# Online Appendix: The Life-Cycle Implications of Temporary Employment Contracts

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## A Further Empirical Results

*Table 9* documents the mean and median reported hours worked by individuals in their primary job depending on whether the primary job was in a temporary or permanent contract in the LISS Netherlands data. The mean and median reported by those whose primary job was in a temporary contract were about 2 hours per week less than those whose primary job was in a permanent contract.

*Table 9: LISS Netherlands Data: Reported Hours Worked in Primary Job*

| Main Job Type | Mean Hours | Median Hours |
|---|---|---|
| Permanent Contract | 34.8 | 36.0 |
| Temporary Contract | 32.3 | 34.0 |

*Table 10* reports the percentage of workers in temporary contracts in the LISS Netherlands data by year and by hours worked per week. The first column reports the sample year, while the second reports the percentage in temporary contracts among respondents working any hours. The last three columns report the percentage in temporary contracts, given that they reported working $\geq 30$, $\geq 35$, and $\geq 40$ hours per week in that primary job, respectively. Thus, the percentage of individuals in temporary jobs does not notably change when we restrict the sample to individuals working full-time.

*Table 10: Percent in Temporary Contracts Restricted by Hours Worked per Week*

| Year | Any Hours | $\geq$ 30 Hours | $\geq$ 35 Hours | $\geq$ 40 Hours |
|---|---|---|---|---|
| 2008 | 10.72% | 10.10% | 10.31% | 11.56% |
| 2009 | 11.36% | 10.53% | 10.51% | 12.08% |
| 2010 | 10.80% | 10.24% | 9.84% | 10.53% |
| 2011 | 11.39% | 10.93% | 11.36% | 12.85% |
| 2012 | 11.97% | 11.48% | 11.02% | 12.60% |
| 2013 | 12.06% | 11.10% | 11.26% | 11.47% |
| 2014 | 13.19% | 12.55% | 11.13% | 12.63% |
| 2015 | 14.42% | 13.33% | 12.59% | 13.37% |
| 2016 | 14.33% | 14.27% | 13.42% | 15.13% |
| 2017 | 15.03% | 15.42% | 14.46% | 15.27% |
| 2018 | 16.01% | 15.31% | 14.50% | 14.95% |
| 2019 | 15.67% | 15.64% | 14.63% | 15.33% |

*Table 11* displays the full results of the panel regression with year fixed effects of annual real income per hour growth on work in a temporary job over two consecutive years and other observables. This table includes the coefficients on dummy variables indicating observations where individuals remained in each listed sector over two successive years. Even after controlling for the sector and other job characteristics, working in a temporary contract is associated with statistically significant lower income growth.

*Table 11: Real Income per Hour Growth Difference*

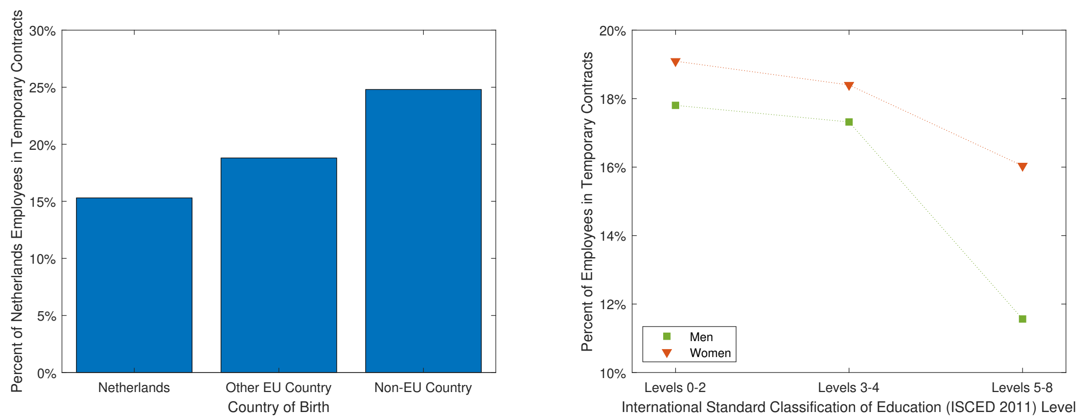
| | Coefficient | Robust Standard Error |
|---|---|---|
| **Temporary Job Both Years** | **-0.0151**$^{**}$ | **(0.0074)** |
| Moved Into Permanent Job | 0.0009 | (0.0094) |
| Moved Out of Permanent Job | -0.0031 | (0.0137) |
| Postsecondary Education | 0.0033 | (0.0118) |
| Potential Experience | 0.0034$^{***}$ | (0.0010) |
| Potential Experience Squared | -0.0001$^{***}$ | (0.0000) |
| Avg. 30-39 Hr Both Years | 0.0027 | (0.0038) |
| Avg. 50-59 Hr Both Years | -0.0476$^{***}$ | (0.0058) |
| Avg. 60-69 Hr Both Years | -0.0781$^{***}$ | (0.0119) |
| Avg. 70 Hrs or More Both Years | -0.0937$^{*}$ | (0.0542) |
| Increase in Avg. Hrs | 0.0947$^{***}$ | (0.0053) |
| Decrease in Avg. Hrs | -0.1426$^{***}$ | (0.0051) |
| Supervisor Role Both Years | -0.0036 | (0.0074) |
| Moved Into Supervisor Role | -0.0044 | (0.0117) |
| Moved Out of Supervisor Role | -0.0133$^{*}$ | (0.0073) |
| Skill Level: Highest Both Years | 0.0775$^{***}$ | (0.0056) |
| Skill Level: Intermediate Both Years | 0.0354$^{***}$ | (0.0043) |
| Skill Level: Lowest Both Years | -0.0609$^{***}$ | (0.0188) |
| Moved Up Skill Level | 0.0372$^{***}$ | (0.0129) |
| Moved Down Skill Level | 0.0258 | (0.0194) |
| First year log income | -1.0146$^{***}$ | (0.1631) |
| First year log income squared | 0.1501$^{***}$ | (0.0318) |
| Male | 0.0078$^{**}$ | (0.0039) |
| Dutch | -0.0079 | (0.0118) |
| Business Services and Finance Sectors | 0.0154$^{***}$ | (0.0058) |
| Agriculture and Mining Sectors | 0.0099 | (0.0105) |
| Recreation, Catering, and other Services | -0.0443$^{***}$ | (0.0114) |
| Education Sector | -0.0126$^{**}$ | (0.0060) |
| Healthcare and Welfare Sectors | -0.0091 | (0.0068) |
| Government Services Sector | 0.0089 | (0.0056) |
| Transportation and Utilities Sectors | -0.0149$^{**}$ | (0.0072) |
| Retail Trade Sector | -0.0332$^{***}$ | (0.0083) |
| Other Sectors | -0.0168$^{***}$ | (0.0064) |
| Constant | 1.5475$^{***}$ | (0.2017) |
| Observations | 10,925 | |
| Individuals | 3,087 | |
| Overall $R^2$ | 0.3048 | |

$^{*}p < 0.1,^{**}p < 0.05,\ ^{***}p < 0.01.$

## A.1 Employment in Temporary Contracts: Demographics

*Figure 12* displays data on the prevalence of temporary contracts for different demographics. The data displayed is from the European Union Labour Force Survey data from the Netherlands in 2019. The left panel shows that immigrants are more likely to be employed in temporary jobs than non-immigrants. Additionally, immigrants from outside the EU are more likely to work in temporary jobs than immigrants from another country within the EU.[1] The left panel of the figure shows the prevalence of temporary contracts by International Standard Classification of Education (ISCED) level and gender. In the Netherlands women are more likely to work in temporary contracts across all education categories.[2]

*Figure 12: Prevalence of Temporary Contracts by Country of Birth and Gender*




# B Aggregate State Transition Probability Functions

This appendix characterizes the transition probability functions determining the aggregate state of the economy $\psi = (u, e^P, e^T)$. These transition functions follow directly from the model timing assumptions stated in Section III. Recall that the first element of $\psi$ is a function $u_a(v, h)$ defining the mass of agents unemployed of age $a$, education $\nu$, and human capital $h$ in the production sub-period of the model. The last two elements of $\psi$ are functions with $e^P_a(\nu, h, z)$ and $e^T_a(\nu, h, z)$ denoting the mass of agents with characteristics $a$, $\nu$, and $h$ employed in permanent and temporary contracts respectively with idiosyncratic productivity $z$ in the model's production sub-period. Additionally, it will be useful to define $\widehat{u}_a(v, h)$, $\widehat{e}^P_a(\nu, h, z)$, and $\widehat{e}^T_a(\nu, h, z)$ as the analogous functions representing the mass of agents in each state during the model's search sub-period.

[1]The data set does not specify race or ethnicity.

[2]However, on average in the EU as a whole, among those in the lowest educational attainment group, men are slightly more likely to work in temporary jobs than women. Among all higher educational attainment groups, women are slightly more likely to work in temporary contracts than men.

Let $g^H$, $g_0^H$ and $j$ respectively denote the probability distribution functions associated with density functions $H$, $H_0$, and $J$ from which $h$ and $\nu$ values are drawn. Equation (13) defines the mass of unemployed new entrants ($a = 1$) of each education and human capital type.

$$\widehat{u}_1(\nu, h') = g^H(h')j(\nu) \tag{13}$$

For agents who are not new entrants to the model, all those who were unemployed in the production sub-period enter the search sub-period unemployed. Still, they may experience changes to their human capital. (14) defines the mass unemployed in the search sub-period for each $h'$ value given the masses previously unemployed in the production sub-period.

$$\begin{aligned}\widehat{u}_a(\nu, h') =&(1-\eta)(1-\pi_U)u_{a-1}(\nu, h') + (1-\eta)\pi_U u_{a-1}(\nu, h'+1) \\ &+ \eta\sum_h g_o^H(h'|h)u_{a-1}(\nu, h) \qquad\qquad \text{if} \quad a > 1\end{aligned} \tag{14}$$

Agents enter the model in the initial search sub-period unemployed. Therefore, no new entrants are employed in the search sub-period. Among those who are not new entrants, all those employed in the previous production sub-period remain employed into the search sub-period, but they may experience an increase in their human capital with probability $\pi_G$ for $G \in \{P, T\}$.

$$\begin{aligned}&\widehat{e}_1^G(\nu, h', z) = 0 \\ &\widehat{e}_a^G(\nu, h', z) = (1-\pi_G)e_{a-1}^G(\nu, h', z) + \pi_G e_{a-1}^G(\nu, h'-1, z) \qquad \text{if} \quad a > 1\end{aligned} \tag{15}$$

Given the masses in each state during the search sub-period, we can now describe the mass of agents in each possible state during the production sub-period of the model. First, equation (16) computes the mass unemployed in the production sub-period by adding together those who were unemployed in the search sub-period and unable to find a job, those who were in permanent contracts but lost their job, and those who were in temporary contracts but lost their job.

$$\begin{aligned}u_a(\nu, h) = \widehat{u}_a(\nu, h)(1 - p(\theta_a^U(\nu, h)) + \int_0^\infty (1-\lambda p(\theta_a^P(\nu, h, z)))F(\tilde{z}_a^P(\nu, h)|z)\widehat{e}_a^P(\nu, h, z)dz \\ + \int_0^\infty (1-\lambda p(\theta_a^T(\nu, h, z)))\left[(1-\kappa)F(\tilde{z}_a^T(\nu, h)|z) + \kappa F(\tilde{z}^\kappa(\nu, h)|z)\right]\widehat{e}_a^T(\nu, h, z)dz\end{aligned} \tag{16}$$

Next, (17) describes the mass employed in a permanent contract in the production sub-period. Those employed in permanent contracts are comprised of those who entered a permanent contract from unemployment, those who entered a permanent contract from search on the job in either a separate temporary or permanent contract, those who were previously in a permanent contract and did not find a new job or get fired, and those who were previously in a temporary contract that expired with probability $\kappa$ and the firm decided to continue employing them in a permanent contract. Recall that all new jobs begin with known idiosyncratic productivity $z_0$, assumed to be the mean of the distribution of possible $z$ draws. Define function $f_0(z_0) = 1$ and $f_0(z) = 0 \ \forall \ z \neq z_0$.

$$\begin{aligned} e_a^P(\nu, h, z') = {} & p(\theta_a^U(\nu, h)) \left(\mathbb{1}_{G_a^U(\nu,h)=P}\right) f_0(z')\widehat{u}_a(\nu, h) \\ & + \int_0^\infty \lambda p(\theta_a^T(\nu, h, z)) \left(\mathbb{1}_{G_a^T(\nu,h,z)=P}\right) f_0(z')\widehat{e}_a^T(\nu, h, z)dz \\ & + \int_0^\infty \lambda p(\theta_a^P(\nu, h, z)) \left(\mathbb{1}_{G_a^P(\nu,h,z)=P}\right) f_0(z')\widehat{e}_a^P(\nu, h, z)dz \\ & + \int_0^\infty (1 - \lambda p(\theta_a^P(\nu, h, z))) \left(\mathbb{1}_{z'>\tilde{z}_a^P(\nu,h)}\right) f(z'|z)\widehat{e}_a^P(\nu, h, z)dz \\ & + \int_0^\infty (1 - \lambda p(\theta_a^T(\nu, h, z)))\kappa \left(\mathbb{1}_{z'>\tilde{z}_a^\kappa(\nu,h)}\right) f(z'|z)\widehat{e}_a^T(\nu, h, z)dz \end{aligned} \tag{17}$$

Finally, equation (18) characterizes the mass employed in a temporary contract with each possible state variable in the production sub-period. Those employed in temporary contracts are comprised of those who were unemployed and successfully found a temporary job, those who were in temporary or permanent contracts and successfully searched on the job for a temporary contract, and those who were in a temporary contract that did not expire and were not fired.

$$\begin{aligned} e_a^T(\nu, h, z') = {} & p(\theta_a^U(\nu, h)) \left(\mathbb{1}_{G_a^U(\nu,h)=T}\right) f_0(z')\widehat{u}_a(\nu, h) \\ & + \int_0^\infty \lambda p(\theta_a^T(\nu, h, z)) \left(\mathbb{1}_{G_a^T(\nu,h,z)=T}\right) f_0(z')\widehat{e}_a^T(\nu, h, z)dz \\ & + \int_0^\infty \lambda p(\theta_a^P(\nu, h, z)) \left(\mathbb{1}_{G_a^P(\nu,h,z)=T}\right) f_0(z')\widehat{e}_a^P(\nu, h, z)dz \\ & + \int_0^\infty (1 - \lambda p(\theta_a^T(\nu, h, z)))(1-\kappa) \left(\mathbb{1}_{z'>\tilde{z}_a^T(\nu,h)}\right) f(z'|z)\widehat{e}_a^T(\nu, h, z)dz \end{aligned} \tag{18}$$

# C Wage Determination

While section III discussed the determination of wages, this appendix describes wage determination in further detail and provides a simple example to clarify the process. Recall that the assumption that jobs provide value $x$ to a worker is quite general and allows us to solve for the model's value and policy functions without any assumptions on how wages are determined precisely. (None of the results regarding separations, job-type selection, etc., rely on a potentially arbitrary assumption about how firms pay wages to workers.) However, wages are not uniquely pinned down by this assumption alone. Value $x$ could be provided to the worker under multiple wage-setting schemes. To solve for wages in the model I assume wages always offer workers fraction $\mu$ of match surplus.

First, an easy example will help clarify wage determination in the model. In a very simple infinite-horizon case without job or worker heterogeneity and without firing costs or on-the-job search, let $U$ be the value of unemployment and $V$ be the joint value of a match (equal to the value to the worker plus the value to the firm). $x$ is the current and discounted expected future employment value a worker gets by taking a job. The benefit to the worker of taking a job is $x$ minus their outside option $U$, while the match surplus is the joint value $V$ minus the worker's outside option of $U$ and minus the firm's outside option value of zero. Therefore, the assumption that the benefit to the worker is fraction $\mu$ of the match surplus means

$$x - U = \mu(V - U).$$

Given the choice of $x$, we can directly determine $\mu = \frac{x-U}{V-U}$. From here, the wage $w$ can be determined given the surplus splitting rule $\mu$. The wage $w$ is such that

$$x = \mu(V - U) + U = w + \beta\left(\mu(V - U) + U\right).$$

Therefore, in this simple example, $w = (1 - \beta)\left[\mu(V - U) + U\right]$. In other words, the worker's expected discounted value of employment $x = \mu(V - U) + U$ equals the expected discounted flow of wages $\frac{w}{1-\beta}$. The same strategy is used to solve for model wages, except we need to account for the worker's continuation value including search on the job, the possibility of separations, and changes in age and productivity variables.

Now, turning to the full model setup described in Section III, the continuation value of employment into the search sub-period at the start of the next period for the worker is defined as follows. Let $\widehat{W}^P$ denote this continuation value in a permanent contract.

$$\begin{aligned}
\widehat{W}^P_a(\nu, h, z) =& \lambda p\left(\theta^{P*}_a(\nu, h, z)\right) x^{P*}_a(\nu, h, z) \\
&+ \left(1 - \lambda p\left(\theta^{P*}_a(\nu, h, z)\right)\right) \int_{\tilde{z}^{P*}_a(\nu,h)}^{\infty} \left[\mu(V^P_a(\nu, h, z') - U_a(\nu, h) + f) + U_a(\nu, h)\right] dF(z'|z) \\
&+ \left(1 - \lambda p\left(\theta^{P*}_a(\nu, h, z)\right)\right) F(\tilde{z}^{P*}_a(\nu, h)|z) U_a(\nu, h)
\end{aligned}$$

Here $x^{P*}(\nu, h, z)$ denotes the $x$ value offered in the sub-market offering $\theta^{P*}_a(\nu, h, z)$. When the worker continues into the next period, they can search with probability $\lambda$ and are successfully matched with probability $\theta^{P*}_a(\nu, h, z)$, in which case the worker receives $x^{P*}_a(\nu, h, z)$. If the worker does not enter a new job, they either remain in their existing job or enter unemployment dependent on their realized idiosyncratic productivity value $z'$. If they remain employed in their existing match, they continue to receive fraction $\mu$ of the match surplus. Given the match continuation value for the worker, the wage in the current period ($w$) can be determined from

$$\mu\left(V_a^P(\nu,h,z)-U_a(\nu,h)+f\right)+U_a(\nu,h)=w+\beta\mathbb{E}\widehat{W}_a^P(\nu,h',z).$$

Given $\mu$, the wage is the difference between the current value to the worker and the future discounted expected value to the worker of continuing employment into the start of the next period.

# D Results Under Alternative Wage Assumptions

This appendix considers how the results regarding wages in the model respond to alternative assumptions on how wages are determined. The original wage results, where wages were assumed to offer the workers a constant fraction of match surplus, will be compared to two common alternative wage assumptions. The first alternative wage assumption considered is that wages are determined via a "piece rate", meaning that each period workers are paid a constant fraction of match production (an assumption made in Griffy (2021) and Herkenhoff et al. (2024), among many others). The second alternative wage assumption is that the worker receives a fixed wage payment while remaining with the same employer.

Determining the piece rate or fixed wage given the optimal contract value $x$ that a worker chooses is more computationally complex than determining what the worker's surplus rate ($\mu$) is given $x$. As described in *Appendix C*, given a worker's choice of $x$, we can directly solve for $\mu=\frac{x-U}{V-U}$, and only need to keep track of the joint match values ($V$) and unemployment value ($U$). However, when determining what piece rate or fixed wage corresponds to a particular choice of $x$, we must first determine the value to the worker of employment at a given piece rate or fixed wage. Therefore, under the alternative wage assumptions, the model code is extended to determine the worker's value $W_a^G(\nu,h,z,w)$ for $G\in\{P,T\}$ for a grid of possible $w$ values, representing either a fixed wage or fixed piece rate $w$. Then, after solving for the worker's optimal contract value $x$ when searching, the $w^*$ value associated with the chosen $x$ value must be determined such that $W_a^G(\nu,h,z,w^*)=x$.

After modifying the model to allow for these alternative wage assumptions, I continue to use the same parameter values displayed in *Tables 3* and *4*. The objective is to determine how responsive the results regarding wages are to different assumptions, given a set of parameter values. Tables *12* and *13* compare the reported model moments regarding wages under the original, piece rate, and fixed-wage assumptions. While many moments do not notably change under the alternative wage assumptions, the estimated wage losses experienced after a job loss are larger when assuming a piece-rate wage, and these estimated losses are much smaller when assuming a fixed wage. Additionally, under the assumption of fixed wages, the model generates significantly less wage dispersion.

*Table 12: Wage Moments Under Alternative Wage Assumptions*

| **Moment** | **Original Wages** | **Piece Rate** | **Fixed Wages** |
|---|---|---|---|
| Mean $<$ age 30 to $>$ age 50 wage ratio | 0.865 | 0.869 | 0.916 |
| Median wage loss following job loss | -0.316% | -0.633% | 0.000% |
| 90th percentile wage loss following job loss | -29.542% | -44.523% | -1.111% |
| Wage dispersion: 90th percentile/median | 1.455 | 1.670 | 1.093 |
| Temporary to permanent contract wage ratio | 1.002 | 1.002 | 1.021 |

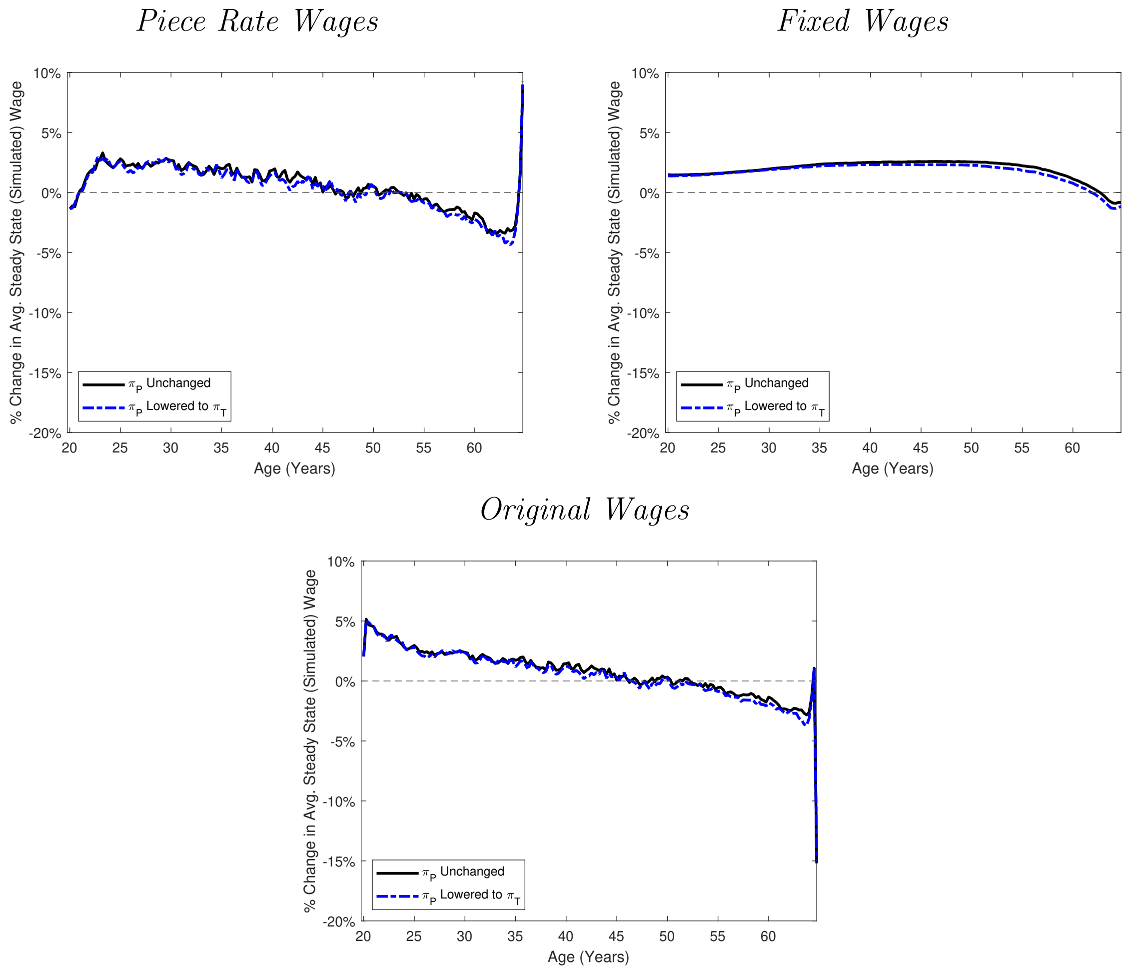
Importantly, *Table 13* shows that the average permanent-temporary wage growth difference is responsive to alternate wage assumptions. Under the original model calibration, the model does not match the wage growth difference associated with employment in a temporary contract with the alternative wage assumptions. The table indicates that this moment is sensitive to the assumption regarding how wages are determined. Calibrations undertaken assuming the alternative wage specifications may allow the model to match the data more closely in this regard, and the results of the paper have proven to be robust to multiple alternative assumptions and separate calibrations (see appendices *H*, *I*, *J*, and *K*). However, this appendix highlights that some results are sensitive to how wages are specified, and future research is needed to determine which wage assumption most accurately reflects reality and whether calibrations under alternative wage assumptions might result in a closer match regarding the model-generated wage growth difference associated with temporary contracts.

*Table 13: Wage and Wage Growth Difference Associated with Temporary Contracts*

| | Original Wages | Piece Rate | Fixed Wages |
|---|---|---|---|
| Wage Penalty | 0.0054*** | 0.0114*** | 0.0247*** |
| Annual Wage Growth Difference | -0.0132*** | 0.0022*** | 0.0009*** |

Finally, *Figure 13* displays the change in the average wage by age after implementing the policy counterfactuals described in Section IV.C under each wage assumption. Recall that the counterfactual considers how eliminating the two-tiered labor market by removing firing costs affects the economy. This policy change is evaluated in two scenarios. The first scenario assumes that eliminating firing costs does nothing to affect the rates of human capital accumulation and is referred to in the figure as the case with "$\pi_P$ Unchanged". The second scenario assumes that firing costs play a role in human capital accumulation by providing incentives for firms to invest in workers' skills and that

*Figure 13: Policy Counterfactual: Change in Average Wage by Age*




without these incentives, the rate of human capital accumulation in permanent contracts ($\pi_P$) drops to the rate in temporary contracts ($\pi_T$), referred to in the figure as the case with "$\pi_P$ Lowered to $\pi_T$".

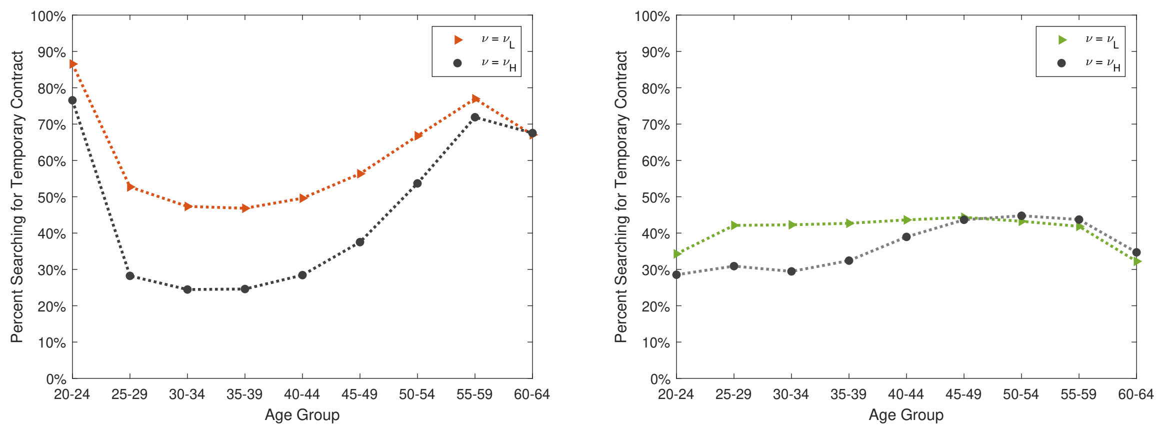
*Figure 13* shows that under the two alternative wage assumptions, the general pattern regarding how wages respond to the policy change by age category is similar to the result generated from the original wage assumption in the main text. Under all wage assumptions, the average wage is higher for younger workers after the policy change, compared to the steady state with firing costs. As workers age, the effect of substantially lower average human capital starts to outweigh the benefit of more vacancies being posted at higher contract values, and we see the average wage decline below the steady state for older age groups. The main difference observed under the different assumptions regarding how wages are determined is at what age the average wage becomes lower after the policy change. Under the original wage assumption, average wages were lower than in the steady state before the policy change after workers reached approximately age 45. This result is similar in the case of piece-rate wages, although the average wage after the policy counterfactual does not decline until agents are closer to age 50. In the case of fixed wages, average wages at the new steady state remain higher for the majority of workers' lives and the average wage does not decline past the previous steady-state level until near age 62.

# E Additional Model Dynamics and Policy Functions

This appendix displays further details regarding the model policy functions. First, *Figure 14* plots the selection decisions of agents into temporary or permanent contracts Most unemployed workers choose to search for temporary contracts. Given the same surplus rate $\mu$, a worker can find a temporary contract more quickly than a permanent contract. The value of posting a vacancy for a temporary contract, given the same $\mu$ value, will be higher for firms than posting a permanent contract. More temporary contract vacancies mean a worker can match more quickly with a temporary contract job. In general, unemployed workers tend to favor quicker matches that will bring them out of unemployment. After finding employment, most workers are more likely to search

*Figure 14: Job Choice by Age and Education*

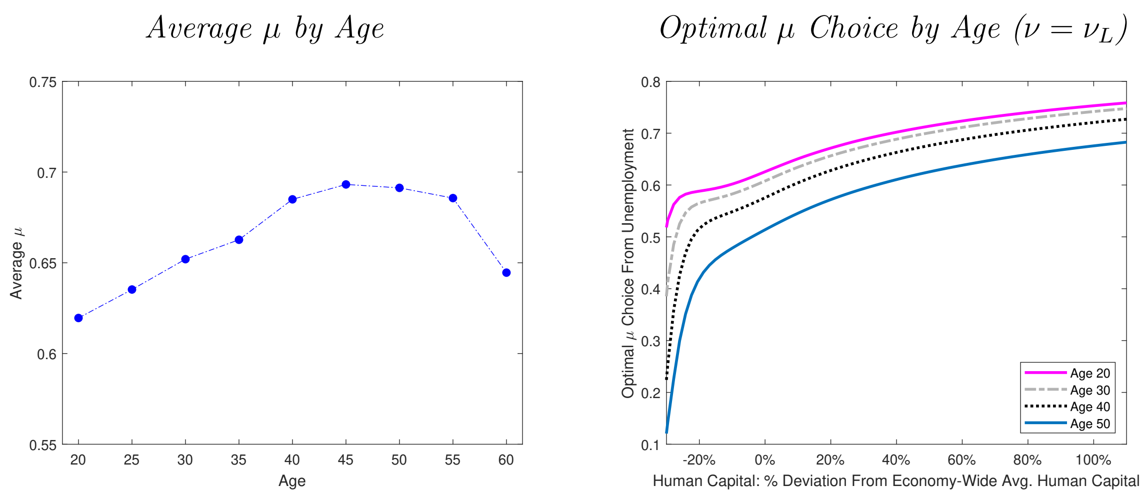
*Job Choice When Unemployed* *Job Choice When Employed*




for permanent contracts that take longer to find but offer greater security and a higher human capital accumulation rate. Movement from temporary to permanent contracts also takes place when temporary contracts expire and firms have the option to convert the contract or costlessly separate. Workers sort into either job type based on education as well. Workers with higher educational attainment, who benefit more from on-the-job learning, are less likely to sort into temporary contracts.

While *Figure 4* in the main text showed that workers on average work in jobs offering higher $\mu$ values as they age, *15* helps us examine this result in greater detail. Recall that $\mu$ specifies the fraction of the match surplus that accrues to the worker. All else equal,

*Figure 15: Optimal $\mu$ Choice by Age*

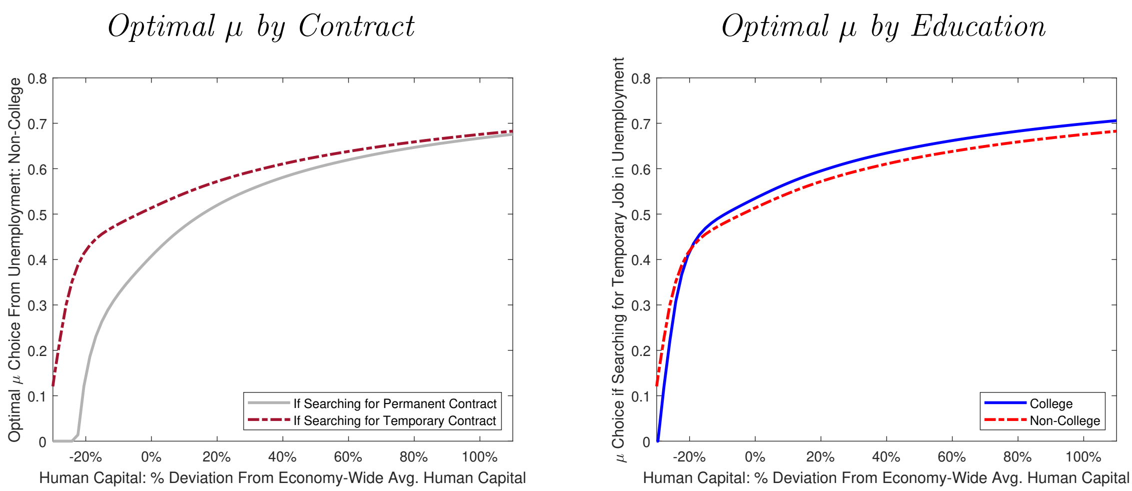



a higher $\mu$ value indicates a higher wage. The left panel of *Figure 15* shows that the average $\mu$ value of employed agents increases with age, as workers can search on the job for more favorable $\mu$ values and generally accumulate human capital, which also enables them to search for higher $\mu$ values. However, the right panel of the figure shows that holding worker characteristics constant, older workers optimally search for lower $\mu$ values. As workers age, the value of hiring them declines, holding human capital fixed. Older workers cannot obtain the same $\mu$ value for a given job-finding probability that younger workers are. This helps explain the reversal of the pattern displayed in the left panel of the figure. Although workers generally obtain higher $\mu$ values from age 20 to 45, at older ages the average $\mu$ value begins to decline. This decline reflects lower expected employment continuation values, eventually outweighing the effects of higher average human capital and accumulated benefits from on-the-job search.

*Figure 16* compares the optimal $\mu$ choices among agents with the same human capital values based on search for a particular contract type and based on education. The left panel of the figure considers a scenario where unemployed agents must search for either a permanent or temporary contract.[3] The figure shows that workers with the same characteristics search for higher $\mu$ values if searching for a temporary contract than when searching for a permanent one. This result is due to two model features. First, from a firm's perspective, the value of employing a worker in a permanent contract may not be as high as employing them in a temporary contract, holding other characteristics constant, especially if there is a high probability that the firm may want to fire the worker in future periods. This is visible in the figure, where the gap between the optimal $\mu$ values is wider at lower human capital values, where the firm has a higher likelihood of wanting to

[3] The left panel of *Figure 16* plots the optimal $\mu$ choices made by age 55 unemployed agents with $\nu = \nu_L$. The results look similar for different ages and education types, but we must fix these characteristics in any plot comparing these policy functions.

*Figure 16: Optimal $\mu$ Choice by Contract and Education*



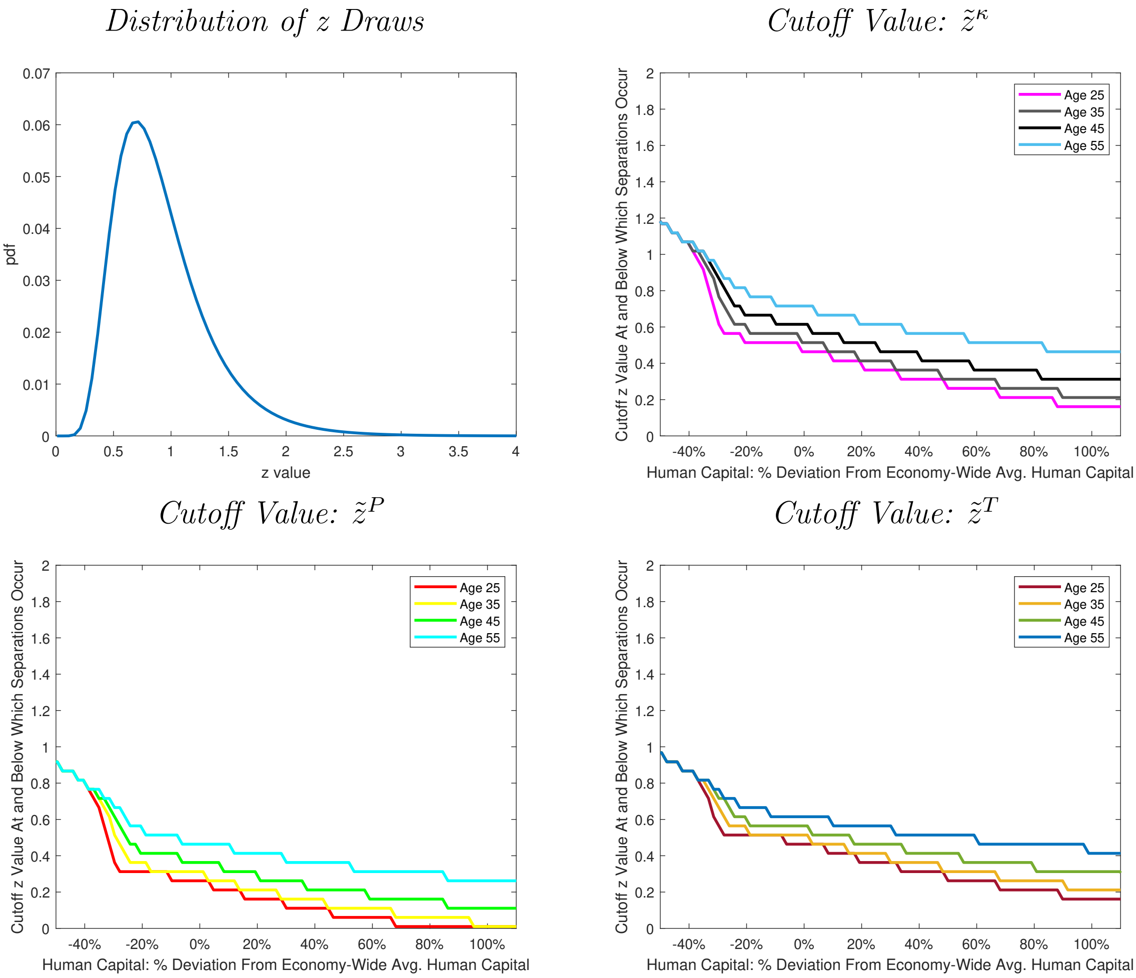

separate in future periods. The second feature of the model contributing to this result is that workers may obtain the same expected discounted value of employment $x$ at a lower $\mu$ value if given some level of employment protection. In other words, a worker might still get a higher expected discounted value of employment in a job offering a lower $\mu$ if that job offers a lower expected separation probability.

Next, *Figure 17* displays how separation decisions vary over the life cycle across different human capital values. The top left panel of the figure displays the distribution from which idiosyncratic productivity $z$ values are drawn in employment. Recall that all newly formed matches start with known idiosyncratic productivity value $z_0$. This assumption is convenient as all created matches last at least one period, simplifying many of the value functions. Then, the idiosyncratic productivity for employed workers is redrawn with probability $\gamma$ each period from Lognormal($\mu_z$ , $\sigma_z^2$ ). The value $z_0$ is assumed to be the mean of this distribution. The parameter estimates of $\mu_z$ and $\sigma_z$ are displayed in *Table 4*.[4] The other panels plot the cutoff values for $z$ at and below which separation occurs. $\tilde{z}^P$ is the cutoff value in permanent contracts, $\tilde{z}^T$ is the cutoff in temporary contracts, and $\tilde{z}^\kappa$ is the cutoff when determining whether to convert a temporary job into a permanent job or costlessly separate. Equations (10), (11), and (12) describe the determination of these cutoff values.

Notice that the separation values increase with age, holding human capital fixed. When deciding whether to preserve the match, the firm and worker internalize the expected discounted continuation value, which is higher at younger ages. However, as workers age, they accumulate more human capital, which increases their productivity at any $z$ value and lowers the optimal separation cutoff. These trade-offs, in addition to the trade-offs describing how the optimal search decisions vary with age shown in *Fig-*

[4]The figure plots the discretized distribution, which is made up of 100 equally spaced possible $z$ values from 0.01 to 5.

*Figure 17: Separation Cutoff Values ($\nu = \nu_L$)*

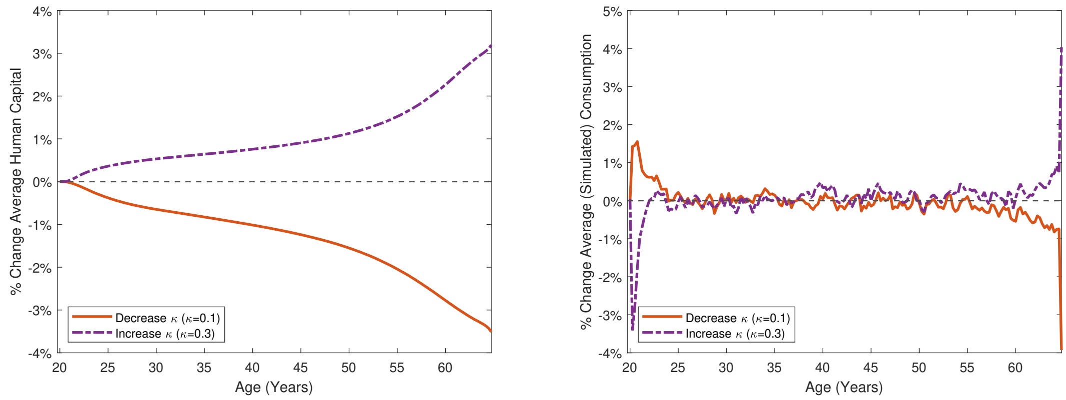



*ure 15* result in the model matching the annual employment-to-unemployment transition probability patterns by age and contract type observed in the data (see *Figure 7*).

# F Additional Policy Counterfactual Results

Countries impose various restrictions on the length of time that firms can employ the same worker in temporary contracts. In this appendix, I consider the effects of policy changes that increase or decrease the temporary contract expiration probability $\kappa$, as described in Section IV.D. The left panel of *Figure 18* compares the average steady-state human capital at each age before and after these policy changes. When the temporary contract expiration probability decreases, firms, on average, can continue to employ a worker without employment protections for a more extended period of time without needing to decide whether to costlessly fire the worker or commit to keeping the worker with employment protections. The figure shows that when $\kappa$ decreases, average human capital declines relative to the original steady-state value, and the gap widens with age.

*Figure 18: Effects of Altering Temporary Contract Expiration Rate $\kappa$ on Steady State Human Capital and Average Consumption*

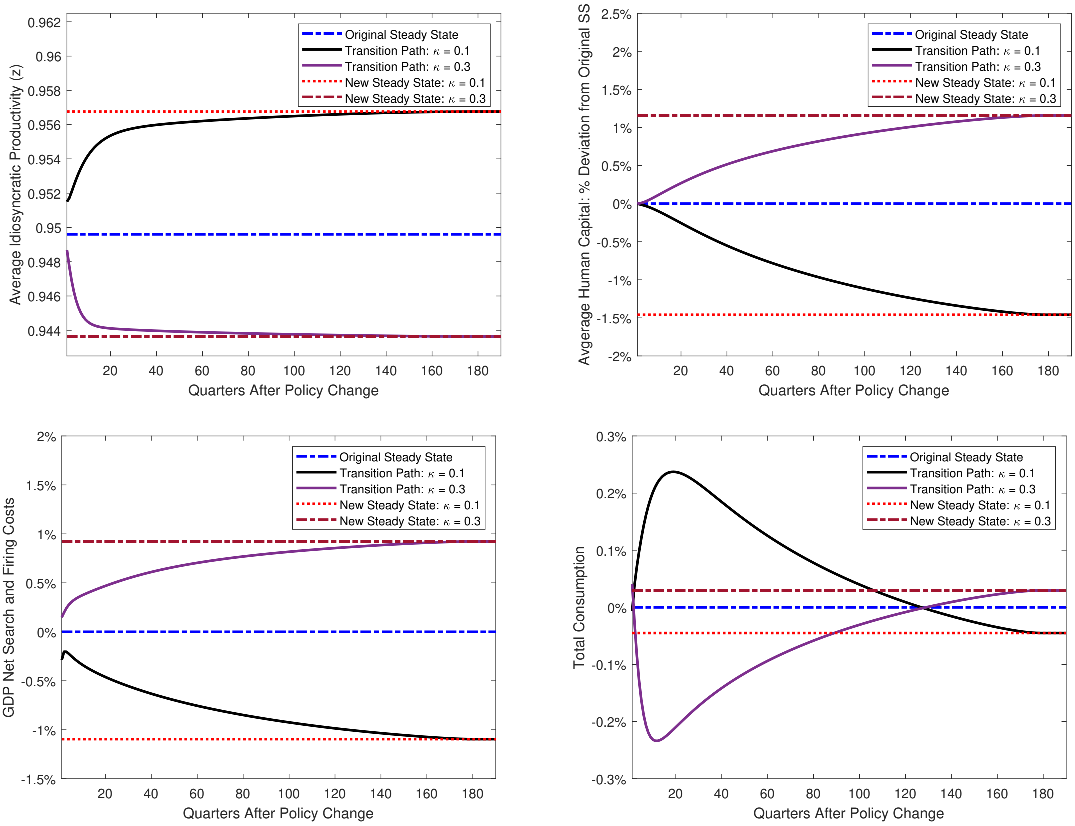



Increasing $\kappa$, which makes firms decide sooner between costlessly firing the worker and giving them employment protections, results in workers moving out of temporary contracts more quickly and slightly increases average human capital with age. The right panel of *Figure 18* shows that average consumption increases when $\kappa$ decreases for younger individuals. However, the opposite is true for older individuals who experience a decrease in steady-state average consumption when $\kappa$ decreases and an increase in average consumption when $\kappa$ increases. This is consistent with the results from section IV.C, which showed that broadly allowing firms to employ workers without employment protections, which can occur for a longer expected duration when $\kappa$ is lower, boosts the job-finding rate of unemployed workers at the expense of generating lower human capital with age. These effects can benefit new entrants who enter the model in unemployment, although at the cost of reducing human capital and average consumption with age.

*Figure 19* displays the transition paths towards each new steady state as $\kappa$ increases or decreases. The top left panel of the figure shows that average idiosyncratic match productivity ($z$) immediately begins to rise when $\kappa$ is lowered to 0.1, while it immediately begins to fall when this probability increases from 0.163 in the original steady state to 0.3. This trend is due to more workers being employed in temporary contracts when $\kappa$ is lower, where there is no cost incurred from the firm and worker separating. Therefore, more matches choose to separate when relatively low $z$ values are realized rather than preserve the match to avoid the firing cost. The transition of average human capital towards its new steady-state level occurs more slowly following the policy change. Human capital is shaped by the experiences of agents in the economy over their entire careers, so human capital only reaches its new steady state level after all agents who populated the model economy before the policy change occurred have time to exit the model.

The bottom left panel of *Figure 19* tracks the progress of GDP (output produced by firm-worker matches) net of search and firing costs as it moves towards its new steady state following each policy change. The bottom right panel tracks total consumption -

*Figure 19: Transition Paths After Altering Temporary Contract Expiration Rate $\kappa$*



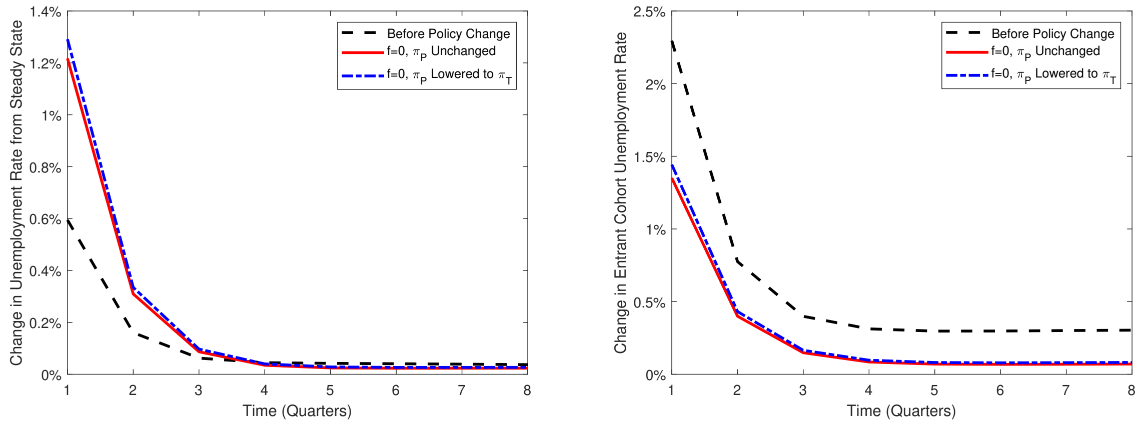

net GDP plus leisure consumption. While net GDP follows a smooth path upward or downward towards its new steady state when $\kappa$ is increased or decreased, the transition path of total consumption is not unidirectional. When the policy change lowers $\kappa$, total consumption initially climbs as firms are more willing to post vacancies when they can employ workers without employment protections for a longer time on average (*Table 8* shows that average market tightness increases in this case). However, in the longer term, total consumption begins to decline as this policy change has negative effects on human capital that take time to accumulate.

# G Business Cycle Responses

This appendix considers how the economy responds to a one-time unexpected negative aggregate shock before and after employment protections are removed. Specifically, consider a negative 2% shock to the productivity of all worker-firm pairs so that production becomes $(1-0.02)g(\nu, h, z)$ in the period of the negative shock and returns to $g(\nu, h, z)$ in all subsequent periods. The top left panel of *Figure 20* displays the change in percentage points of the total unemployment rate in the economy to the aggregate shock. It shows that during the period of the shock, the total unemployment rate increases by approximately 0.6 percentage points when firing costs are present to dissuade job destruction of permanent contracts, but unemployment increases by slightly more than 1.2 percentage points in an economy without these firing costs. The right panel of *Figure 20* shows that

*Figure 20: Unemployment Response to Negative Aggregate Shock*

*Change in Total Unemployment* *Change in Age 20 Cohort Unemployment*

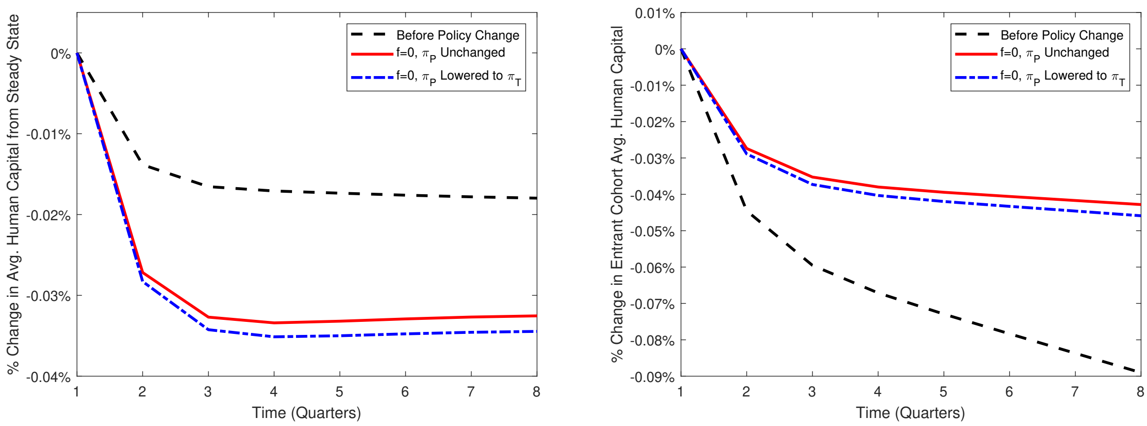



the unemployment response of those aged 20 when the shock occurs differs significantly from the aggregate response. This panel tracks the cohort of individuals who entered the economy at age 20 during the period of the shock and compares their unemployment rate under each policy to the case when no shock occurs. Unlike the aggregate unemployment response, unemployment among this cohort is more responsive when firing costs are applied to permanent contracts, as these costs restrict the number of vacancies available for this new cohort.

*Figure 21* aids in understanding the unemployment responses of the economy as a whole compared to the cohort of new entrants by displaying the shock's effect on average human capital. The left panel of the figure shows the impact on total average human

*Figure 21: Human Capital Response to Negative Aggregate Shock*

*Total Average Human Capital* *Age 20 Cohort Average Human Capital*



capital in the economy. In contrast, the right panel shows the effect on the cohort of individuals who were new entrants when the shock occurred. While the shock does not result in a significant reduction in total average human capital, which evolves slowly over the life cycle, the reduction is approximately twice as large when firing costs are not present to dissuade job destruction of permanent contracts. However, the human capital effect is significantly different for those who were new entrants (age 20) when the shock occurred. The presence of firing costs on permanent contracts makes it more challenging for new entrants to secure jobs. The aggregate shock prolongs the period of unemployment for new entrants, leading to a lasting scarring effect on their human capital. This scarring effect is a crucial issue, as it continues to hinder this cohort's ability to find and retain jobs, compared to an identical cohort that did not experience the shock.

# H Results With Age-Dependent Retirement Probability

This appendix considers an alternative model setup where rather than assuming all agents retire at age 65 (after 180 quarters in the model), agents face a retirement probability each period dependent on their age and could continue working until age 70 (at most 200 quarters in the model).[5] Agents who retire are assumed to exit the model and never return to the labor force. In this setup, the value functions are slightly altered so that (2), (5), and (7) become (19), (20), and (21) respectively. Notice that the only alterations in these value functions are that there is a probability $R(a)$ that the agent will exit the model before the next period, and the maximum age that agents can attain before exiting the model is $\overline{a}_{70yr}$.

$$U_a(\nu, h) = b + (1 - R(a))\beta\mathbb{E}[\widehat{U}_{a+1}(\nu, h')] \tag{19}$$

$$V_a^P(\nu, h, z) = g(\nu, h, z) + (1 - R(a))\beta\mathbb{E}\left[\widehat{V}_{a+1}^P(\nu, h', z)\right] \tag{20}$$

$$V_a^T(\nu, h, z) = g(\nu, h, z) + (1 - R(a))\beta\mathbb{E}\left[\widehat{V}_{a+1}^T(\nu, h', z)\right] \tag{21}$$

With this change in the model, the parameters previously listed in *Table 4* are re-calibrated while those assigned parameter values listed in *Table 3* are unchanged. *Table 14* lists how the altered and re-calibrated model matches the targeted data moments.

[5] Specifically, the quarterly exit probability values for age groups (in years) [20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-65, 65-69] are respectively [0, 0, 0, 0.00038, 0.00033, 0.00037, 0.00114, 0.00488, 0.01430, 0.07525]. In the data, only 5.5% of workers aged 70-74 participate in the labor force.

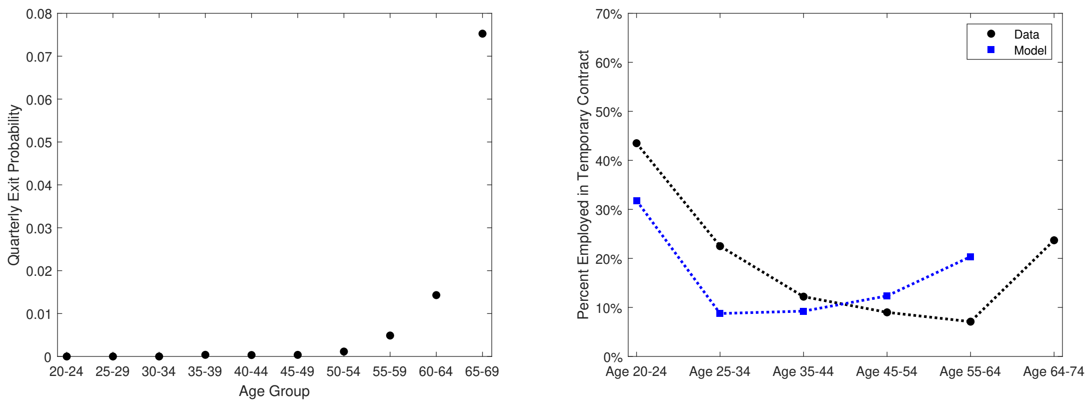
*Table 14: Jointly Calibrated Parameter Values*

| Parameter | Parameter Estimate | Targeted Moment | Data | Model |
|---|---|---|---|---|
| $\lambda$ | 0.066583 | Quarterly job-to-job transition probability | 0.035 | 0.036 |
| $\pi_P$ | 0.213689 | Mean < 30 to > 50 wage ratio | 0.510 | 0.889 |
| $\pi_T$ | 0.205510 | Avg. permanent-temporary wage growth difference by age group | 0.392% | 0.469% |
| $\pi_U$ | 0.731278 | Median wage loss following job loss | -0.427% | 0.047% |
| $\eta$ | 0.042310 | 90th percentile wage loss following job loss | -34.490% | -30.87% |
| $\sigma_h$ | 0.106324 | Ratio of unemployment rate if 20-34 to 35-54 | 1.676 | 1.389 |
| $\mu_z$ | -0.136070 | Ratio of % in temporary contracts if 20-34 vs. 35-64 | 2.960 | 3.150 |
| $\sigma_z$ | 0.436215 | Wage dispersion: 90th percentile/median | 1.793 | 1.488 |
| $c$ | 0.180252 | Ratio of total unemployment to college unemployment | 1.364 | 1.491 |
| $\ell$ | 1.295515 | Job vacancy rate | 3.200 | 5.610 |
| $\gamma$ | 0.427499 | Quarterly probability of remaining employed | 0.970 | 0.978 |
| $\kappa$ | 0.167750 | Qrtrly temporary to permanent contract probability | 0.121 | 0.150 |
| $\alpha_L$ | 0.286119 | Temporary to permanent contract wage ratio | 0.646 | 1.000 |
| $\alpha_H$ | 0.357740 | Ratio of % in temporary contracts: college vs. non-college | 0.768 | 0.684 |
| $f$ | 0.539394 | Total percent employed in temporary contracts | 16.425% | 14.484% |
| $b$ | 0.924493 | Prime-age unemployment rate | 2.600% | 1.345% |

Next, *Figure 22* displays both the model exit probability for each age group and the percentage of workers in each group in temporary contracts. The percentage of workers aged 65-69 in temporary contracts in the model is 27.02%. It appears that extending the possible working life of individuals in the model does not do much to help the model match the relatively low percentage of individuals aged 55-64 in temporary contracts. Additional considerations apart from those present in the model, such as selection into retirement and the impact of accumulated assets on search decisions, could play an important role in fully capturing this trend among older individuals.

*Figure 22: Model With Age-Dependent Retirement Probability*

*Quarterly Exit Probability* *% in Temporary Contracts by Age*




Next, consider how the results of the main policy counterfactual, displayed previously in *Table 6* differ when the model is extended with workers potentially working until age 70 and facing an age-dependent probability of retirement. Recall that this counterfactual considers eliminating the two-tiered labor market by removing firing costs. The table presents the results of the policy change under two scenarios. The "no $\pi$ effect" case assumes the removal of firing costs does nothing to affect human capital accumulation incentives, so the rate of human capital accumulation in permanent jobs ($\pi_P$) is unchanged. The "full $\pi$ effect" scenario assumes that without the incentives brought on by imposing firing costs, $\pi_P$ drops to $\pi_T$, the rate of human capital accumulation in temporary jobs. *Table 15* shows that under the alternative model setup presented in this appendix, the main policy counterfactual results do not differ greatly. In both cases, the removal of

*Table 15: Estimated Effects of Eliminating Firing Costs for Permanent Contracts*

| | No $\pi$ Effect | Full $\pi$ Effect |
|---|---|---|
| Quarterly % of Jobs Ending in Separation | +4.69pp | +4.83pp |
| Quarterly % of Unemployed Finding Job | +1.83pp | +1.41pp |
| Total Unemployment Rate | +6.28pp | +6.51pp |
| Average Human Capital | -8.81% | -9.93% |
| Average Idiosyncratic Productivity ($z$) | +4.96% | 5.08% |
| GDP Net of Search & Firing Cost | -5.48% | -5.99% |

firing costs increases the job-finding rate as well as the rate of job separation and results in an overall increase in the unemployment rate. In this case, the effect on the job-finding rate among unemployed agents is notably more negligible, while all other effects are of approximately the same magnitude as with the original model.

# I Results with Additional Temporary Contract Assumptions

This appendix extends the model to consider two additional assumptions regarding the nature of temporary contracts. First, I.1 extends the model to allow firms to convert a temporary contract into a permanent one at any time (before the contract expires with probability $\kappa$) by paying conversion cost $\zeta$. Then, I.2 considers a setup where firing costs apply to temporary contracts except in renewal periods where the temporary contract can be renewed or ended costlessly.

## I.1 Endogenous Temporary to Permanent Contract Conversion Choice Prior to $\kappa$ Shock Realizations

Consider an additional endogenous choice added to the model described in Section III. Rather than only allowing the conversion of temporary contracts into permanent ones when temporary contracts expire with probability $\kappa$, allow firms to make a conversion choice every period. Specifically, before the start of the next period, a firm can always pay cost $\zeta$ to convert a temporary contract into a permanent one. This alters equation (7) into (22) below.

$$V_a^T(\nu, h, z) = g(\nu, h, z) + \beta \max \left\{ \mathbb{E}\left[\widehat{V}_{a+1}^T(\nu, h', z)\right], -\zeta + \mathbb{E}\left[\widehat{V}_{a+1}^P(\nu, h', z)\right] \right\} \tag{22}$$

With this change in the model, the parameters previously displayed in *Table 4* are re-calibrated while the assigned parameters in *Table 3* are unchanged. *Table 16* reports the new parameter estimates and the new model-generated moments. Extending the

*Table 16: Jointly Calibrated Parameter Values: Endogenous Temporary to Permanent Contract Conversion Choice Prior to $\kappa$ Shock Realizations*

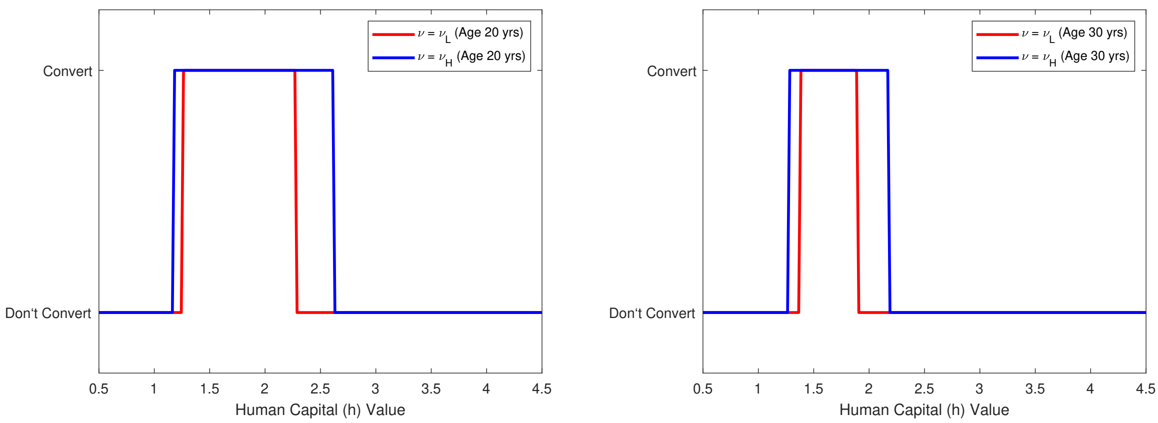
| **Parameter** | **Parameter Estimate** | **Targeted Moment** | **Data** | **Model** |
|---|---|---|---|---|
| $\lambda$ | 0.073393 | Quarterly job-to-job transition probability | 0.035 | 0.037 |
| $\pi_P$ | 0.223522 | Mean $<30$ to $>50$ wage ratio | 0.510 | 0.842 |
| $\pi_T$ | 0.202922 | Avg. permanent-temporary wage growth difference by age group | 0.392% | 0.199% |
| $\pi_U$ | 0.768907 | Median wage loss following job loss | -0.427% | -0.434% |
| $\eta$ | 0.079059 | 90th percentile wage loss following job loss | -34.490% | -37.642% |
| $\sigma_h$ | 0.090316 | Ratio of unemployment rate if 20-34 to 35-54 | 1.676 | 1.680 |
| $\mu_z$ | -0.168307 | Ratio of % in temporary contracts if 20-34 vs. 35-64 | 2.960 | 2.979 |
| $\sigma_z$ | 0.436248 | Wage dispersion: 90th percentile/median | 1.793 | 1.561 |
| $c$ | 0.061197 | Ratio of total unemployment to college unemployment | 1.364 | 1.171 |
| $\ell$ | 1.275268 | Job vacancy rate | 3.200 | 7.480 |
| $\gamma$ | 0.415719 | Quarterly probability of remaining employed | 0.970 | 0.978 |
| $\kappa$ | 0.143474 | Qrtrly temporary to permanent contract probability | 0.121 | 0.125 |
| $\alpha_L$ | 0.355448 | Temporary to permanent contract wage ratio | 0.646 | 1.009 |
| $\alpha_H$ | 0.377664 | Ratio of % in temporary contracts: college vs. non-college | 0.768 | 0.773 |
| $f$ | 0.521762 | Total percent employed in temporary contracts | 16.425% | 16.462% |
| $b$ | 0.902479 | Prime-age unemployment rate | 2.600% | 1.150% |

model to allow this conversion option at cost $\zeta$ introduces $\zeta$ as an additional parameter to estimate with no obvious empirical target (as the temporary to permanent contract conversion rate is already targeted and reflects movements due to search on the job as well). Rather than include $\zeta$ in the joint calibration, I consider values of $\zeta$ relative to the vacancy posting cost $c$ that result in conversions occurring. Notice that the value of $c$ under this extended model is already less than half of its estimate in the model presented in Section III. (The vacancy posting cost is only around 0.061 rather than 0.176 in the original model.) Still, allowing $\zeta = c$ in this case results in no endogenous conversions of temporary to permanent contracts before expiring. Endogenous contract conversions only begin to occur when $\zeta$ is near half the cost of posting a vacancy, and the following results make the assumption $\zeta = 0.5c$.

*Figure 23* displays the temporary to permanent contract conversion choice for different ages and human capital values. First, notice that the range of human capital values at which firms find it optimal to convert contracts narrows from age 20 to 30. By age 40 and above, no firms find it optimal to convert contacts. This age effect can best be understood by recognizing that the benefit of converting an existing match from a temporary to a permanent contract lies in gaining the faster expected human capital accumulation rate in permanent contracts ($\pi_P > \pi_T$). The benefit of a faster expected human capital accumulation rate is most significant for young workers. Next, notice

*Figure 23: Temporary to Permanent Contract Conversion at Cost $\zeta$*

*Age 20 Workers* *Age 30 Workers*




that endogenous contract conversions occur among firms employing workers with mid-level human capital. Generally, firms are more likely to want to fire less productive, low human capital workers (there is a greater range of $z$ values below which the match productivity is too low.) Therefore, the decision to convert low-human capital workers is influenced by the higher expected probability that it would be optimal to separate from them, which can most easily be done in a temporary contract. As workers accumulate human capital, the probability that it would be optimal to separate declines, but so does the return to more human capital accumulation. After a certain point, converting the contract to obtain a higher human capital accumulation rate at cost $\zeta$ becomes no longer optimal.

Next, consider how the results of the main policy counterfactual, previously reported in *Table 6* differ when the model is extended to allow for the endogenous conversion of temporary to permanent contracts in any period at cost $\zeta$. *Table 17* displays the new results of this policy counterfactual under the extended model. The table shows that

*Table 17: Estimated Effects of Eliminating Firing Costs for Permanent Contracts*

| | No $\pi$ Effect | Full $\pi$ Effect |
|---|---|---|
| Quarterly % of Jobs Ending in Separation | +5.73pp | +6.30pp |
| Quarterly % of Unemployed Finding Job | +1.46pp | +0.69pp |
| Total Unemployment Rate | +6.04pp | +6.99pp |
| Average Human Capital | -10.35% | -13.258% |
| Average Idiosyncratic Productivity ($z$) | +5.07% | +5.81% |
| GDP Net of Search & Firing Cost | -2.05% | -5.58% |

the policy counterfactual results are similar under this model compared to the model described in the main text. In both cases, removing firing costs increases job separation and job-finding rates, resulting in an overall increase in unemployment. In this case, the impact on the job-finding rate of unemployed agents is notably smaller, and the reduction in GDP net of costs is a bit muted as well, while all other effects are of approximately the same degree as those in the main text.

## I.2 Firing Costs Applied to Temporary Contracts with Contract Renewal Option

Now, consider an alternative model setup considering the renewal option of temporary contracts. Recall that a worker can be employed in a string of successive temporary contracts with the same firm. Still, there are limits on the number of successive temporary contracts or time spent in temporary contracts with the same firm across countries. In the Netherlands, an employee must receive a permanent contract after three consecutive temporary contracts or three years of temporary contracts. In the model presented in the main text, the temporary contract expired with probability $\kappa$, representing that these contracts could no longer be renewed, and the firm must either employ the worker in a permanent contract or costlessly separate from the worker. Now, consider a setup that more explicitly considers the renewal of successive temporary contracts and the costs associated with separating from these contracts before they are up for renewal.

Specifically, consider the following alteration to the model presented in the main text. Temporary contracts come up for renewal each period with probability $\phi$. When a contract is up for renewal, the firm and worker could costlessly separate or continue in a temporary contract. With probability $\kappa$, a temporary contract expires and cannot be renewed; in this case, the firm and worker must continue in a permanent contract or costlessly separate. If a temporary contract has not expired and is not up for renewal, the firing cost $f$ applies in case of separation. This alters equation (6) to the following

$$
\begin{aligned}
&\widehat{V}_a^T(\nu,h,z) = \max_{G,x}\left\{\lambda p(\theta_a^G(x,\nu,h,z))x\right. \\
&+ (1-\lambda p(\theta_a^G(x,\nu,h,z)))(1-\kappa)(1-\phi)\left[\int_{\tilde{z}_a^T(\nu,h)}^{\infty} V_a^T(\nu,h,z')dF(z'|z) + F(\tilde{z}_a^T(\nu,h)|z)\left[U_a(\nu,h)-f\right]\right] \\
&+(1-\lambda p(\theta_a^G(x,\nu,h,z)))(1-\kappa)\phi\left[\int_{\tilde{z}_a^\phi(\nu,h)}^{\infty} V_a^T(\nu,h,z')dF(z'|z) + F(\tilde{z}_a^\phi(\nu,h)|z)U_a(\nu,h)\right] \\
&\left.+(1-\lambda p(\theta_a^G(x,\nu,h,z)))\kappa\left[\int_{\tilde{z}_a^\kappa(\nu,h)}^{\infty} V_a^P(\nu,h,z')dF(z'|z) + F(\tilde{z}_a^\kappa(\nu,h)|z)U_a(\nu,h)\right]\right\}. \qquad (23)
\end{aligned}
$$

With this alternative model, the parameters displayed previously in *Table 4* are re-calibrated and are reported in *Table 18.* The assigned parameters reported in *Table 3* remain unchanged. The probability $\phi$ that a temporary contract is up for renewal is set to equal $\kappa \times 3$, making this occurrence three times as likely as contract expiration, aligning roughly with legislation surrounding contract expiration after successive renewals in the Netherlands.

Notice that in this particular model alteration, the model has difficulty matching many of the model moments. Although the model in the main text and the other alternative

*Table 18: Jointly Calibrated Parameter Values*

| Parameter | Parameter Estimate | Targeted Moment | Data | Model |
|---|---|---|---|---|
| $\lambda$ | 0.038895 | Quarterly job-to-job transition probability | 0.035 | 0.020 |
| $\pi_P$ | 0.216201 | Mean $< 30$ to $> 50$ wage ratio | 0.510 | 0.857 |
| $\pi_T$ | 0.203129 | Avg. permanent-temporary wage growth difference by age group | 0.392% | 0.751% |
| $\pi_U$ | 0.632647 | Median wage loss following job loss | -0.427% | 0.072% |
| $\eta$ | 0.088026 | 90th percentile wage loss following job loss | -34.490% | -34.375% |
| $\sigma_h$ | 0.111814 | Ratio of unemployment rate if 20-34 to 35-54 | 1.676 | 1.688 |
| $\mu_z$ | -0.169395 | Ratio of % in temporary contracts if 20-34 vs. 35-64 | 2.960 | 3.453 |
| $\sigma_z$ | 0.483134 | Wage dispersion: 90th percentile/median | 1.793 | 1.557 |
| $c$ | 0.162953 | Ratio of total unemployment to college unemployment | 1.364 | 1.064 |
| $\ell$ | 1.294493 | Job vacancy rate | 3.200 | 3.354 |
| $\gamma$ | 0.486667 | Quarterly probability of remaining employed | 0.970 | 0.978 |
| $\kappa$ | 0.230319 | Qrtrly temporary to permanent contract probability | 0.121 | 0.201 |
| $\alpha_L$ | 0.332990 | Temporary to permanent contract wage ratio | 0.646 | 0.984 |
| $\alpha_H$ | 0.342911 | Ratio of % in temporary contracts: college vs. non-college | 0.768 | 0.879 |
| $f$ | 0.241528 | Total percent employed in temporary contracts | 16.425% | 8.426% |
| $b$ | 0.908059 | Prime-age unemployment rate | 2.600% | 1.485% |

models considered in the appendices can match the percentage of all workers employed in temporary contracts reasonably well, this setup falls notably short. With firing costs applying equally to temporary contracts as to permanent contracts, the benefit of choosing a temporary contract in the search phase is lower. The model is unable to match both the relative wage growth difference between the two contracts and the percentage of employees in temporary contracts under this setup.

While the model moments differ significantly with this alternative model, *Table 19* shows that the results generated by the model when removing the firing cost do not differ notably from the results displayed in the main text. In both cases, removing the

*Table 19: Estimated Effects of Eliminating Firing Costs*

| | No $\pi$ Effect | Full $\pi$ Effect |
|---|---|---|
| Quarterly % of Jobs Ending in Separation | +4.27pp | +4.72pp |
| Quarterly % of Unemployed Finding Job | +2.23pp | +1.60pp |
| Total Unemployment Rate | +5.02pp | +5.70pp |
| Average Human Capital | -7.55% | -9.76% |
| Average Idiosyncratic Productivity ($z$) | +3.93% | +4.38% |
| GDP Net of Search & Firing Cost | -2.39% | -3.56% |

firing costs increases job separations, the job-finding rate among the employed, the total employment rate, and average idiosyncratic match productivity. Importantly, the policy change reduces average human capital among all agents in the model, just as in *Table 6*.

While the results regarding the removal of firing costs are similar, the idea of a policy change that would remove the two-tiered labor market could easily be extended in this case to simply remove the option of firing without cost whenever a temporary contract is up for renewal or expires. In this scenario, the firing cost is applied equally to all contracts.

*Table 20: Estimated Effects of $\kappa = 0$, $\phi = 0$*

| | |
|---|---|
| Quarterly % of Jobs Ending in Separation | -0.23pp |
| Quarterly % of Unemployed Finding Job | -0.93pp |
| Total Unemployment Rate | -1.05pp |
| Average Human Capital | +0.91% |
| Average Idiosyncratic Productivity ($z$) | -0.67% |
| GDP Net of Search & Firing Cost | +3.43% |

*Table 20* reports the results of this alternative policy, and the results are roughly the opposite of the results associated with eliminating the two-tiered labor market by removing firing costs. The policy change lowers both the probability of a job separation and job-finding among the employed. However, the total unemployment falls slightly, and average human capital rises.

# J Results with Firm Heterogeneity

The model in the main text does not allow for the possibility that firms may fundamentally differ in the jobs they create, resulting in jobs that differ in the rate of human capital accumulation they provide and that may inherently be more or less likely to be turned into temporary contracts. While this paper does not examine data with characteristics necessary to adequately draw this sort of conclusion empirically, this appendix extends the model presented in Section III to consider the possibility of inherent firm heterogeneity. Specifically, consider two possible types of firms $y \in y_L, y_H$. Given the firm's type, the rate of human capital accumulation in a job of type $G \in \{P, T\}$ becomes $\pi_G \times y$. Additionally, the cost of posting a vacancy is $c(y^2)$. This assumption that the vacancy posting cost, in addition to the rate of human capital accumulation, is increasing in $y$ is necessary for both $y_L$ and $y_H$ job types to exist in equilibrium.

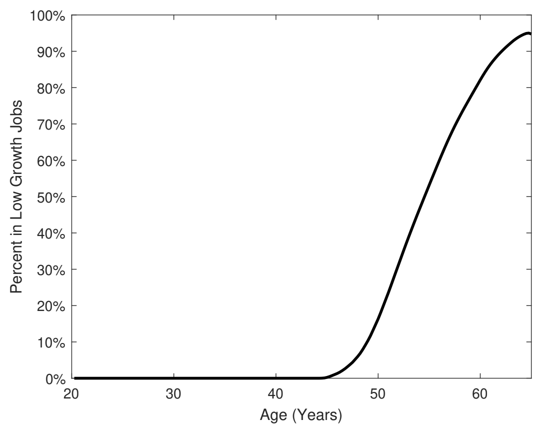
With this additional heterogeneity added to the model, an additional state variable $y$ is added to all value functions except those of the unemployed ((1) and (2)), and the vacancy posting cost becomes $c(y^2)$. In any period, agents searching for a job can search among temporary and permanent jobs of either firm type $y \in \{y_L, y_H\}$. With these model changes, the assigned parameters previously displayed in *Table 3* are unchanged, while those reported in *Table 4* are re-calibrated. *Table 21* reports the new parameters and model moments. Additionally, I let $y_L = 1$ and $y_H = 1.2$. This model alteration results

*Table 21: Jointly Calibrated Parameter Values*

| Parameter | Parameter Estimate | Targeted Moment | Data | Model |
|---|---|---|---|---|
| $\lambda$ | 0.093491 | Quarterly job-to-job transition probability | 0.035 | 0.040 |
| $\pi_P$ | 0.214019 | Mean $<30$ to $>50$ wage ratio | 0.510 | 0.835 |
| $\pi_T$ | 0.204479 | Avg. permanent-temporary wage growth difference by age group | 0.392% | 0.340% |
| $\pi_U$ | 0.742688 | Median wage loss following job loss | -0.427% | -0.316% |
| $\eta$ | 0.044753 | 90th percentile wage loss following job loss | -34.490% | -30.735% |
| $\sigma_h$ | 0.101319 | Ratio of unemployment rate if 20-34 to 35-54 | 1.676 | 1.519 |
| $\mu_z$ | -0.176633 | Ratio of % in temporary contracts if 20-34 vs. 35-64 | 2.960 | 2.964 |
| $\sigma_z$ | 0.461918 | Wage dispersion: 90th percentile/median | 1.793 | 1.481 |
| $c$ | 0.163711 | Ratio of total unemployment to college unemployment | 1.364 | 1.102 |
| $\ell$ | 1.307894 | Job vacancy rate | 3.200 | 3.951 |
| $\gamma$ | 0.40958 | Quarterly probability of remaining employed | 0.970 | 0.981 |
| $\kappa$ | 0.155642 | Qrtrly temporary to permanent contract probability | 0.121 | 0.139 |
| $\alpha_L$ | 0.314585 | Temporary to permanent contract wage ratio | 0.646 | 1.022 |
| $\alpha_H$ | 0.333263 | Ratio of % in temporary contracts: college vs. non-college | 0.768 | 0.813 |
| $f$ | 0.539734 | Total percent employed in temporary contracts | 16.425% | 16.192% |
| $b$ | 0.918010 | Prime-age unemployment rate | 2.600% | 0.974% |

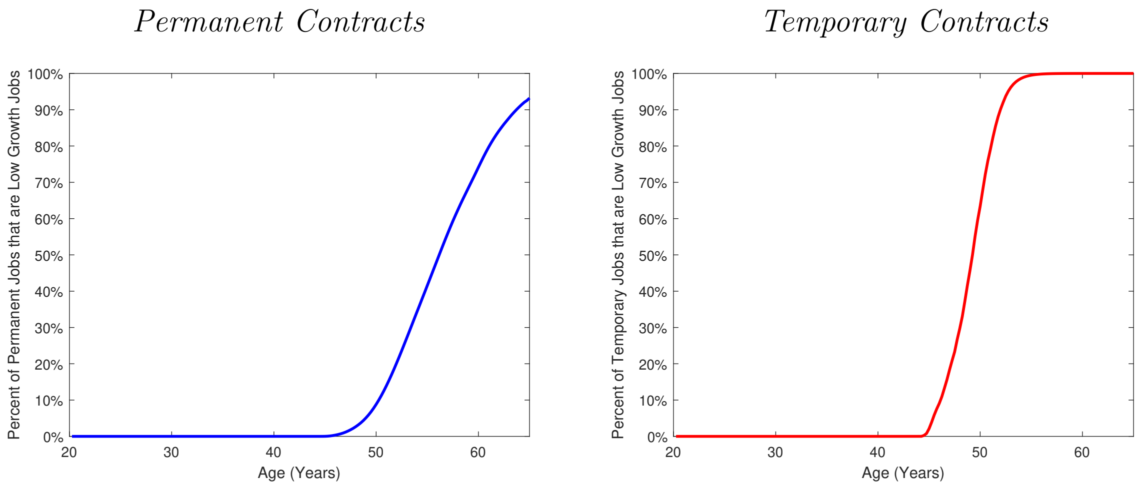
in agents sorting into not only temporary and permanent contracts but also low human capital growth ($y_L$) and high human capital growth ($y_H$) jobs with higher associated vacancy posting cost $c(y_H)^2$. *Figure 24* shows how the share of jobs that are endogenously low human capital growth ($y_L$) evolves with age. Before around age 45, workers in the model choose only high-growth ($y_H$) jobs because the benefit of higher human capital growth is greatest when young. After around age 45, workers shift strongly towards low human capital growth jobs associated with a lower vacancy posting cost.

*Figure 24: Percent of Workers in Low Growth Jobs by Age*




Overall, around 16% of employed workers are in temporary contracts, while slightly more than 20% work low human capital growth jobs. 15.4% of all permanent jobs are low-growth jobs, while 51.3% of all temporary jobs are low-growth. Therefore, this model setup generates an outcome where temporary contracts are more likely to occur in low-growth jobs, generating an additional explanation as to why workers in these jobs experience slower wage growth. Still, in matching the data moments, running the model calibration without any restrictions still estimates $\pi_P > \pi_T$. *Figure 25* plots the percentage of workers in each job type that are in low-growth jobs. The figure shows that the transition from high to low-growth jobs occurs more quickly among those in temporary contracts. However, the transition to low-growth jobs begins to occur at almost exactly the same age (45) in both contract types.

*Figure 25: Percent of Workers in Low Growth Jobs by Job Type*




Finally, consider how extending the model to allow for inherent firm heterogeneity influences the results of eliminating the two-tiered labor market by removing firing costs. *Table 22* shows that the results of the policy change are similar to those discussed in the main text and shown in *Table 6*. Removing firing costs increases both the job destruction rate as well as the probability that unemployed agents find jobs. However, the effect on job destruction is more dominant in the sense that the policy change raises the overall unemployment rate. Key to this finding is that although the average idiosyncratic productivity value is higher, the policy change results in notably lower average human capital among all agents.

*Table 22: Estimated Effects of Eliminating Firing Costs for Permanent Contracts*

| | No $\pi$ Effect | Full $\pi$ Effect |
|---|---|---|
| Quarterly % of Jobs Ending in Separation | +4.412pp | +4.689pp |
| Quarterly % of Unemployed Finding Job | +2.121pp | +1.647pp |
| Total Unemployment Rate | +5.940pp | +6.364pp |
| Average Human Capital | -9.277% | -11.044% |
| Average Idiosyncratic Productivity ($z$) | +4.886% | +5.158% |
| GDP Net of Search and Firing Cost | -5.359% | -6.181% |

# K Firing Cost Dependent on Worker Human Capital

Institutional details in the Netherlands could increase the cost of firing workers with greater tenure. The statutory notice period increases with tenure, and severance payments typically are influenced by tenure and salary at the time of termination. The cost $f$ displayed in the value functions in Section III represents the costs of firing apart from transfer payments, as direct transfer payments do not affect the joint match value. Güell (2010) argues a large portion of separation costs involve the legal fees and time associated with dismissal conflicts rather than direct transfers to workers. However, differences in required notice periods in dismissal conflicts due to greater worker tenure and/or productivity could result in firing costs that are influenced by worker tenure and productivity.

To address concerns that firing costs may increase with tenure and productivity, I consider a simple alteration of the model presented in Section III by allowing the firing cost to vary with human capital, which significantly contributes to differences in productivity and wages and is generally increasing in tenure. Rather than fixed firing cost $f$, I consider a firing cost $fh^{\alpha_\nu}$ in permanent contracts so that the firing cost is increasing in the portion of production $g(\nu, z, h) = zh^{\alpha_\nu}$ that is due to human capital ($z$ is the idiosyncratic match productivity and can be redrawn over time).

With this model alteration, the assigned parameters displayed in *Table 3* are unchanged, while I re-calibrate all parameters previously reported in *Table 4*. *Table 23* reports the updated parameters and model-generated moments. Notice that with firing

*Table 23: Jointly Calibrated Parameter Values*

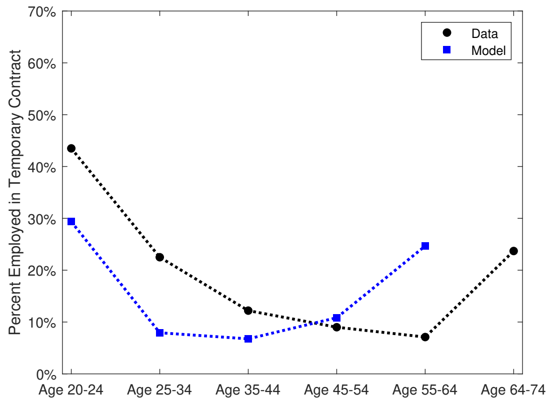
| **Parameter** | **Parameter Estimate** | **Targeted Moment** | **Data** | **Model** |
|---|---|---|---|---|
| $\lambda$ | 0.040152 | Quarterly job-to-job transition probability | 0.035 | 0.027 |
| $\pi_P$ | 0.221212 | Mean < 30 to > 50 wage ratio | 0.510 | 0.864 |
| $\pi_T$ | 0.214248 | Avg. permanent-temporary wage growth difference by age group | 0.392% | 0.774% |
| $\pi_U$ | 0.747525 | Median wage loss following job loss | -0.427% | -0.325% |
| $\eta$ | 0.064754 | 90th percentile wage loss following job loss | -34.490% | -32.739% |
| $\sigma_h$ | 0.100976 | Ratio of unemployment rate if 20-34 to 35-54 | 1.676 | 1.352 |
| $\mu_z$ | -0.155851 | Ratio of % in temporary contracts if 20-34 vs. 35-64 | 2.960 | 3.455 |
| $\sigma_z$ | 0.426129 | Wage dispersion: 90th percentile/median | 1.793 | 1.464 |
| $c$ | 0.169295 | Ratio of total unemployment to college unemployment | 1.364 | 1.177 |
| $\ell$ | 1.299696 | Job vacancy rate | 3.200 | 3.735 |
| $\gamma$ | 0.419812 | Quarterly probability of remaining employed | 0.970 | 0.976 |
| $\kappa$ | 0.159680 | Qrtrly temporary to permanent contract probability | 0.121 | 0.147 |
| $\alpha_L$ | 0.315758 | Temporary to permanent contract wage ratio | 0.646 | 0.983 |
| $\alpha_H$ | 0.343347 | Ratio of % in temporary contracts: college vs. non-college | 0.768 | 0.741 |
| $f$ | 0.208053 | Total percent employed in temporary contracts | 16.425% | 14.160% |
| $b$ | 0.914758 | Prime-age unemployment rate | 2.600% | 1.897% |

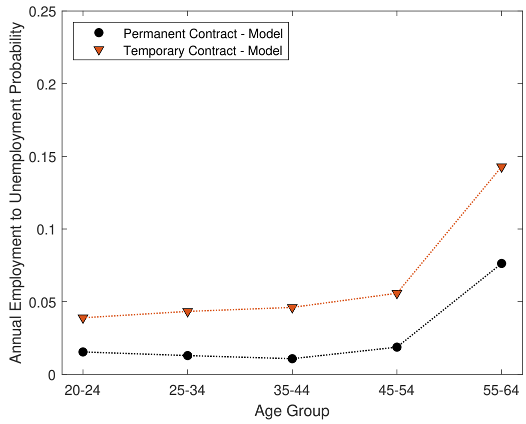
cost $fh^{\alpha_\nu}$ applied to separations from permanent contracts, the estimated value of $f$ is notably lower than in the main text. This leads to an environment where the firing cost is generally lower for younger agents and increases with age. *Figure 26* explores whether this assumption helps the model better align with the data regarding the percentage of old and young workers in temporary contracts. With the firing cost generally increasing with age, the high firing cost applied to older workers could keep them tied to their permanent contracts and reduce the percentage of older workers in temporary contracts. However, the higher firing cost for older workers also makes firms less willing to post permanent contract vacancies for older workers. Thus, older workers who lose their jobs have more difficulty finding work in a permanent contract under this assumption. The left panel of the figure shows that with these two competing effects, this alternate model does not do better in terms of matching the percentage of older workers in temporary contracts.

Next, the right panel of *Figure 26* shows how the annual transition probabilities

*Figure 26: Human Capital Dependent Firing Cost: Model Dynamics*

*Temporary Contracts by Age* | *Annual EU Transitions*




from employment to unemployment (EU) for various ages differ when the firing cost is increasing in worker human capital. Compared to the model in the main text, the EU transition probability is slightly higher among younger workers in permanent contracts, who have lower human capital on average. The annual EU transition probability still increases with age in the model, aligning with the data, as this annual probability reflects not only the quarterly separation rates but also the job-finding rates. Firing costs that generally increase with age not only influence the separation rate of older workers from permanent jobs, they also influence the rate at which these workers can find employment.

With these additional considerations brought about by the assumption that the firing cost is increasing in worker human capital, *Table 24* considers how the results of the main policy counterfactual differ. The table shows that the main results are unaltered in that the model still predicts that eliminating the two-tiered labor market by removing firing costs will increase unemployment and negatively affect average human capital. The estimated effect on human capital is notably smaller than predicted in the main

*Table 24: Estimated Effects of Eliminating Firing Costs for Permanent Contracts*

| | No $\pi$ Effect | Full $\pi$ Effect |
|---|---|---|
| Quarterly % of Jobs Ending in Separation | +2.218pp | +2.364pp |
| Quarterly % of Unemployed Finding Job | +2.364pp | +1.905pp |
| Total Unemployment Rate | +3.016pp | +3.273pp |
| Average Human Capital | -4.716% | -5.809% |
| Average Idiosyncratic Productivity ($z$) | +2.281% | +2.423% |
| GDP Net of Search and Firing Cost | -2.793% | -3.311% |

text, likely because, in this setup, the firing cost applies more strongly to high human capital workers who are less likely to lose their jobs even when the firing cost is removed. However, despite the much lower effect on human capital, the policy counterfactual results qualitatively remain the same.

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