Labor Market Conditions and Military Enlistment*

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Abstract

This paper seeks to address the question of how local labor markets affect military enlistment across each state. Hitherto studies have focused on the relationship between national unemployment and military enlistment, disregarding geographical heterogeneity which may cause one part of the country to react stronger than others. Using census data, we find that in general, on an individual level, Black Americans are much more likely to join the military than white Americans, females are much less likely to join the military than males, and Asian Americans are less likely to join than white Americans. Additionally, we find that white Americans are more sensitive to labor market fluctuations than Asian Americans are, and that Black Americans are not significantly more or less sensitive to labor market conditions, suggesting that a different mechanism explains their overrepresentation in the military.

Introduction

Ever since the U.S. military became an all-volunteer service in 1973, the decision to join has been entirely up to a civilian. What drives the decision for a young adult to enlist in the armed forces? This question is twofold,

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as it concerns both the behavior of the military in its attempts to recruit volunteers, and it questions which segments of the population join the military in an effort to maximize lifetime utility. Individuals are faced with a risky job prospect by serving in the military. So, why does one volunteer to serve for years if there is risk of death or injury?

One potential framework for understanding why people enlist in the military is that they see it as a guaranteed job with generous benefits. For example, the Department of Veteran Affairs (VA) offers lifetime health insurance, help with financing a home loan, support for educational loans, among other benefits. The military *qua* employer is useful to understand who joins the military, at what time, and why they chose the military specifically. This assumes that the military must act like a firm that advertises certain wages and amenities to recruit a sufficient number of candidates within the labor market; likewise, it assumes that civilians make a decision to enlist in the military based off maximizing their lifetime utility subject to certain constraints, albeit education, networks, or geography.

This paper aims to address the question of who joins the military and under what circumstances someone joins the military. In our framework, we assume that labor market conditions factor heavily into one's decision to join the military. If there is high unemployment, people in areas with less infrastructure may be more willing to undertake the risk associated with serving in the military, because for them the payoff is highest. Alternatively, higher advertised wages could be associated with fewer people willing to enlist in the military. Likewise, areas with more robust infrastructure may allow for alternative options for a young adult, like education or a trade. Given these assumptions, it is reasonable to think that some groups will be over-represented. Specifically, it may be the case that certain races will be over-represented in the military due to structural heterogeneity in educational and vocational opportunities in historically underdeveloped parts of the country. By measuring labor market conditions, we can get a richer view of which young adults are actually enlisting.

This is the first paper to account for geographical variation and local labor markets. Previous studies have focused on national samples of youth to see which end up joining the military. The key flaw with those design studies is that they do not account for differences across geographies. It is reasonable to think that wealthier segments of the country will not be hit as hard by recessions, and therefore may not see an increase in the number of people who seek to serve in the military for a recession-proof job; in poorer areas, young people with fewer educational and labor market opportunities may feel more compelled to join the military in a time of economic crisis.

Exploiting geographical variation between states and counties gives us a much richer view of the relationship between youth labor markets and military enlistment.

Our estimation strategy groups Americans by birth year and state of birth, since the latter is the most precise estimator of birthplace available. We examine the relationship between different labor market measurements when each cohort turns 18 to see how they respond to different labor market conditions. In total, we measure responses to the state unemployment rate, the log of average hourly wage in each state, the job opening rate in each state, and the employment-to-population ratio in each state. We take annual averages for each of these variables and see how 18-year-old Americans from the same birth cohort respond to each.

To account for geographical differences, one necessarily must use measurements at different geographical levels. We choose states because it allows for a much more precise estimation method. We also considered using commuter zone data from David and Dorn (2013), which would provide data based on local labor markets. However, since we only know the state of birth – and not the county – we think that this estimation technique is susceptible to migration bias more than a state-level specification.

This estimation strategy is one of the main contributions to the literature on military enlistment and labor. Most studies that examine volunteer military enlistment rely on national-level longitudinal datasets, like the National Longitudinal Survey of Youth (NLSY) or Monitoring the Future (MTF) datasets. These data are interesting in their own ways, but they do not provide the richness of census data.

Studies that examine these datasets tend not to focus on the underlying mechanisms that drive certain geographic zones to have a higher propensity of enlistment. However, this paper provides an initial estimation method and results for at least one hypothesis: that worse labor market conditions lead to higher rates of military enlistment.

Using American Community Survey (ACS) data provided by IPUMS, we find that the only significant predictor of whether an individual joins the military is the natural log of the average posted wage in each state. Other labor market considerations do not yield significant results for individuals.

We find that in general, on an individual level, Black Americans are much more likely to join the military than white Americans, females are much less likely to join the military than males, and Asian Americans are less likely to join than white Americans. These results are consistent with previous studies. Our novel contributions come from isolating the effects of labor market conditions on these specific races.

We find that Native Americans and other races do not see a significantly different effect of labor market metrics on their propensity to serve compared to all samples. However, we find that Asian Americans are much less sensitive to labor market changes than other races, which can partially explain their lower rates of enlistment. Likewise, for white Americans, we find that they are more sensitive than other races to labor market cycles. We also find that Black Americans are not significantly more sensitive to these fluctuations than other races, which leaves us to wonder why they exhibit higher enlistment rates.

This paper is outlined as follows: section one provides a literature review to contextualize this estimation technique and the underlying forces that drive (or in our case, do not drive) young adults to enlist in the military. Section two provides our specific hypotheses for how each different labor market measurement affects enlistment. We also provide information about how the military advertises its wages and benefits like a firm. Section three outlines in detail our empirical strategy and different specifications for estimating these effects. Section four discusses the data we use to answer our question, and why this data should be preferred to previously-used datasets. Finally, section five discusses results of our many regressions. Our appendix also contains estimates using individual observations aggregated by state of birth.

1 Literature Review

Labor economists have long studied the effects of serving in the military. However, there is a noticeable gap in estimation techniques before and after the mandatory draft. A lot of papers exploit the randomness of the draft to estimate causal effects of serving in the military. Angrist (1990) for example demonstrates that Vietnam veterans earned significantly less in their lifetime than non-veterans. A newer study from Angrist revisits the Vietnam veteran data to show that while veterans suffered a wage penalty, they saw faster wage growth on average than non-veterans Angrist et al. (2011).

We face a different, slightly more difficult challenge. Instead of using the random variation in who serves (because the draft was randomized) to estimate differential long-term effects on wage and education, we must find variables that explain a person's willingness to serve. That said, we can learn a lot from reading previous studies that try to answer the question of who joins the military and for what reasons.

Bachman et al. (2009) use panel data from Monitoring the Future (MTF), which is a collection of survey data from high school seniors across 1976-1996. While they only find correlation among demographic groups, they find that African Americans and southern Americans are overrepresented in the military, and have a higher propensity for enlisting after high school. What they do not tell us is where these African Americans come from specifically, or why they are overrepresented. Their status in the military is likely a combination of numerous socioeconomic factors, but the paper does not control for birth cohorts, for example. This elides a foundational part of whether someone chooses to serve in the military or not.

Segal et al. (1998) use the same MTF dataset to analyze how gender affects one's propensity to serve. They find that for women, demographic characteristics are not as predictive of service as they are for men. However, they find that the proportion of women who express the desire to serve is about equal to that of men, suggesting that their propensity scores do not predict enlistment as well as they do for men. We will test the differential effects of labor market conditions on gender as well to see if our results accord.

Lutz (2008) finds that the effects of race on service are insignificant, suggesting that serving in the military is open to all races. She also finds no significant difference in service between children of immigrants and children of native citizens. Importantly, though, she finds that family income is an important predictor of whether or not someone serves, suggesting that some poorer Americans view the military as a career plan. This paper uses the National Education Longitudinal Study (NELS) and controls for race, class (using household income as a measurement), and immigrant status. Our paper, then, provides a more robust estimation technique of specific factors that drive enlistment. Future work should consider using our estimation technique to see if there are differential effects across different classes, however.

Bachman et al. (1997) finds that young men who are willing to serve in the military tend to enlist within two years of graduation, which further confirms our estimation technique. If anything, our model underreports the true relationship between labor market conditions and military enlistment. This paper uses MTF survey data as its main data source, and does not account for age or geographical variation.

Our paper also contributes to the vast body of literature concerned with adverse effects of recessions. Hoynes et al. (2012) seminal paper on the subject of the Great Recession provides a frame for us to view differential race and age effects. She finds that black men and young people in general were impacted the most from the Great Recession. This gives us a way of contextualizing the differential effects occasioned by poor labor market conditions.

Since our paper explicitly deals with American youths, we also hope to contribute to the literature concerning the effects of poor labor markets on youth decisions. Forsythe (2016) for example provides evidence that firms tend to discriminate against youth workers during recessions. This could lead young adults to instead choose the guaranteed ”recession-proof” job of serving in the military.

To summarize, our paper contributes in two main ways. First, we build on previous studies trying to estimate propensity to serve in the military. For a young adult to make such a consequential decision so early in their lives, there must be some mechanism driving their decisions more than race or gender correlates. Indeed, this paper attempts to at least partially explain why an otherwise healthy young person would serve in the military. We provide an estimation technique that measures age and geographic heterogeneity to accomplish this.

Secondly, we contribute to the rich body of work concerned with youth employment outcomes and the differential scarring effects of poor labor markets. Weak labor markets provide fewer opportunities for youths to develop their human capital, making joining the military a potentially more attractive long-run decision. We hope to help estimate this effect in order to get a more accurate view of how poor labor market conditions affect the youth in the United States.

2 Hypotheses

2.1 Human Capital Considerations

The theoretical underpinnings of this model require us to think of the military as an employer of last resort. However, not just anyone joins the military. Specifically, we examine cohorts based on the year they turn 18. This is typically the year one graduates from high school and therefore has a few paths ahead of them. In our model, these 18-year-olds can either enlist in the military, enroll in higher education, or enter the workforce.

This naturally leads to the main question we are concerned with: Why would a young person commit years of their early life to joining the military? Assuming alternatives exist, what about the military attracts the people it does? It could be a combination of preferences and beliefs, both about the role of the military as a force for good, and the role of the military as a way to develop human capital.

In our framework, we assume that a worker seeks to maximize lifetime utility from human capital. They consider lifetime wage, amenities from work, future growth potential, and risk tolerance. These considerations are important because they are typically what employees look for when they consider job offers, with the exception of risk tolerance. Risk tolerance allows us to see if the people who do enlist in the military are comfortable with the risk that service entails. On this front, there are two possibilities: risk-loving people may be more inclined to enlist in the military due to intrinsic preferences, or risk-averse people may see the combination of wages, amenities, and future growth as outweighing their considerations of risk. In this case, otherwise risk-averse individuals see the military as providing better returns to their time spent as an employee than they would see in a different occupation.

This leads to an additional insight: where people grow up and turn 18 has a direct impact on their future prospects. For example, people living in areas with poorer infrastructure may be more inclined to join the military than, say, people who live in areas with more robust infrastructure and job opportunities. Places that do not offer as many means to improve one's social capital will likely have more enlistees out of high school.

This makes sense in cases where one's job does not provide opportunities for upward mobility, especially given one's skillset. Low-skill workers may have more growth potential if they serve in the military, rather than working in low-skill sectors. The military provides both a means to pursue technical training and a means to enroll in higher education with partial or full scholarships. The long-term investment of enlisting in the military could, in many cases, end up maximizing human capital.

2.2 On the Military

It is useful to provide some additional information about how the military operates like a firm. Traditionally, military recruitment took place in public centers with a high concentration of youths, like shopping malls and high schools. However, the military has adapted a new strategy of advertising via online social networks. Per a New York Times report, "General Muth said, the Army wants to frame enlistment as a patriotic detour for motivated young adults who might otherwise be bound for a corporate cubicle — a detour that promises a chance for public service, travel and adventure" Phillips (2019). Likewise, a different report from NYT reveals that "New marketing plays up future careers in medicine and tech, as well as generous tuition benefits for a generation crushed by student debt. The messaging often notes that most Army jobs are not in combat fields" Philipps and Arango (2020).

These two articles provide additional context for understanding not only how the military advertises itself, but which kinds of citizens it wishes to attract. It advertises itself as a fun, dynamic alternative to an otherwise sterile career. The military also is sure to advertise its many benefits, meaning that prospective soldiers are aware of the amenities they stand to gain.

William (2006) also provides specific evidence from Chicago that the military disproportionately targets schools that have the most minorities. Recruiters will specifically target high schools that have the highest rates of poverty and the highest composition of racial minorities.

Our hitherto discussion of the military's recruitment strategy has suggested that, if reports of its recruitment strategy are true, the military must overrepresent minorities. Indeed, the Department of Defense (DoD) released a demographic report in 2020 confirming just that. Department of Defense and Policy (2020) reports that 17% of active service members are African American, whereas according to the Census Bureau, only 13% of the country is African American. Additionally, white Americans are underrepresented, with 67% of the military self-reporting as white; the census bureau reports that 76.2% of the country self-reports as white.

All of this is to say that certain groups may or may not be more responsive to the recruitment strategy the military practices. If there is a difference in racial composition in the military compared to the general population, there should be some explanation for that gap. Thus, our paper exploits an economic channel of influence to explain potential differences in propensity to join the military.

With this in mind, we predict that weak labor markets will be associated with higher military enlistment rates. When there is a strong deviation from the mean, I expect there to additionally be strong co-movements in the same direction. If unemployment rises due to a recession, some people may view the military as a "recession proof" career path. Likewise, during times of low unemployment, we expect there to be fewer people needing to resort to the military as their career path.

3 Empirical Strategy

Our task is to examine the relationship between labor market conditions and one's willingness to serve. For this, we need to examine outcomes at the state-level using a number of different specifications. We run OLS with fixed effects to see the relationship between a labor market measure and whether someone joins the military when they turn 18. OLS provides the most conservative estimate of standard errors, so we choose this specification. Our appendix has a probit model specification that we ultimately cannot endorse because of the larger standard errors it computes. Thus, the model

$$Serves_{st} = \alpha + \beta LaborMarketMeasure_{st} + \delta_s + \tau_t + \epsilon_{ts} \tag{1}$$

estimates the effect of some labor market measure on the average proportion of each state in the military. $Serves_{st}$ is the whether or not someone in state s decides to serve in the military at time t. β_{st} is the labor market measure for each state at time t. Additionally, δ_s is state-level fixed effects and τ_t is time-fixed effects. Using fixed effects in our case is especially helpful, as we wish to look at deviations from average levels. Not only do we control for unobserved heterogeneity, but we also get a nicer interpretation.

There are a few important things to note. We will only be examining cohorts who turn 18 in 2001-2019. Using these 18 years of data allows us to avoid Covid-era data, which is likely to give us inaccurate measurements (due to high unemployment and everyone staying at home i.e., not joining the military). We think it makes more sense to analyze annual changes in military enlistment, rather than monthly or quarterly. Additionally, we will be using the average annual labor market measure in the year each birth cohort turns 18. We chose this specification because labor market data at the state-level is much more precise for the full labor market. The youth labor market data is much noisier. Additionally, the any youth measure of labor market health will be highly correlated with the adult measure anyway, so we choose the adult measure for good measure.

What is important about this identification strategy is that it allows us to measure the relationship between some labor market estimate when someone turns 18 and whether or not they serve in the military. Now, we also include a vector of demographic controls, such as race and gender, to see how these different groups respond to poor labor market conditions.

This regression specification gives us a more precise, one-time measurement of whether someone who is 18 decides to join the military. By grouping cohorts and geographical units, we can be more confident in our outcomes. We also cluster our standard errors by geographical unit.

There is an alternative specification that groups individuals by states to measure how changes to the labor market affect the proportion of each state serving. We examine these results as well. To achieve this specification, it is important to collapse data by state of birth and year of birth and to weigh observations.

3.1 Measuring Labor Markets

Measuring labor market health is notoriously difficult, given the shortcomings of many key variables like unemployment rate. We choose our specific measurements in order to consider as many possible angles as possible. This means that we measure the demand, the supply, and the equilibrium condition. However, one could argue that of all of these, unemployment rate represents a market failure. It is a case where there is an excess supply of labor and not enough demand, putting the market into disequilibrium.

Of these variables, we will test to see which dimensions of the labor market contribute to enlisting in the military. Papers which only consider measures like unemployment rates unfortunately do not provide as robust of an analysis that could be considered.

4 Data

This project requires data on state-level labor market measures, as well as the number of people in each state actively serving in the military. If we were to consider commuter zones, we would need county-level data in order to aggregate counties into commuter zones per the specifications outlined in David and Dorn (2013).[1] For this paper, though, we choose to focus on state-level measurements. We now turn to our primary data sources.

4.1 American Community Surveys

We use microdata from the American Community Surveys (ACS) to aggregate the proportion of each geographic unit in the military. Additionally, the microdata allows us to view the population status of an individual (adult, kid, or active service) by birth cohort and state of birth. We remove all observations except those who are able to be grouped by birthplace (domestic) and birth cohort. This leaves us with slightly over 11 million observataions.

[1] Aggregating county-level data importantly gives us more precise estimates for how many people choose to enlist in the military. It also provides a more sophisticated measurement of local labor markets and economies than the state-level provides. Measuring commuter zones gives us more accurate estimates for the effect of the local labor market on military service. Though, this falls apart when we try to measure people by birth cohorts, since the migration between commuter zones is likely to strongly bias our results. Future work should consider an identification strategy that gets as granular as commuter zones.

4.2 Bureau of Labor Statistics

The Bureau of Labor Statistics (BLS) also provides comprehensive state labor market data, which we exploit. From the BLS, we use six different time series: average hourly wage, unemployment rate, job opening rate, labor force participation rate, and employment to population ratio. These provide estimates for the supply side of the market, the demand side, and equilibrium conditions.[2]

4.3 Summary Statistics

Table One shows summary statistics for state economies. We see that for our sample, the mean proportion of people serving in the military is approximately 2%, which is slightly below the DoD's reported 5%. Additionally, we see that our unemployment rate hovers around the natural rate at about 6%. However, since our sample contains the Great Recession period, unemployment has a maximum extreme value of 14%.

The job opening rate is pretty consistently low: at most, 7% of jobs are advertised as open. The mean rate is 3%. This rate is lower than expected. Interestingly, the employment-to-population ratios and labor force participation rates both have similar point estimates. This should not be too surprising, considering they measure similar segments of a state's population.

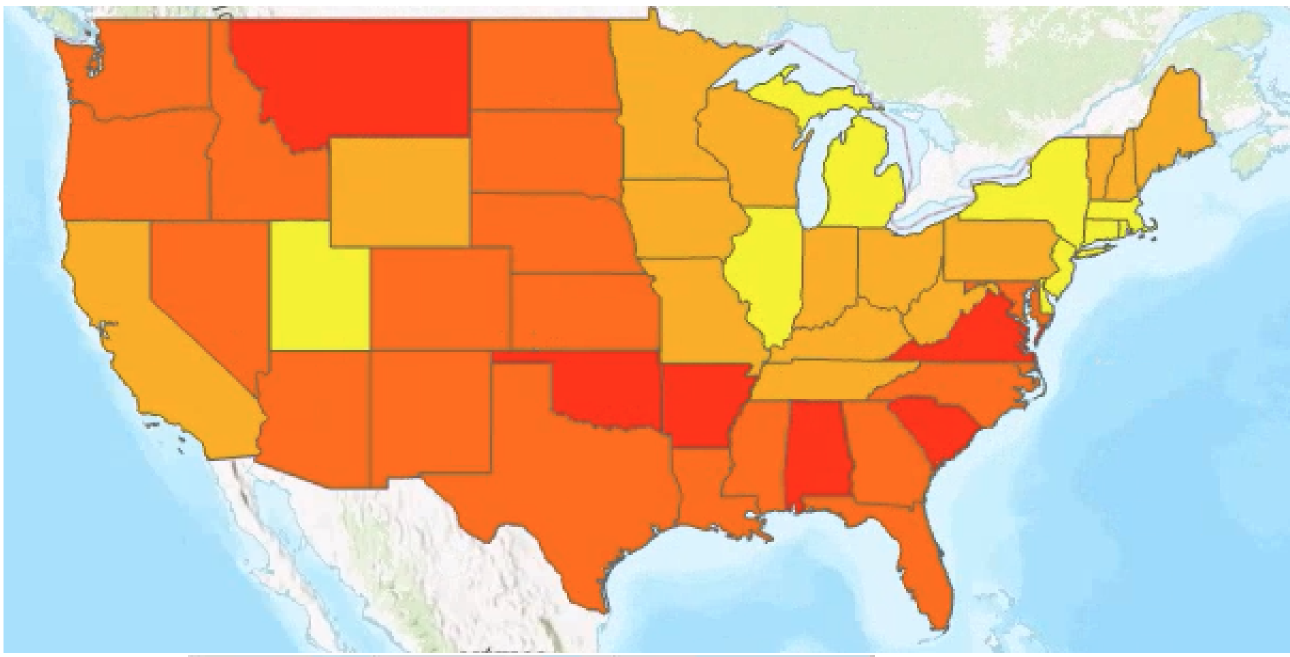
We also plot the 18-year average service rate for each birthplace. As we see, there are higher rates of service among southern states and central states, compared to either coast. These results are also broadly consistent with labor economic literature discussing which segments of the country are hit hardest by recessions.

5 Results

This section outlines the results from our regressions. We first run regressions at the individual-level for each different labor market measurement. We include fixed effects dummies to get more precise standard errors. We also include a vector of demographic covariates. After that, we collapse the

[2] Our wage variable is not just for low-skill labor. We average all hourly wages provided by the BLS to come up with our result. Future work should try to isolate an effect using only wages for low-skill positions.

Figure 1: Figure showing the rates of service by birth state. This is calculated as an 18-year average. As we see, there are higher rates of service among southern states and central states, compared to either coast.



Symbol	Upper value	Label
	≤ 0.012595	0.010935 - 0.012595
	≤ 0.014377	0.012596 - 0.014377
	≤ 0.016306	0.014378 - 0.016306
	≤ 0.018927	0.016307 - 0.018927
	≤ 0.022644	0.018928 - 0.022644

Variables	Summary of State Economies				
	Mean	Std. Dev.	Min.	Max	Obs
Active Service Proportion	0.02	0.15	0.00	1.00	11,076,722.00
Employment to Population Ratio	0.61	0.04	0.50	0.72	11,076,722.00
Mean Hourly Wage	22.76	4.69	12.12	36.25	11,076,722.00
Job Opening Rate	0.03	0.01	0.02	0.07	11,076,722.00
Labor Force Participation Rate	0.65	0.03	0.53	0.75	11,076,722.00
Unemployment Rate	0.06	0.02	0.02	0.14	11,076,722.00
White	0.76	0.43	0.00	1.00	11,076,722.00
Black	0.12	0.33	0.00	1.00	11,076,722.00
Asian	0.16	0.37	0.00	1.00	11,076,722.00
Female	0.49	0.50	0.00	1.00	11,076,722.00
Other Race	0.11	0.31	0.00	1.00	11,076,722.00
Native American	0.01	0.11	0.00	1.00	11,076,722.00

Table 1: Summary statistics for state economies

data by each racial category in order to see if there are differential effects of these labor market metrics. We collapse data using a weight provided by the census bureau. Our appendix shows results for grouping individuals into their states and seeing how the proportion of a state that serves changes with each change in labor market measurement.

5.1 Individual Estimation

Estimations of the relationship between unemployment and military can be found in table 2. We get a p-value of about .2, meaning this is not significant at most conventionally accepted levels. It does not seem to be the case, then, that increased unemployed is associated with a higher propensity to enlist in the military.

We should also note that our demographic findings reflect findings from previous studies as well. Black Americans are much more likely to enlist in the military than white Americans are; females are much less likely to enlist than males. We can see how at an individual level, results like these can lead to conclusions of overrepresentation in the military.

Table 2: OLS Results for Unemployment Rate

	Military	Military + Race	Military + Race + Gender
Unemployment Rate	0.0321	0.0323	0.0325
	(0.0252)	(0.0253)	(0.0255)
Asian		-0.00501**	-0.00508**
		(0.00108)	(0.00108)
Black		0.00305*	0.00308*
		(0.00129)	(0.00130)
Native American		-0.00107	-0.00101
		(0.00172)	(0.00169)
Other		-0.00182	-0.00175
		(0.00147)	(0.00148)
Female			-0.0267**
			(0.000712)
Fixed Effects	✓	✓	✓
Observations	11076722	11076722	11076722
Adjusted R^2	0.012	0.012	0.020

Standard errors in parentheses
This specification is an OLS that groups observations by birth state and cohort.
Note that white and male are both omitted for multicollinearity.
From this table we see that our p-value for unemployment is about .2, meaning we cannot accept .
these results as significant. However, we do see that Black Americans
enlist much more than white Americans. Females also enlist much less
often than their male counterparts. We also see that
Asian Americans enlist significantly less than white Americans.
Standard errors are clustered by birthplace.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Estimating the relationship between the employment-to-population ratio likewise yields no significant results at any acceptable confidence level (Table Three). We do find evidence consistent with previous OLS results, though: that Black Americans are more likely to join the military than white Americans, and that females are significantly less likely. Asian Americans are also less likely, which is significant at the 1% level. These results should tell us that the employment-to-population ratio is not the best predictor of whether an individual will join the military or not.

One surprising result came from estimating the effect of the job opening rates (Table Four). There is no significant effect of job opening rates on joining the military. This result surprises us because we expected that periods of high job openings would simultaneously occasion an increase in military enlistment.

Our estimation results for the effect of log hourly wage might partially explain results found in our job opening rate table. We find a significant negative relationship between the log of hourly wages and one's propensity to enlist (Table Five). As wages increase, one's likelihood of joining the military declines. This could explain our results in the previous table because perhaps job openings are not associated with high enough pay. In other words, there is excess demand in the labor market, but individuals are not willing to accept a firm's posted wage (i.e., their willingness to pay) and therefore there is no relationship between job postings and enlistment. This would suggest that demand-side considerations do not strongly factor into one's ultimate decision to enlist.

We also estimate the relationship between the labor force participation rate in a state and one's willingness to enlist in Table Six. The idea here is that not all states are impacted in the same way by a recession, and this labor force participation rate captures the heterogeneity in participation rates. This result, however, ends up to be marginally significant at the 10% level, suggesting that there is a positive relationship between the labor force participation rate and one's propensity to enlist. These results cut against our initial hypothesis that periods of poor labor market health would be associated with higher rates of unemployment.

Table 3: OLS Estimates for Employment-to-Population Ratio

	Military	Military + Race	Military + Race + Gender
Emp.-Pop. Ratio	0.0271	0.0275	0.0279
	(0.0279)	(0.0281)	(0.0282)
Asian		-0.00501**	-0.00509**
		(0.00108)	(0.00108)
Black		0.00305*	0.00309*
		(0.00129)	(0.00130)
Native American		-0.00107	-0.00101
		(0.00171)	(0.00169)
Other Race		-0.00181	-0.00175
		(0.00147)	(0.00147)
Female			-0.0267**
			(0.000711)
Fixed Effects	✓	✓	✓
Observations	11076722	11076722	11076722
Adjusted R^2	0.012	0.012	0.020

Standard errors in parentheses
This specification is an OLS that groups observations by birth state and cohort.
This specific regression allows for interaction terms between races
to see if different races face different unemployment rates.
Note that white and male are both omitted for multicollinearity.
From this table we see that our p-value for unemployment is about .2, meaning we cannot accept .
these results as significant. However, we do see that Black Americans
enlist much more than white Americans. Females also enlist much less
often than their male counterparts. We also see that
Asian Americans enlist significantly less than white Americans.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4: OLS Estimates for Job Opening Rate

	Military	Military + Race	Military+Race+Gender
Job Opening Rate	-0.0558	-0.0579	-0.0572
	(0.0937)	(0.0945)	(0.0950)
Asian		-0.00501**	-0.00509**
		(0.00108)	(0.00108)
Black		0.00305*	0.00308*
		(0.00129)	(0.00130)
Native American		-0.00107	-0.00101
		(0.00172)	(0.00169)
Other Race		-0.00182	-0.00175
		(0.00147)	(0.00148)
Female			-0.0267**
			(0.000712)
Fixed Effects	✓	✓	✓
Observations	11076722	11076722	11076722
Adjusted R^2	0.012	0.012	0.020

Standard errors in parentheses
This specification is an OLS that groups observations by birth state and cohort.
Note that white and male are both omitted for multicollinearity.
From this table we see that our p-value for job opening is about -.5, meaning we cannot accept these results as significant. However, we do see that Black Americans enlist much more than white Americans. Females also enlist much less often than their male counterparts. We also see that Asian Americans enlist significantly less than white Americans.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: OLS Estimates for Log of Average Hourly Wage

	Military	Military+Race	Military+Race+Gender
Log Wage	-0.0259^{+}	-0.0258^{+}	-0.0261^{+}
	(0.0131)	(0.0132)	(0.0133)
Asian		-0.00502**	-0.00509**
		(0.00108)	(0.00108)
Black		0.00306*	0.00309*
		(0.00129)	(0.00131)
Native American		-0.00105	-0.000984
		(0.00172)	(0.00169)
Other		-0.00181	-0.00174
		(0.00147)	(0.00148)
Female			-0.0267**
			(0.000712)
Fixed Effects	✓	✓	✓
Observations	11076722	11076722	11076722
Adjusted R^2	0.012	0.012	0.020

Standard errors in parentheses
This specification is an OLS that groups observations by birth state and cohort.
Note that white and male are both omitted for multicollinearity.
From this table we see that our test statistic for job opening is about .05, making it significant at the 5% level. We also see that Black Americans enlist much more than white Americans. Females also enlist much less often than their male counterparts. We also see that Asian Americans enlist significantly less than white Americans. These results are interesting because they reflect different equilibrium conditions: the higher the average wage, the less likely a person is to join the military. These results accord with our initial thinking that if alternatives for building human capital exist, young adults will choose to pursue those.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: OLS Estimates for Labor Force Participation Rate

	Military	Military+Race	Military+Race+Gender
Labor Force Participation Rate	0.0549	0.0555	0.0562
	(0.0335)	(0.0338)	(0.0340)
Asian		-0.00502**	-0.00509**
		(0.00108)	(0.00108)
Black		0.00306*	0.00309*
		(0.00129)	(0.00131)
Native American		-0.00107	-0.00100
		(0.00171)	(0.00169)
Other		-0.00181	-0.00175
		(0.00147)	(0.00147)
Female			-0.0267**
			(0.000711)
Fixed Effects	✓	✓	✓
Observations	11076722	11076722	11076722
Adjusted R^2	0.012	0.012	0.020

Standard errors in parentheses
This specification is an OLS that groups observations by birth state and cohort.
Note that white and male are both omitted for multicollinearity.
From this table we see that our test statistic for job opening is about 1.6, making it marginally significant at the 10% level. We also see that Black Americans enlist much more than white Americans. Females also enlist much less often than their male counterparts. We also see that Asian Americans enlist significantly less than white Americans. These results reflect broad labor market conditions: when there is more labor market participation, fewer people choose to enlist. Based on our previous hypotheses, we think this is part is a reaction of younger adults who don't see the military as the best career option.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

5.2 Racial Differences

To estimate the different effects these labor market measures have on different races, we collapse data by race and run fixed effects regressions controlling for year of birth and state of birth. We will report three tables of results, since when we ran this for Native Americans and Other races, we found no significant results. Likewise, these two variables did not differ significantly in previous tables.

We first examine the distinct effects on Black Americans in Table Seven. We find no significant effects of these labor market metrics on Black Americans specifically, suggesting that these variables impact Black Americans the same as they do white Americans. This finding is incredibly surprising given previous discussions of why certain races join the military more than others. This suggests that labor market conditions may impact Black Americans differently, but it won't have a significantly different effect on them joining the military. We believe that, given their overrepresentation, this finding warrants much more research into the mechanisms by which Black Americans join significantly more.

Perhaps the most counter intuitive results are found in Table Eight: white Americans are more reactive to different wages, the employee-to-population ratio, and the job offer rate than other races. The signs of these interaction terms point in the same direction, which could explain the underrepresentation of white Americans in the military.

For our results collapsed by Asian (Table Nine), we find interesting results: all interaction terms except for unemployment are significant. However, these point estimates go in the opposite direction of the original point estimates for all individuals, meaning that Asian Americans seem to be less sensitive to labor market conditions. This could explain their severe underrepresentation in the military.

For example, we have evidence that a one percent increase in the employment-to-population ratio is associated with a 4 percent increase in a white person's propensity to serve. Likewise, a one percent increase in the hourly wage is associated with a .7% decrease in the probability that a white person will enlist. This result is probably economically significant, considering annual pay increases are around 2-5%.

Table 7: Collapsed by Black OLS Estimates

	Military	Military	Military	Military	Military
Log Wage	-0.0582**				
	(0.0191)				
Female	-0.0270*	-0.0263*	-0.0262*	-0.0262*	-0.0264*
	(0.0114)	(0.0112)	(0.0111)	(0.0112)	(0.0112)
Black	0.0244	-0.0152	-0.00330	-0.0137	0.00330
	(0.0198)	(0.0171)	(0.00362)	(0.0191)	(0.00344)
Black × Wage	-0.00805				
	(0.00625)				
Emp.-Pop. Ratio		0.0353			
		(0.0786)			
Black × EPR		0.0247			
		(0.0289)			
Job Opening Rate			-0.00261		
			(0.178)		
Black × JOR			0.105		
			(0.0981)		
Lab. Participation Rate				0.0527	
				(0.0843)	
Black × LFPR				0.0212	
				(0.0302)	
Unemployment Rate					0.0295
					(0.0613)
Black × UR					-0.0572
					(0.0467)
Observations	1899	1899	1899	1899	1899
Adjusted R^2	0.442	0.437	0.437	0.437	0.437

Standard errors in parentheses

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$

Table 8: Collapsed by White OLS Estimates

	Military	Military	Military	Military	Military
Log Wage	-0.0233^{+}				
	(0.0132)				
Female	-0.0128	-0.0135	-0.0132	-0.0134	-0.0137
	(0.00894)	(0.00898)	(0.00911)	(0.00895)	(0.00916)
White	0.0245**	-0.00665	0.00617**	-0.00908	0.00317*
	(0.00625)	(0.00581)	(0.00173)	(0.00673)	(0.00118)
White × Wage	-0.00715**				
	(0.00194)				
Emp.-Pop.-Ratio		0.0479*			
		(0.0233)			
White × EPR		0.0155			
		(0.00950)			
Job Opening Rates			0.0450		
			(0.110)		
White × JOR			-0.0995*		
			(0.0458)		
Lab. Participation Rate				0.0618*	
				(0.0292)	
White × LFPR				0.0184^{+}	
				(0.0103)	
Unemployment Rate					-0.00318
					(0.0269)
White × UR					-0.00412
					(0.0168)
Observations	1900	1900	1900	1900	1900
Adjusted R^2	0.833	0.831	0.830	0.831	0.829

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 9: Collapsed by Asian OLS Estimates

	Military	Military	Military	Military	Military
Log Wage	-0.0279^{+}				
	(0.0166)				
Female	-0.0218	-0.0223	-0.0221	-0.0222	-0.0224
	(0.0163)	(0.0161)	(0.0164)	(0.0161)	(0.0161)
Asian	-0.0277**	0.00786	-0.00834**	0.0109	-0.00323**
	(0.00625)	(0.00694)	(0.00163)	(0.00801)	(0.00107)
Asian × Wage	0.00812**				
	(0.00198)				
Emp.-Pop. Ratio		0.0601*			
		(0.0257)			
Asian × EPR		-0.0179			
		(0.0113)			
Job Opening Rate			-0.0699		
			(0.0963)		
Asian × JOR			0.158**		
			(0.0473)		
Lab. Participaiton Rate				0.0883**	
				(0.0306)	
Asian × LFPR				-0.0216^{+}	
				(0.0123)	
Unemployment Rate					0.0151
					(0.0257)
Asian × UR					0.000575
					(0.0171)
Observations	1900	1900	1900	1900	1900
Adjusted R^2	0.726	0.724	0.724	0.724	0.722

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

We have reported the collapsed, isolated effects of different labor market metrics on races that either had significant interaction terms, or that were significantly different from white Americans in our original OLS specification. We have partially explained how white Americans are more reactive to the labor market than other races, and that Asian Americans are less sensitive, potentially leading to their underrepresentation.

6 Conclusion

We have tested a number of potential mechanisms by which an individual decides to enlist in the military. For now, our focus has been on economic and labor considerations, conceiving of the military as a sort of "recession-proof" job that sees an increase in popularity during times of economic downturn. To test this hypothesis, we develop a cohort-specific estimation strategy, as well test this strategy for a number of different labor market metrics. We try to measure the supply-side, demand-side, and equilibrium conditions of how the labor market affects enlistment.

Hitherto studies have focused primarily on the demographic features of enlistees rather than the determinants of their enlistment decision. To get a more accurate measure, we estimate individual-level effect of the unemployment rate, the employment-to-population ratio, the log of hourly wage, the labor force participation rate, and the job openings rate to see which – if any – have an effect on an individual's enlistment decision.

We find that in general, on an individual level, Black Americans are much more likely to join the military than white Americans, females are much less likely to join the military than males, and Asian Americans are less likely to join than white Americans. These results are consistent with previous studies. Our novel contributions come from isolating the effects of labor market conditions on these specific races.

We see that Native Americans and other races do not see a significantly different effect of labor market metrics on their propensity to serve compared to all samples. However, we find that Asian Americans are much less sensitive to labor market changes than other races, which can partially explain their lower rates of enlistment. Likewise, for white Americans, we find that they are more sensitive than other races to labor market cycles. We also find that Black Americans are not significantly more sensitive to these fluctuations than other races, which leaves us to wonder why they exhibit higher enlistment rates.

There are a lot of potential considerations for future work based off this paper. We suggest exploiting the political boundaries that states provide to measure effects of education spending, job training programs, and political party affiliations on enlistment. Maybe these factors will better explain enlistment than what we have measured in this paper. Additionally, if better data on birthplace exists, we highly encourage others to construct commuter zones; by definition, they are local labor markets. Measuring labor market fluctuations at the commuter zone level would yield more precise results for the effect of the labor market on enlistment rates.

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7 Appendix

Data below shows estimates of aforementioned labor market estimates for individuals aggregated by state of birth. The outcome of interest here is the proportion of each state serving, rather than just a single individual. The state-level outcomes show different results on a demographic level. For example, at the state-level, Asian Americans are much more like to join the military than white Americans, and Black Americans are less likely to join. There is not a clear reason for why this is the case, however it warrants further investigation.

Like with the individual-level specification, these estimates find that the log of hourly wage and labor force participation rate are both significantly related to military enlistment decisions. Both go in the same direction as well. At the state-level, a one-percentage increase in wages are associated with a two percent reduction in the proportion of a state that serves, which is massive considering that the average percent of a state in the military is around 1.5%.

Table 10: State-level OLS estimates

	Military	Military+Race	Military+Race+Gender
Job Opening Rate	-0.0409	-0.0208	-0.0205
	(0.0775)	(0.0560)	(0.0561)
Asian		0.319**	0.319**
		(0.0753)	(0.0748)
Black		-0.270**	-0.271**
		(0.0831)	(0.0826)
Native American		-0.354**	-0.354**
		(0.0792)	(0.0788)
Other Race		-0.0557*	-0.0554*
		(0.0266)	(0.0265)
Female			-0.00959
			(0.0117)
Observations	950	950	950
Adjusted R^2	0.945	0.950	0.950

Standard errors in parentheses
This specification is an OLS that aggregates individuals to
the state-level. We include fixed effects.
Note that white and male are both omitted for multicollinearity.
From this table we see that our test statistic for job opening is about -.6, meaning we cannot accept these results as significant. However, we do see that Black Americans
enlist much more than white Americans across states. Females also enlist much less
often than their male counterparts. We also see that
Asian Americans enlist significantly more than white Americans at the state-level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 11: State-Level OLS Estimates

	Military	Military+Race	Military+Race+Gender
Employment-Pop. ratio	0.0523*	0.0388*	0.0389*
	(0.0199)	(0.0161)	(0.0161)
Asian		0.307**	0.308**
		(0.0746)	(0.0741)
Black		-0.263**	-0.263**
		(0.0822)	(0.0816)
Native American		-0.359**	-0.359**
		(0.0760)	(0.0756)
Other Race		-0.0540*	-0.0536*
		(0.0260)	(0.0258)
Female			-0.0102
			(0.0112)
Observations	950	950	950
Adjusted R^2	0.946	0.951	0.951

Standard errors in parentheses
This specification is an OLS that aggregates individuals to
the state-level. We include fixed effects.
Note that white and male are both omitted for multicollinearity.
From this table we see that our p-value for employment-to-population
ratio is significant at the 5% level, meaning that there is a significant
positive relationship. We also see that Black Americans
enlist much less than white Americans. Females also enlist much less
often than their male counterparts. We also see that
Asian Americans enlist significantly more than white Americans.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 12: State-Level OLS Estimates

	Military	Military+Race	Military+Race+Gender
Unemployment Rate	-0.00381	-0.00815	-0.00847
	(0.0189)	(0.0187)	(0.0187)
Asian		0.319**	0.320**
		(0.0755)	(0.0750)
Black		-0.270**	-0.270**
		(0.0834)	(0.0830)
Native American		-0.357**	-0.357**
		(0.0788)	(0.0784)
Other Race		-0.0558*	-0.0554*
		(0.0266)	(0.0264)
Female			-0.00979
			(0.0116)
Observations	950	950	950
Adjusted R^2	0.945	0.950	0.950

Standard errors in parentheses
This specification is an OLS that aggregates individuals to
the state-level. We include fixed effects.
Note that white and male are both omitted for multicollinearity.
From this table we see that our test-statistic for unemployment is insignificant
We also see that Black Americans enlist much less than white Americans.
Females also enlist much less at the state-level
than their male counterparts. We also see that
Asian Americans enlist significantly more than white Americans.
These results are consistent with our other state-level estimates.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 13: State-level OLS estimates

	Military	Military+Race	Military+Race+Gender
Labor Force Participation Rate	0.0683**	0.0476*	0.0476*
	(0.0251)	(0.0193)	(0.0192)
Asian		0.305**	0.305**
		(0.0734)	(0.0729)
Black		-0.263**	-0.264**
		(0.0805)	(0.0800)
Native American		-0.351**	-0.351**
		(0.0756)	(0.0752)
Other Race		-0.0536*	-0.0532*
		(0.0255)	(0.0254)
Female			-0.00964
			(0.0112)
Observations	950	950	950
Adjusted R^2	0.946	0.951	0.951

Standard errors in parentheses
This specification is an OLS that aggregates individuals to the state-level. We include fixed effects.
Note that white and male are both omitted for multicollinearity.
From this table we see that our test-statistic for Labor Force Participation Rate is highly significant. We also see that Black Americans enlist much less than white Americans. Females also enlist much less at the state-level than their male counterparts. We also see that Asian Americans enlist significantly more than white Americans.
These results are consistent with our other state-level estimates.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 14: State-level OLS estimates

	Military	Military+Race	Military+Race+Gender
Log Hourly Wage	-0.0232^{+}	-0.0219^{+}	-0.0220^{+}
	(0.0138)	(0.0116)	(0.0116)
Asian		0.311**	0.311**
		(0.0745)	(0.0739)
Black		-0.259**	-0.259**
		(0.0818)	(0.0811)
Native American		-0.313**	-0.312**
		(0.0758)	(0.0750)
Other		-0.0567*	-0.0563*
		(0.0267)	(0.0265)
Female			-0.0113
			(0.0114)
Observations	950	950	950
Adjusted R^2	0.946	0.952	0.952

Standard errors in parentheses
This specification is an OLS that aggregates individuals to
the state-level. We include fixed effects.
Note that white and male are both omitted for multicollinearity.
From this table we see that our test-statistic for log hourly wage is
significant at the 10% level. We also see that Black Americans enlist
less than white Americans. Females also enlist much less at the state-level
than their male counterparts. We also see that
Asian Americans enlist significantly more than white Americans.
These results are consistent with our other state-level estimates.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$