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Optimal Long-Run Talent Management of the Department of Defense Acquisition Workforce in Response to COVID-19: A Dynamic Programming Approach

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Abstract

As the economic impact of the COVID-19 pandemic lingers, with the speed of recovery still uncertain, the state of the civilian labor market will impact the public sector. Specifically, the relatively stable and insulated jobs in the Department of Defense (DoD) are expected to be perceived as more attractive for the near future. This implies changes in DoD worker quit behavior that present both a challenge and an opportunity for the DoD leadership in retaining high-quality, experienced talent. We use a unique panel dataset of DoD civilian acquisition area workers and a dynamic programming approach to simulate the impact of the pandemic on worker retention rates under a variety of recovery scenarios. We find that workers will choose not to exit from the DoD while the civilian sector suffers from the impact of the pandemic. This allows leadership to more easily retain experienced workers. However, once the civilian sector has recovered enough, these same workers will quit at an accelerated rate, making gains in talent only temporary. These results imply that while the DoD can take short-run advantage of negative shocks to the civilian sector to retain and attract high quality workers, long-run retention will be achieved through more fundamental reforms to personnel policy to make DoD jobs more attractive, no matter the state of the civilian labor market.

Introduction

The initial impact of the COVID-19 pandemic on the U.S. civilian labor market was massive, with unemployment spiking to 15% in September 2020. While most world economies contracted in 2020, there is some consensus among economists of a relatively robust recovery in the near future, with average global economic growth projected to be about 5.5% in 2021 (International Monetary Fund, 2021). In the United States, the unemployment rate has already recovered partway since the nadir. However, the trajectory of recovery remains unclear, dependent on a host of public health programs, government stimulus, and the macroeconomic environment.

While the civilian labor market has seen extraordinary swings in employment numbers, the government sector has been somewhat immune to the short-term effects of the pandemic. We examine the potential impacts of the gyrations and continuing uncertainty in the civilian labor market on the labor market decisions of public-sector workers, focusing on the civilian acquisition workforce (AWF) in the Department of Defense (DoD). While senior DoD leadership has historically been concerned with losing qualified senior civilian workers to the private sector, the labor market impact of COVID-19 may present a pressing need to adjust personnel policy as well as an opportunity to leverage the stability of DoD positions to compete against the draw of the private firms.

We solve a dynamic programming model of worker attrition behavior, where long-lasting shocks in the civilian labor market are explicitly modeled. In particular, the model allows for a negative AR(1) shock to the civilian sector, which slowly recovers through time. After calibrating the model parameters to the AWF using a unique panel administrative personnel dataset that tracks the civilian DoD labor force over the span of thirty years, we simulate civilian-side labor market shocks that correspond to economic recoveries of varying speeds and forecast the retention behavior of the workforce.

We find that a persistent negative shock to the civilian sector (plus insulation of the government/DoD labor market from the shock), for our case, the COVID-19 pandemic, leads workers to devalue jobs in the private sector in the short-run and remain in the government sector for a longer period of time. Depending on the severity and persistence of the shock, it may take more than a decade for workers to return to valuing civilian jobs as they did before the pandemic. This relative increase in attractiveness of government jobs is only temporary, however, and workers will accelerate their exit from the government sector into the private sector once the economic recovery is well underway. That is, the attrition rate when the economy recovers turns out to be higher than the rate that would have prevailed had there not been the global pandemic.

The following section describes in more detail the labor market impact of COVID-19 on the private sector and the long-run career trajectories of the typical AWF worker. Then, we explain the dynamic programming model, while the section after that describes the dataset and calibrates the model parameters to the AWF data. Then, we simulate potential COVID-19 scenarios going forward, and project the attrition behavior of the workforce under differing scenarios of economic recovery. Finally, our paper concludes, and the Appendix explores the retention effects of a one-time bonus.

The Impact on Unemployment Arising from COVID-19

The short-run impact of COVID-19 has been extraordinary, with the unemployment rate spiking to almost 15% from near historical lows (3.5%) in 2 months. As Figure 1 shows, even during the Great Recession, the unemployment rate peaked at 10.6%. The Congressional Budget Office (CBO) projects that the U.S. economy will grow 4.6% in 2021, after contracting 3.5% in 2020. These are significantly upwardly revised estimates from its report in July 2020, when the CBO projected a growth rate of 4%. Correspondingly, employment has recovered sharply since September 2020 (Congressional Budget Office, 2021).

However, when the economy can return to business as usual and the vigor with which it can rebound remain unclear. Public health factors such as the efficacy of vaccines and their distribution, the discovery of more infectious variants of COVID-19, and sustained use of masks and social distancing until herd immunity is reached, will all play a role. In addition, the recovery of the rest of the world, additional federal, state, and local fiscal stimuli, as well as permanent changes in the economy such as expanded work-from-home and reconfiguration of global supply chains, may impact the private-sector labor market for years to come.

The impact of such changes to the private sector will inevitably affect the public sector, especially for the civilian workforce within the DoD. The uncertainty in the private sector and the comparably stable government sector is expected to alter their long-term career trajectories. Figure 2 shows the attrition rate of DoD AWF workers, reproduced from Ahn and Menichini (2019). The sample covers September 1987 to December 2018. Approximately 30% of workers leave the DoD after about 8 years of service. By approximately 25 years of experience, roughly three-quarters of employees have left. While these attrition rates are relatively low compared to many civilian industries, DoD leadership still expresses a desire to hold on to highly skilled, senior civilian workers.[1]

[1] For example, "Highly educated, skilled, and experienced government acquisition professionals are vital now and, in the future, to provide warfighters the products they need" (DoN, 2018). Or, "All this relies on our most important asset, our people, and the approaches we take to recruit, train, and retain the workforce we need to compete and win in support of our national defense strategy." - The Hon. James F. Geurts, ASN (RD & A)

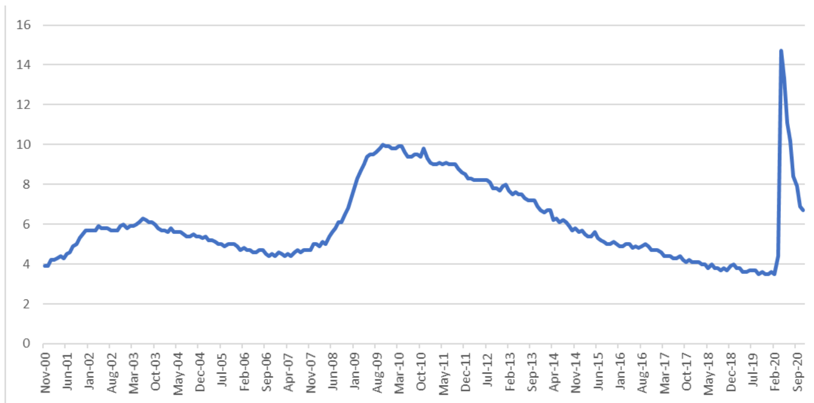

Figure 1. Civilian Unemployment Rate. (Bureau of Labor Statistics)

While the shock of COVID-19 has been felt in almost every sector of the labor market, the government sector has notably been shielded from the worst of the impact. As Figure 3 shows, as of November 2020, government workers experienced an unemployment rate around 4%, which is lower than workers in the education and health services fields, which have received much wider media coverage of labor shortages due to the health risks from their proximity to the pandemic.

While job stability has always been a draw for the government sector, the state of the economy as well as the continuing uncertainty about the speed of economic recovery, should make jobs in the DoD relatively much more attractive. Indeed, this argument is parallel to what has been known for a long time in military recruiting: demand for military jobs is countercyclical to the state of the civilian economy. With the backdrop of this large, negative, persistent, and unpredictable shock to the civilian labor market, we model the long-run labor market decisions of civilian DoD employees using a dynamic programming framework.

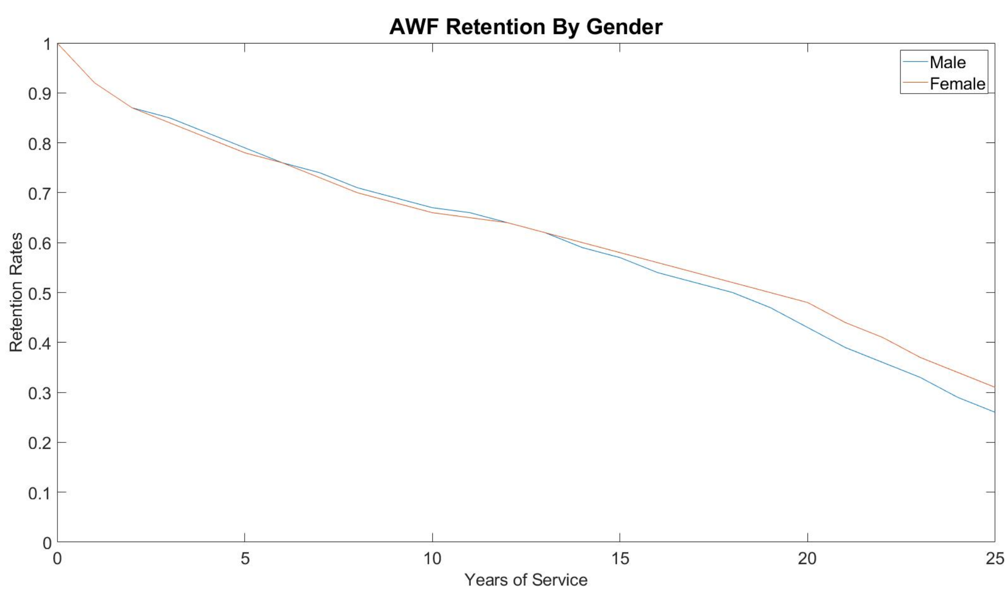

Figure 2. Career Trajectories of DoD AWF Employees. (Ahn & Menichini, 2019)

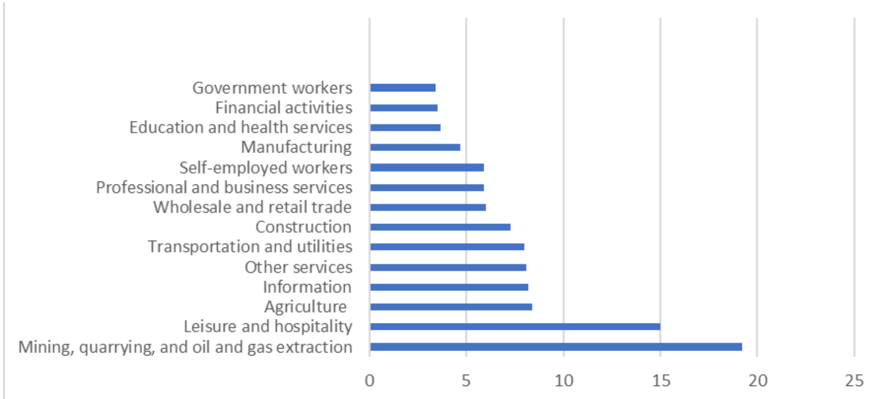

Figure 3. Unemployment Rate by Sector, November 2020. Bureau of Labor Statistics)

Model

In this section, we describe the different parts of the dynamic programming model of employee attrition that will be used to produce policy simulations.

We assume AWF workers are rational decision-makers who make career choices in order to maximize utility over their lifetime. The individual evaluates, at each decision point, all the costs and benefits involved in each possible choice, including pecuniary as well as non-pecuniary elements, which we describe here. At the beginning of each period (i.e., 1 year in this paper) the worker chooses between leaving the AWF to continue their career in the private sector, and staying in the public sector one more period.[2]

We next describe all the costs and benefits (including monetary and non-monetary elements) that the individual trades off at every decision point. We assume that the pecuniary components include

- AWF compensation, including basic pay, health insurance, locality adjustment, bonuses, etc.
- Compensation in the private sector.

We also assume the AWF employee is included in the Civil Service Retirement System (CSRS), and model public retirement accordingly.[3] For employees working in the private sector, we assume they are contributing to a 401(k) plan where the employer matches up to 10% of gross pay.[4]

The non-pecuniary components refer to the individual's taste or preference for a job in the AWF versus a career in the private sector. These components attempt to capture the taste of those agents who prefer the higher predictability and stability of public sector employment, even at the cost of a lower salary compared to the private sector, and vice versa. To capture these relative preferences, we use taste parameters reflecting monetary-equivalent preferences for careers in the private versus the public sectors.

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[2] We further assume that leaving the AWF is an irreversible decision.

[3] The dataset contains employees from both the extinct CSRS and the current Federal Employee Retirement System (FERS). We model the CSRS because there are more individuals belonging to that system than FERS.

[4] As we note in the data section, the modal AWF employee has a bachelor's degree or above and earns close to $100,000 at their highest paygrade. Workers with these characteristics in the civilian sector most often have employer matching 401(k) options.

In particular, we use the following notation to construct the dynamic model:

- W_t^m indicates compensation in the AWF (including all pecuniary components) in period t
- W_t^c denotes compensation in the private sector in period t
- ω^m is the public sector taste parameter, which captures the monetary-equivalent preference for a career in the AWF
- ω^c is the private sector taste parameter, which captures the monetary-equivalent preference for a private sector career
- T denotes the labor time horizon (number of working periods before final retirement)
- $\beta = \frac{1}{1+r}$ is the discount factor, where r represents the subjective discount rate
- $E[.|\varepsilon_{t-1}]$ indicates the expectation operator, given the shock in the previous period
- ε_t^m and ε_t^c are the random shocks affecting government and civilian jobs, respectively, in period t

The maximization problem faced by the AWF worker can be described by the following set of equations:

$$V_t^L = W_t^c + \omega^c + \beta E[V_{t+1}^L|\varepsilon_t^c] + \varepsilon_t^c \quad (1)$$

$$V_t^S = W_t^m + \omega^m + \beta E[V_{t+1}|\varepsilon_t^c, \varepsilon_t^m] + \varepsilon_t^m, \text{ and} \quad (2)$$

$$V_t = Max[V_t^L, V_t^S] \quad (3)$$

In these equations, super-index S denotes the agent's choice to continue working one more period in the AWF (i.e., S = Stay). Alternatively, super-index L indicates the individual's choice to quit the AWF job to continue their career in the private sector (i.e., L = Leave). Therefore, V_t^S denotes the (present) value of remaining in the public sector one more period, while V_t^L indicates the (present) value of switching to the private sector. Equation 3 implies that the individual will decide to be part of the AWF force in every period in which $V_t^S > V_t^L$, and will leave the force as soon as the opposite is true.

Regarding stochastic variables ε_t^m and ε_t^c, we assume they are independent and mean reverting over time (t dimension). The specification of the random shocks is the following:

$$\varepsilon_t^c = \mu_c + \rho_c \varepsilon_{t-1}^c + \tau_t^c, \tau_t^c \sim N(0, \sigma_c^2) \quad (4)$$

$$\varepsilon_t^m = \mu_m + \rho_m \varepsilon_{t-1}^m + \tau_t^m, \tau_t^m \sim N(0, \sigma_m^2), \text{ and} \quad (5)$$

$$\tau_t^c \text{ independent of } \tau_t^m \quad (6)$$

That is, the shocks evolve independently of each other, oscillating around their own long-run (unconditional) mean over time. In the context of equations 1–3, these innovations could be interpreted as random shocks to salaries in the civilian and private sectors (i.e., W_t^m and W_t^c, respectively) stemming from, for instance, fluctuations in the business cycle. Ashenfelter and Card (1982) find that nominal wages are well represented as AR(1) processes. Accordingly, equations 4 and 5 define AR(1) representations for the error terms. These AR(1) processes play an important role for our main results as they allow shocks to persist over time; that is, to gradually fade as time passes.[5] As we explain in more detail later, we use parameter ρ to define the speed at which the economy (and wages) recovers from a shock (such as from

[5] As opposed to white noise processes, where shocks do not persist over time (i.e., they return to the mean immediately), or random walk processes, where shocks do not return to the mean.

the COVID-19 outbreak). In terms of the optimization problem described in equations 1–3, random shocks ε_t^m and ε_t^c indicate state variables observed by the AWF worker at the time of the decision.

Data Description and Model Calibration

In this section, we describe the AWF sample as well as the selection and calibration of the parameter values necessary to implement the dynamic programming model described previously. In the next section, we show those parameters provide a good approximation of the long-run labor market outcomes for the representative worker in the AWF.

DATA: The Acquisition Workforce

The DoD Acquisition workforce is comprised of approximately 150,000 employees, covering the period September 1987–December 2018. Civilians make up about 90% of the workforce, while active duty makes up the remaining 10%. The AWF's mission is the "timely and cost-effective development and delivery of warfighting capabilities to America's combat forces" (DoD, 2015). The AWF is responsible for overseeing equipping and sustaining the military, spending over $1 trillion in FY2021. About 26% of the AWF belongs to the engineering career field, followed by contracting at 19%. Historically, the AWF was sharply reduced in size and capability during the 1990s. The DoD has been working to rebuild the AWF starting in 2008, increasing the AWF by approximately 30,000 employees over 7 years.

For this analysis, we restrict our sample to workers who were ever in the contracting, industrial property management, or purchasing fields.[6] Our sample workers were born after January 1, 1950, but before December 31, 1980. Workers with birthdates outside this range are either too old, in that the environment in which they made their labor decisions may not be reflective of current jobs in the AWF, or too young, in that these workers have not had time to make labor decisions that are pivotal to their careers. Restricting the sample nets us over 2 million worker-month records, with over 13,000 unique workers tracked through their careers. Table 1 presents some summary statistics for our sample.

The workforce is predominantly white and female. Over half the workforce has a bachelor's degree or above. Compared to the civilian sector, careers in the AWF is stable, with the average career length lasting well over a decade. This workforce is also highly paid, with the average worker earning almost $100,000 toward the end of their career. The average worker in this sector begins her/his career at age 33, which indicates that the position in the AWF is not her/his first job. In fact, a large number of these workers have prior military experience.

To rigorously assess the impact of the civilian sector on the attractiveness of the DoD position, every worker in the dataset must be "assigned" a civilian wage that they can expect to earn. To accomplish this, we estimate a hedonic regression using the Outgoing Rotation Group (ORG) of the Current Population Survey (CPS). As this dataset contains a representative sample of workers in the United States, including, most importantly, those who are in the government sector, it is possible to make an apples-to-apples comparison with workers in the private sector.[7]

We run a hedonic regression using the individual sociodemographic characteristics, professional and education experience, and locality indicators from the ORG of the CPS which broadly match the AWF variables summarized in Table 1 to obtain predicted civilian and government sector wages. The difference in the wages across private and public sectors, conditioned on individual characteristics, defines the government sector "wage penalty."

[6] These fields correspond to Occupation Codes 1102, 1103, and 1105, respectively.
[7] See Ahn and Menichini (2020) for a detailed description.

Table 1. Summary Statistics

Variables	Mean	Std. Dev.	Min	Max
Female	0.632			
Minority	0.278			
Disability	0.202			
Prior Military Service	0.619			
Has Bachelor's Degree	0.547			
Has Post-graduate Degree	0.332			
Gained Additional Education in AWF	0.441			
Career Length in AWF (in years)	12.0	(8.6)	0.1	25.8
Age at Entry	33.0	(8.2)	15	65
Age at Exit	48.2	(10.55)	20	68
Position Type: Professional	0.657			
(Ever Held) Technical	0.245			
Blue-Collar	0.018			
White-Collar	0.297			
Ever Rated Not Fully Satisfactory	0.575			
Highest Salary	95,143.67	(30,410.74)	27,397	189,600
Observations	13,590			

Calibration Results

Before simulating the model described in equations 1–3, we need to start defining the parameter values, which we show in Table 2 and subsequently describe. We can observe in Table 2 that all parameter values, except compensation, are constant over the career of the AWF employee.

As we described in the section Data: The Acquisition Workforce, estimates from the hedonic regressions suggest that income in the private sector (i.e., W_t^c) is, on average, around 17.61% higher than in the AWF (i.e., W_t^m) for individuals with similar characteristics. For this reason, after initially normalizing W_t^m=1, we let W_t^c=1.1761. We then add the income from the different retirement systems and, thus, compensation changes over time. The data described in that same section show that the longest observed labor time horizon among all individuals is 25 years. For that reason, we let T=25. The subjective discount factor is assumed to be 0.95, implying an interest rate of 5.26%.[8]

Table 2. Parameter Values

Parameter	*Value*
W_t^{m}	1
W_t^{c}	1.1761
T	25
β	0.95
ω^{m}	1.2782
ω^{c}	1
μ_m	0
μ_c	0
ρ_m	0.90
ρ_c	0.90
σ_m	0.005
σ_c	0.005

Regarding the taste parameters, we calibrated parameter ω^m so that the survival curve predicted by the model approximates the empirical survival curve as closely as possible via grid search (we show the graphical results of this calibration in the next section). In more technical terms, the calibration exercise searches for the value of ω^m that minimizes the summed squared distance between the points of the empirical AWF survival curve and the points of the survival curve predicted by the model. As Table 2 displays, we normalize $\omega^c = 1$ and, from the calibration exercise, we obtain $\omega^m = 1.2782$.[9] These values imply that the representative AWF employee prefers the AWF over the private sector.

The remaining parameter values in Table 2 refer to the stochastic process of the error terms ε_t^m and ε_t^c. We follow Ashenfelter and Card (1982) to define the parameter values that govern the AR(1) processes of those terms. Accordingly, we let parameters μ_m and μ_c be equal to zero, we assume values of 0.005 for the standard deviation of the errors, σ_m and σ_c, and let the mean-reversion coefficients ρ_m and ρ_c be equal to 0.9. These values depict the historical behavior of the error terms. In particular, those observed values of the mean-reverting coefficients suggest that wages have a high level of persistence over time and, thus, that the effects of shocks require a long time to disappear.

Model Solution and Policy Simulations

In this section, we describe our policy simulations to forecast the evolution of the behavior of the representative AWF worker under a number of scenarios with differing speed

[8] This interest rate is similar to the average 30-Year T-Bond Constant Maturity Rate reported by the Federal Reserve Bank of St. Louis for the period covered by the data set.

[9] Ahn and Menichini (2020) estimate a similar dynamic model where economic shocks to the civilian and public sectors are i.i.d. with mean zero. They find the difference between military and private sector taste parameters (i.e., $\omega^m - \omega^c$) to be around 0.2, which, reassuringly, is not far from the result of the calibration exercise.

rates of economic recovery from a large, abrupt, and unanticipated negative impact (i.e., COVID-19) to the private sector. This is a major systematic event that adversely affects all sectors of the economy, except for the public or government sector, which we assume keeps its employment constant.[10] The latter is consistent with the assumption of independent errors in equation 6.

Concisely, we "shock" the model with a large negative civilian error draw at a specified point in time. Then, we allow the system to recover and converge back to the steady state. We start analyzing retention behavior assuming the economy recovers according to the empirical historical speed. However, given the observed recovery from the current pandemic seems to be, so far, much faster than normal, we also study the retention implications of different scenarios for the speed of recovery. We "control" the speed of recovery of the economy by setting the autoregressive term, ρ, which controls the velocity at which shocks gradually disappear over time.

While the private sector goes through its gyrations, at every period, the representative AWF agent in our model surveys the current state of the private sector, forecasts the evolution of the state of the economy, and makes the *ex ante* optimal decision to stay or leave the AWF. We describe the simulation procedure in more detail next.

We solve the model described in equations 1–3 via backward induction (see Rust [1987] for an empirical treatment). That is, we start from the final period (i.e., t=T=25) and decide whether to stay one more (final) period in the AWF or to leave for the private sector. We then move one period backward (i.e., t=24) and select to stay one more period or to leave the AWF, considering the value from the optimal decision in period T=25. We continue moving backward, deciding rationally in every period, until we reach the present period (i.e., t=0). This solution characterizes the retention behavior of a representative AWF employee in all possible states of the economy.

We then stochastically simulate the model forward (i.e., over the 25 years of work) 100,000 times, which produces the stay/leave decisions of 100,000 employees in all possible different situations over the labor period. These simulations summarize the retention behavior of the representative employee, which we show in Figure 4. The figure exhibits the calibrated, model-predicted survival curve of the representative individual (blue line) and displays the cumulative probability of the worker staying in the force after a certain period of time. For example, the figure suggests that the likelihood that the employee is still part of the AWF after 10 years is about 65%. The figure also shows the empirical survival curve for the AWF employees (red line) from the data described in the section Data: The Acquisition Workforce, suggesting that the calibrated model predicts actual behavior quite closely.

[10] While our negative shock is the COVID-19 pandemic, any future unanticipated national shock to the economy and/or public health that is concentrated in the private sector can be expected to operate in a similar manner.

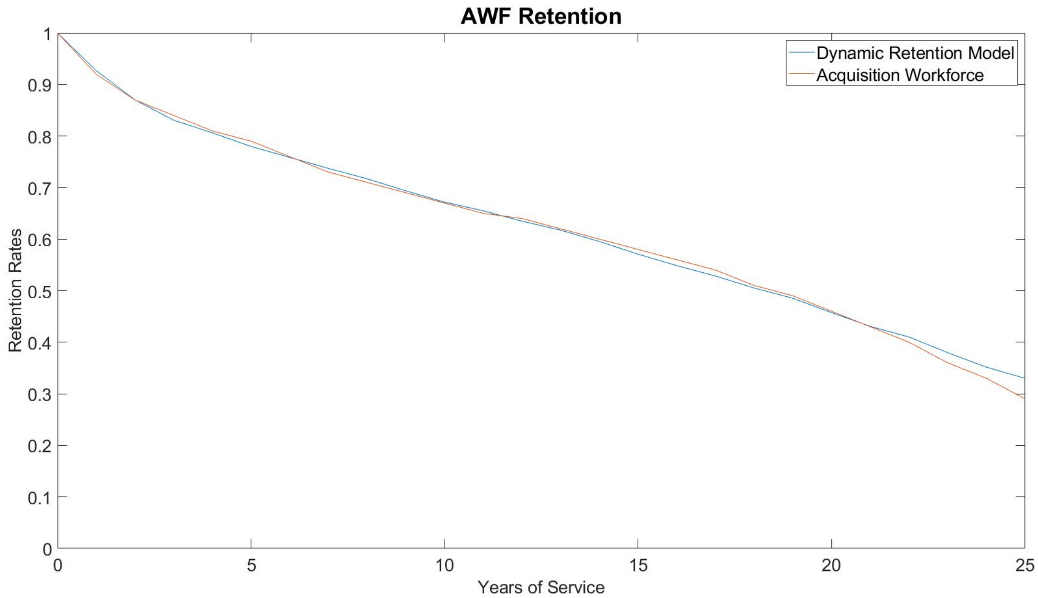

Figure 4. Retention Behavior

Associated with the previous survival curves are the yearly, model-predicted probabilities of leaving the AWF, which we show as the blue line in Figure 5. The attrition rate is relatively low every year, as is shown by the fact that the likelihood of leaving is always below 10% per year, and below 5% in the great majority of years. In addition, the attrition rate is high initially, and diminishes through time before increasing again toward the end of the individual's career. For instance, the probability that the employee departs from the AWF in year 10 is around 2%. As before, we also show the empirical likelihood of leaving (red line) for comparison purposes.

We then proceed to shock the model with a large negative error on the civilian side (i.e., ε_t^c) at year 10. The shock is equivalent to 3 standard deviations below the mean and is intended to capture the large effect of the sudden appearance of COVID-19. In economic terms, given the calibration shown in Table 2, this shock could be interpreted as a roughly 1.5% reduction in the civilian salary, W_t^c, while the public sector salary, W_t^m, remains unchanged. The fact that the error terms (both ε_t^m and ε_t^c) are mean reverting over time implies that the impact of the negative shock on the civilian salary gradually disappears as time passes. As mentioned before, the speed of return to the pre-shock state will depend on the mean-reversion coefficient, ρ.

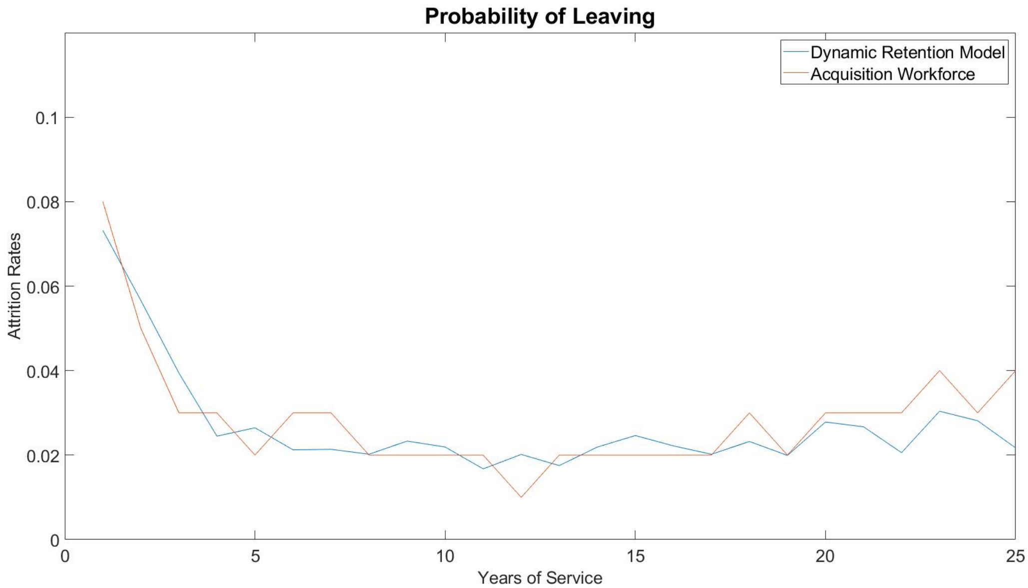

Figure 5. Probability of Leaving

In Figure 6 we show, given the initial negative shock, how the shocks are expected to evolve over time for four different values of the coefficient of mean-reversion. The purple bars depict the historical case, which is based on the observed historical mean-reversion coefficient of ρ=0.9. It is clear that the historical coefficient implies it would easily take a decade or more to return to normality. However, after a year of the appearance of the virus, the economy seems to be recovering much faster than suggested by historical terms. We attempt to capture the faster rebound by reducing the coefficient of mean-reversion (i.e., via a quicker dissipation of the shock). Accordingly, we analyze three different scenarios featuring dissimilar speeds of recovery, all of which are faster than the historical speed. Scenario 1, with the blue bars and ρ=0.3, represents the case of a relatively faster return to the pre-COVID economy. On the other hand, the yellow bars in scenario 3, with ρ=0.7, reflect a slower recovery to normality as compared to scenario 1. In between are the red bars of scenario 2, showing an intermediate speed of recovery with ρ=0.5. Even in the more optimistic recovery scenario 1, it is clear that the effects of the large negative shock remain in place for some years.[11]

[11] The magnitude and persistence of shocks are speculative, although they are informed by very recent (and ongoing) research. Many scholars are currently attempting to forecast the long-run impact of COVID-19 on the economy. See Petrosky-Nadeau and Valetta (2020), for example.

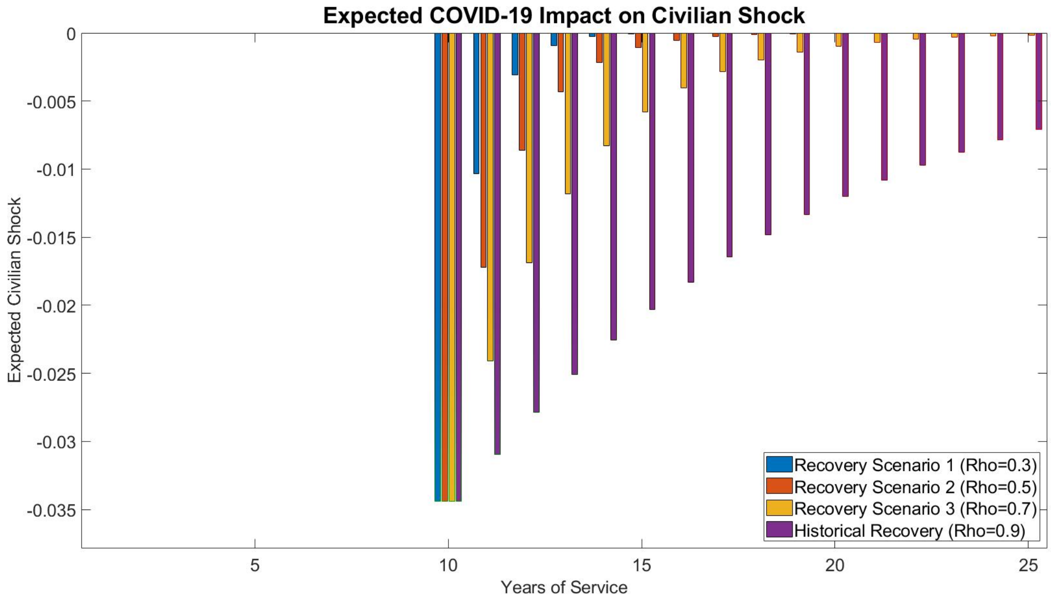

Figure 6. Expected Impact of COVID-19 on Civilian Shock

The effect on retention behavior of the representative AWF worker can be observed in Figure 7. The figure shows that, during the initial 10 years, the retention behavior is equivalent to the blue line in Figure 4. At year 10, the COVID-19 shock happens, and the retention behavior changes considerably. As we mentioned before, we study the attrition behavior in four different contexts. The green line shows the retention impact of the virus under historical terms (i.e., ρ=0.9). The other lines depict the expected retention behavior for three faster rates of economic recovery (i.e., ρ=0.3, ρ=0.5, and ρ=0.7 for recovery scenarios 1, 2, and 3, respectively). In all cases there is a kink and sudden flattening of the curve, suggesting that the individuals stay longer in the AWF, in an attempt to avoid the sharp negative effect of the virus shock on the civilian labor market. Depending on the speed of recovery, it might take a substantial amount of time for the employee to return to the pre-shock retention behavior. For instance, in the historical case it takes around 10 years for the representative employee to return to the pre-virus retention behavior, while in scenarios 1, 2, and 3, the return to normality takes roughly 2, 3, and 5 years, respectively. These long-lasting effects on retention behavior have important implications for the hiring policies of the public sector.

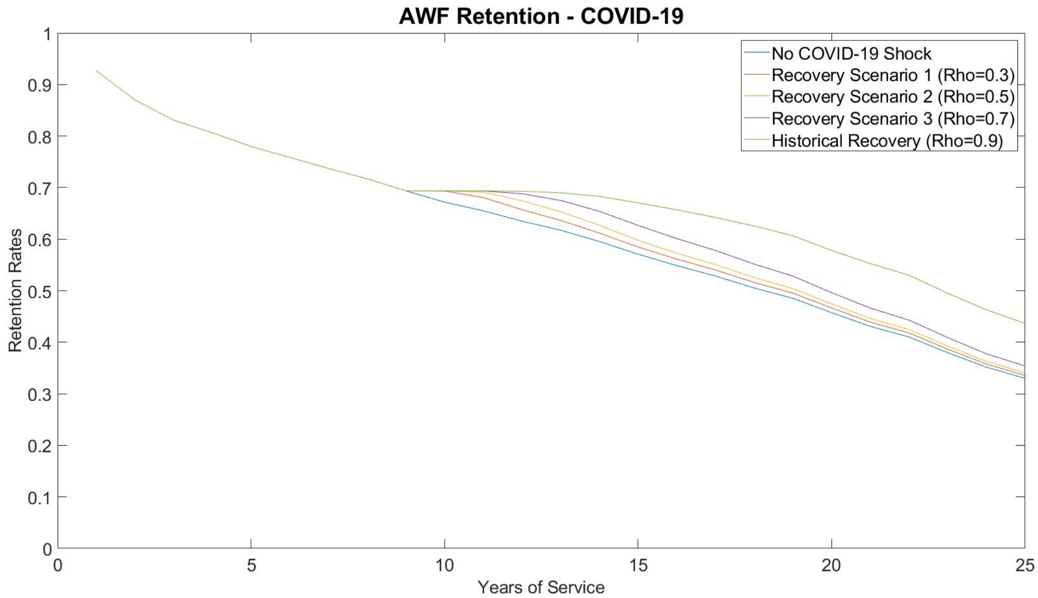

Figure 7. Retention Impact of COVID-19

It is worth noting that the time required to return to the "original" behavior specified above does *not* mean that all workers will choose to delay leaving the AWF by several years due to the impact of COVID-19. Instead, all workers will process the negative shock in the civilian economy as making the AWF job more attractive. Until the shock fully dissipates, the DoD position will be more attractive than had there not been the global pandemic. However, given the substantial wage premium in the civilian sector, the pandemic shock does not need to completely disappear before workers who were planning to move to the civilian sector resume their plans.

To complement the analysis of the return to the pre-COVID context, we present Figure 8. The figure shows the model-predicted yearly probabilities of leaving the AWF for the four different values of parameter ρ. The green line shows the attrition behavior in the historical recovery scenario, confirming that it takes around 10 years to return to the pre-COVID retention behavior (the latter is represented by the no-COVID-19-shock blue line). The red, yellow, and purple lines, reflecting faster speeds of economic rebound, suggest that around 2, 3, and 5 years, respectively, are required to eliminate the effects of the COVID-19 shock on retention. In all four scenarios, the likelihood of leaving the AWF goes roughly to zero in the year of the shock, and then slowly starts to return to the no-shock levels as time passes and the effects of the shock dissipate.

It is also important to note that, after the return to normality, the probability of leaving is higher in the slower recovery scenarios and lower in the faster rebound scenarios. More generally, after the COVID-19 shock dissipates, in all cases with shock, the likelihood of leaving is higher than in the no-shock case, with that probability increasing in parameter ρ. Indeed, the slower the recovery from the pandemic (i.e., higher ρ value), the larger the magnitude of exit probability after the recovery. This outcome suggests that, as more people decide to stay longer in the AWF during the pandemic, when the economy returns to normal, the pent up demand to leave for the private sector is expressed as higher attrition rates in the later years. This implies an opportunity as well as a problem for the AWF leadership. While a slower recovery may induce more employees to stay longer, it cannot be a permanent solution to retain high ability workers. A higher ρ will result in a much sharper exit of workers from the AWF once the civilian economy recovers.

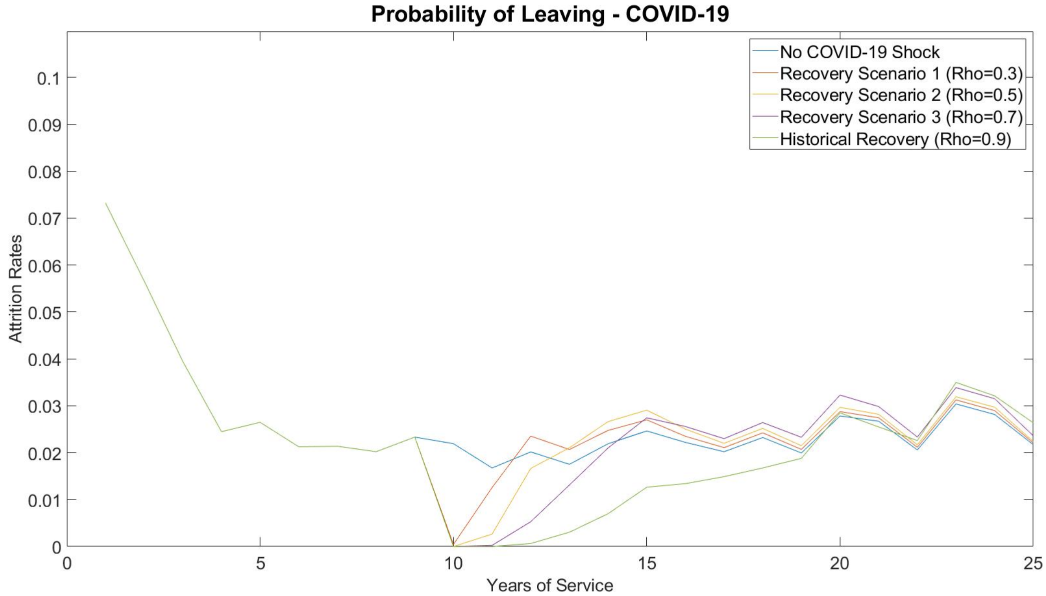

Figure 8. Likelihood of Leaving with COVID-19

In order to retain these workers, fundamental (and traditional) personnel policy reforms will be required. For example, a pay increase or expansion of benefits before the civilian sector fully recovers may permanently induce senior workers to remain in the AWF. Similarly, a one-time retention bonus, set far enough into the future when the civilian economy is back to normal, could prevent that exit.[12]

Conclusions

As of early 2021, the overall unemployment rate in the U.S. stands at 6.7%, an 8 percentage point decrease in just 8 months from the worst unemployment rate in almost 90 years arising from the COVID-19 global pandemic, yet still almost double the unemployment rate from just 1 year ago. While the recovery has been as dramatic as the decline, the future remains very much in doubt. For example, in December 2020, payrolls shrank by 140,000. Outlook has considerably brightened since, but the whiplash in long-run forecast of economic recovery itself adds uncertainty to future labor market prospects in the civilian market.

In this environment, we analyzed the potential impact of the economic recovery on the labor market trajectory of the AWF. The contrast in stability of jobs in the government compared to the private sector should increase the attractiveness of DoD jobs, especially if the recovery proves to be slow or unpredictable. We built and calibrated a dynamic programming model of employee retention behavior, analyzed the impact of a negative persistent shock to the civilian sector, and simulated different recovery paths.

[12] While it is beyond the scope of this paper to calculate optimal policy to retain workers as the civilian sector recovers, Figure 9 in the Appendix shows the attrition rates of AWF workers with a) no change in compensation after the COVID-19 shock and b) a one-time bonus of 25% of monthly salary at the 25 year of service mark. The bonus induces experienced workers to remain longer in the AWF.

Our results show that government positions become more attractive the larger the magnitude of the negative shock to the civilian economy, and the slower the economic recovery, such that workers may value government positions more highly compared to the pre-pandemic period for several years.

While this environment can reduce attrition of the average worker from the AWF, leadership should understand that, eventually, recovery of the civilian sector will push down the relative desirability of government jobs. This may lead to a speedy exodus of many senior-level workers who were being held back due to economic uncertainty. Personnel planning without considering the temporary reduction in attrition at the beginning of the shock may lead to over-hiring, especially at the junior-levels. On the other hand, short-sighted reductions in hiring due to the initial impacts of the negative shock may lead to a hollowing out of the workforce, once the impact of the shock wanes. In addition, as the economy recovers, there may be fundamental structural changes to the labor market that remain, changing the valuation of both government and private sector jobs in unpredictable ways. Forward-looking leaders should regard these simulation results not as predictions of the future, but as guides to help set personnel policies that are flexible enough to adjust to and even take advantage of the gyrations in the civilian economy.

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Appendix

As we describe in Section 5, the AWF will face a higher-than-normal employee attrition rate when the COVID-19 shock disappears and the economy fully recovers. In this appendix, we study one particular way by which that expected effect could be counteracted. In particular, we analyze the effect of a one-time bonus on the probability of leaving the AWF when the economy returns to normality. We assume the bonus is equivalent to 25% of the individual's monthly salary and is paid at year of service 25 (with the virus shock occurring at year 10). Figure 9 shows the main results of this exercise. The expected bonus has a fairly small effect on employee attrition in the early- and mid-career years, as the attrition rates are almost equivalent with and without the bonus. However, as expected, the effect of the bonus is more visible in the final years of the employee's career, when the economy has fully recovered from the COVID-19 shock. Without the bonus (red line), the attrition rates are substantially higher than with the bonus (yellow line), suggesting that, indeed, a bonus would induce experienced workers to stay longer in the AWF after the recovery. To finish, the bonus is just one of the tools available to the AWF to affect individual retention behavior (for instance, salary raises would be another useful tool).

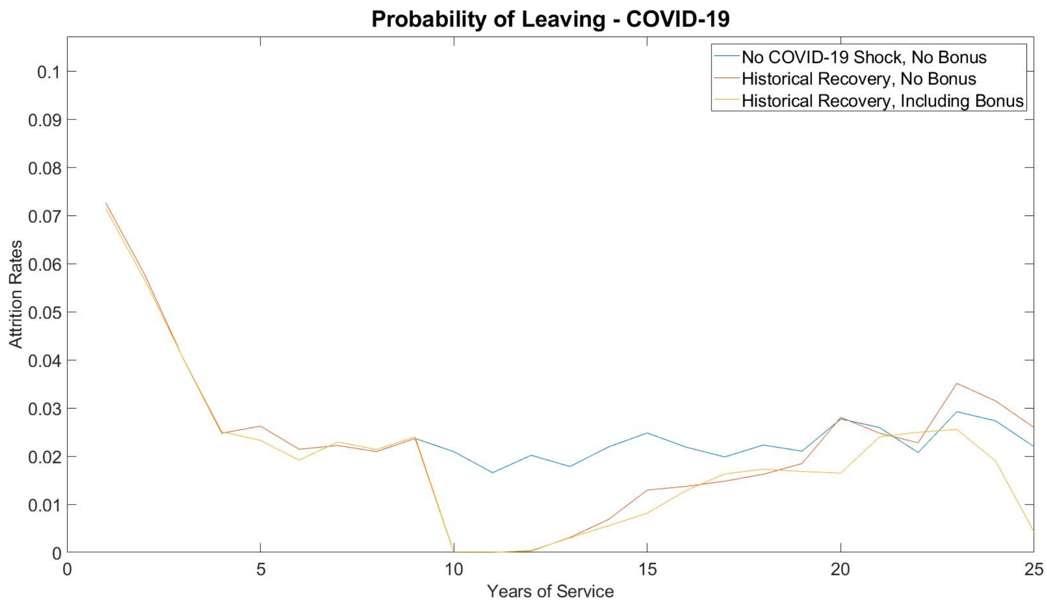

Figure 9. Likelihood of Leaving with COVID-19 and a Bonus at 25 Years of Service

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