.12)	(0.66)	(0.99)	(0.63)	(0.79)	(-0.27)	(0.53)	(0.28)
BAA-AAA	4.24	3.70	2.73	1.77	1.54	0.97	1.93	2.16
	(7.32)	(8.78)	(9.24)	(8.14)	(7.47)	(5.15)	(6.21)	(6.16)
$t \times 10^{-3}$	0.22	0.09	0.06	0.05	0.03	0.03	0.04	0.06
	(4.26)	(2.60)	(2.61)	(2.47)	(1.55)	(2.18)	(2.38)	(3.26)
N	263	263	263	263	263	263	263	263
Adjusted R^2	0.55	0.54	0.56	0.46	0.36	0.36	0.51	0.56

Table IA.VI: Alternate time-trend specifications of cross-sectional results in Table 7 of our main paper. The regression is the same as the one we report in Table 7 of our main paper, except that results in columns (1)—(4) are obtained without any time-trend while those in columns (5)—(8) are obtained using an industry-specific time-trend. All variable definitions and data-sources are the same as in Table 7 of our main paper. The regressions are run with industry-level fixed effects at the 3-digit NAICS code level. Standard errors are clustered at the 2-digit NAICS code level. Numbers in parentheses are t-statistics.

	No time-trend				Industry-specific time-trend			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log GDP$ (cycle)	-1.54	5.29	-1.66	5.18	-1.81	3.81	-1.85	3.77
	(-1.95)	(4.50)	(-1.97)	(4.21)	(-2.75)	(4.01)	(-2.57)	(3.58)
$\beta_I^{\text{CAPM}} \times \log GDP$		-6.58		-6.57		-5.41		-5.41
		(-4.26)		(-4.32)		(-3.99)		(-3.99)
$\beta_I^{\text{LP}} \times \log GDP$			0.27	0.23			0.10	0.06
			(0.32)	(0.36)			(0.14)	(0.11)
Observations	2560	2560	2560	2560	2560	2560	2560	2560
Adjusted R^2	0.91	0.91	0.91	0.91	0.96	0.96	0.96	0.96

Table IA.VII: Time-series results reported in Table 8 of our main paper without a linear time-trend. The regression is the same as the one we report in Table 8 of our main paper, as is the sample period and the right hand side variables. Standard errors are Newey-West with 4 lags. Numbers in parentheses are t-statistics.

	u_{t+1}^Y			u_{t+1}^P			$u_{t+1}^Y - u_{t+1}^P$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	-0.26		-0.15	-0.12		-0.04	-0.15		-0.11
	(-2.07)		(-1.28)	(-1.51)		(-0.62)	(-2.79)		(-2.18)
BAA-AAA		1.08	0.98		0.66	0.63		0.42	0.36
		(4.15)	(3.85)		(4.13)	(3.80)		(3.29)	(2.91)
N	263	263	263	263	263	263	263	263	263
Adjusted R^2	0.05	0.16	0.17	0.03	0.17	0.17	0.06	0.10	0.13

Table IA.VIII: Employment, labor productivity, and discount rates. Predictive regressions of one-quarter ahead employment rates. The dependent variables are: the employment rate of young workers (emp^Y) who are individuals between the ages 20-24, the employment rate of prime-age workers (emp^P) who are between the ages 35-44 years, and the difference in these employment rates. Right hand side variables are labor productivity and the BAA-AAA spread. The data is quarterly between 1951Q1 to 2016Q4. We take quarterly averages of monthly BLS series LNU02300036 (aggregate, young), LNU02300091 (aggregate, prime-age), LNU02300038 (women, young), LNU02300334 (women, prime-age), LNU02300037 (male, young), and LNU02300173 (male, prime-age). All variables other than the BAA-AAA credit spread are de-seasonalized. The labor productivity series is de-trended using an HP filter with bandwidth 1600. Standard errors are Newey-West with 4 lags. Numbers in parentheses are t-statistics.

A. Aggregate

	emp^Y_{t+1}			emp^P_{t+1}			$\text{emp}^P_{t+1} - \text{emp}^Y_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	13.47		18.74	1.32		3.07	-12.15		-15.67
	(0.39)		(0.48)	(0.05)		(0.11)	(-0.65)		(-0.79)
BAA-AAA		33.57	46.63		13.36	15.50		-20.21	-31.12
		(0.34)	(0.43)		(0.17)	(0.18)		(-0.59)	(-0.86)
t	0.03	0.03	0.03	0.06	0.06	0.06	0.03	0.03	0.03
	(4.00)	(3.85)	(3.82)	(12.13)	(11.51)	(11.47)	(10.31)	(10.79)	(10.89)
N	264	264	264	264	264	264	264	264	264
Adjusted R^2	0.27	0.27	0.27	0.75	0.75	0.75	0.71	0.71	0.71

B. Women

	emp^Y_{t+1}			emp^P_{t+1}			$\text{emp}^P_{t+1} - \text{emp}^Y_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	0.14		31.84	-10.53		7.18	-10.67		-24.66
	(0.00)		(0.69)	(-0.23)		(0.14)	(-0.35)		(-0.79)
BAA-AAA		258.1	280.2		151.6	156.6		-106.5	-123.7
		(1.87)	(1.90)		(1.05)	(1.00)		(-1.90)	(-2.19)
t	0.10	0.09	0.09	0.16	0.16	0.16	0.06	0.07	0.07
	(10.28)	(9.89)	(9.81)	(16.94)	(15.81)	(15.64)	(18.59)	(18.15)	(18.07)
N	264	264	264	264	264	264	264	264	264
Adjusted R^2	0.69	0.71	0.71	0.84	0.85	0.85	0.79	0.80	0.80

C. Men

	emp^Y_{t+1}			emp^P_{t+1}			$\text{emp}^P_{t+1} - \text{emp}^Y_{t+1}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor prod. (cycle)	33.00		-0.70	13.40		-2.53	-19.60		-1.84
	(1.13)		(-0.02)	(0.83)		(-0.17)	(-0.95)		(-0.08)
BAA-AAA		-297.5	-298.0		-139.1	-140.9		158.4	157.1
		(-5.85)	(-5.09)		(-5.36)	(-5.05)		(3.50)	(3.04)
t	-0.06	-0.05	-0.05	-0.04	-0.04	-0.04	0.02	0.02	0.02
	(-10.39)	(-9.25)	(-9.37)	(-16.76)	(-16.37)	(-16.72)	(4.19)	(3.30)	(3.31)
N	264	264	264	264	264	264	264	264	264
Adjusted R^2	0.69	0.74	0.74	0.84	0.87	0.87	0.25	0.31	0.31

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