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INVESTIGATIONS OF SORTING AND NON-WAGE MARKET CLEARING: THREE ESSAYS IN LABOR ECONOMICS

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ABSTRACT

This dissertation is comprised of three essays in labor economics. The first investigates a natural experiment in the internal labor market policies of the US Air Force. The second bounds the causal effects of attaining a college double major. The third studies the causes and consequences of queueing for government sector jobs in Brazil.

The US Department of the Air Force, like many large organizations with rigid and centralized internal labor markets, has recently introduced an algorithmically-assisted person-job matching system to replace their older, manual procedure. This change has been touted as a way to improve both organizational efficiency and to increase the satisfaction of its workforce. In this chapter, I leverage parallel trends and plausibly unexpected variation in the timing of the roll-out of this program in order to calculate its effect on one of the few margins of adjustment available in the military context: retention of personnel. I find that the system had meaningfully large effects on those who actively interacted with it: officers' average quit rate fell by 37%. While still being introduced for enlisted members, the average quit rate for the initial treatment group in the enlisted force has fallen by 76%. These improvements, comparable in effect to a $25,000 retention bonus, are especially notable for having essentially zero marginal cost to implement.

Double majoring has become an increasingly salient phenomenon in recent years, as the returns to higher education have grown. Currently, over 15 percent of college graduates in the U.S. graduate with more than one major. While much research exists on the returns to different individual majors, less is known about the causal effects of double majoring. This chapter provides novel estimates on the returns to double majoring. We improve upon prior studies that rely on controls for observable characteristics by addressing selection concerns in two notable ways. First, by including institution fixed effects, we

control for institution-specific differences that may influence both the decision to double major and subsequent earnings. Second, we adopt a partial identification approach to address non-random selection into double majoring within institutions, providing informative bounds on the returns to double majoring. Results broadly align with estimates from prior studies at the aggregate level but reveal notable gender differences. Women experience an earnings return to double majoring of between 2 to 5 percent, while the return for men is statistically negligible. Our analysis suggests that this discrepancy is primarily attributable to signaling effects in the labor market, which may help to offset the gender pay gap.

Finally, we show that public sector jobs in Brazil are characterized by price and quantity controls in the form of wages larger than those of private sector counterparts but with a limited number of employment contracts (analogous to a quota). Entrance to public sector jobs is decided according to the results of a double-blinded admission exam. The resulting combination prevents the usual price mechanism from equating the value of supplying labor to private or public sector jobs. We show that the equilibrium mechanism operates through increases in the candidate-to-vacancy ratios that reduce the likelihood of success at any attempt to access a public sector job. In our empirical analysis, we look at exams administered between 2007 and 2017. We show that the value of time spent waiting actually exceeds the average gain, dissipating all rents that would otherwise be generated by the public wage premium.

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The Power of Choice: The Effect of Algorithmic Person-Job Matching on Department of the Air Force Retention

"Ensuring the right Airman is in the right job at the right time is the best way to maximize performance and retention of the most effective Airmen"

— National Academies of Science, Engineering, and Medicine, *Strengthening U.S. Air Force Human Capital Management: A Flight Plan for 2020-2030*

1.1. Introduction

It has been over 50 years since the draft was ended and the all volunteer military force began in the US. This has largely been a success, improving overall macroeconomic efficiency and increasing the human capital that is available to the military (Warner and Asch 2001). However, the shift to all voluntary contracts has made it especially important to precisely tailor pay and benefits in order to ensure the correct amount of military labor remains available for national security needs.

Despite this, the military remains particularly constrained as an employer due to its lack of lateral entry (higher-ranking positions are filled exclusively from the current cohort of lower-ranked individuals), its lack of wage discretion (military wages are set exogenously by Congress), and the nearly continuous churn in the location to which workers must be assigned.[1] The combination of the first two features means the military can only adjust its overall supply of labor via manipulating its rates of recruitment and/or separation. The

1. Each location of assignment lasts roughly 3 years

Figure 1: DAF Bases

last feature means there is significant scope for the present value of service to vary with idiosyncratic location preferences as assignments change over the course of a career.

Prior to 2018, the Department of the Air Force (DAF) generated all individual-assignment matches with pen-and-ink in a central bureaucracy. Worker preferences would be solicited in advance of any reassignment, but they were not central to this process.[2] Recognizing the potential for improving worker retention via improving the subjective value of assignment matches, the DAF developed the "Talent Marketplace" (TM) system in 2018. TM is a web-based program which allows individuals to look up all of the assignments for which they are eligible, assignment owners to look up all of the individuals who are eligible for their assignment, and for each side of the market to submit rank-ordered preferences over the other. The deferred acceptance (DA) algorithm (Gale and Shapley 1962) is periodically run on these preferences in order to produce an individual-optimal stable assignment match. The assignment managers then take this match as a first draft in the updated assignment process.[3]

After an extended period of roll-out by job specialty, by the end of 2019, all line officers at or below the rank of lieutenant colonel were using the system (Bailey 2019). As of the end of 2023, a small initial cohort of the enlisted force were also using the system, with roll-out still ongoing for this group. The DAF's stated goal is to expand TM to encompass as many assignment functions as possible, including all enlisted assignments, with the expectation that this will be a "positive retention influence" on the force and will increase the efficiency of the assignment matching process (Kelly 2019).

Using an anonymized monthly administrative panel of DAF personnel, including the full

2. The Department of the Air Force includes both the Air Force and the Space Force

3. It is unclear why the algorithm is not directly applied. Even if some desiderata are being left unmet by the algorithm, however, the introduction of automation is still reducing overhead for the assignment managers and providing information to marketplace participants, which are benefits in themselves.

preference rankings in TM from each assignment match cycle, I am able to estimate several causal estimands for the effect of the TM program on DAF personnel retention. Ideally, I would also investigate changes in productivity to get a sense of the government's share of the match surplus as well as estimate the overall increase in in surplus created by the TM-generated matches. Retention is the natural outcome of interest in this paper since measures of these other interesting quantities are unavailable.[4]

I find that effects are both economically and statistically significant, with a decrease in separations of 0.18 percentage points for officers and 0.44 percentage points for enlisted within the first two years of using the system (a 37% and 76% reduction from baseline, respectively). This translates to approximately 16,000 additional individuals retained per year and $25,000 per person in retention bonus pay forgone. I also find moderate heterogeneity by job specialty and rank, but, surprisingly little variation in effects by the rank order of the assignment to which an individual is matched. I attribute this to the post-match edits that are made prior to the official assignment, although I do not have the data required to pin down the reason for these edits. Likely, there are further Pareto improvements to be made to the system

The rest of the paper proceeds as follows. Section 1.2 reviews the literature, Section 1.3 lays out the theory, Section 1.4 describes the empirical methods, and Section 1.5 describes the data. Results are presented in Section 1.6 and discussed in Section 1.7. Section 1.8 concludes.

4. In particular, there is no real analog of profit and loss in the military context outside of wins and losses in major conflicts. Oblique measures of productivity, such as performance reports are likely the best that we could do in the short term. Unfortunately, these were not available in the data.

1.2. Literature Review

This paper relates to three major strands of literature. The first is the theory of discrete matching markets in particular and mechanism design in general. The second is a multifarious literature describing the internal labor market (ILM) practices within large organizations. Last is the intersection of dynamic discrete choice, military retention, and dynamic spatial trade models.[5] I will review each of these in turn.

Mechanism design was not born with the groundbreaking Gale and Shapley (1962), but with the advent of discrete algorithmic matching, such design arguably found the largest vehicle through which it could be practically applied. Building on several similarly influential early papers, the unique benefits and constraints of one-to-one and many-to-one matching were quickly established in the theory (see, e.g. Shapley and Scarf 1974; Hylland and Zeckhauser 1979; Kelso and Crawford 1982; Roth 1982) and found an early application to the national medical resident matching program (NRMP) in the US (Roth 1984). Further applications of matching theory in market design settings accelerated after the turn of the century (e.g. radio spectrum auctions: Roth, 2002; school choice: Abdulkadiroğlu and Sönmez, 2003; kidney exchange: Roth, Sönmez, and Ünver, 2005; the job market for economists: Roth, 2008; online dating: Hitsch, Hortaçsu, and Ariely, 2010).[6]

While these papers tended to emphasize the role of matching in creating well-functioning markets where none existed before, current work focuses much more on the potential for optimizing some aspect of extant markets.[7] Abdulkadiroğlu, Pathak, and Roth (2009) describe the redesign of the high school match in New York City, which ensured stability and strategy-proofness despite schools' indifference over similarly-situated students.[8] Che and

5. A small intersection, to be sure, but one that I argue nevertheless well-describes this problem

6. For a review, see Sönmez and Ünver (2011)

7. Typically, these optimizations are, in the framework of Sönmez (2023), “unsolicited” rather than “commissioned,” which adds an additional layer to the market design challenge

8. The initial theory required preferences to be strict

Tercieux (2019) use data from this same setting in New York to show how improvements can be made to the algorithm to improve the efficiency of the student-school match while preserving (asymptotic) stability. Bates et al. (2023) find that achieving an equitable distribution of teachers across schools requires a core allocation (as guaranteed in DA) rather than allowing either side to dominate. Baron et al. (2024) show that the assignment of child protective services (CPS) investigators to child welfare cases can be implemented such that both the welfare of investigators and CPS outcomes are improved.

Most relevant for my setting is Davis, Greenberg, and Jones (2023), who investigate the 2019 introduction of the DA algorithm to an online marketplace which assigns US Army officers to Army units.[9] They find that within the first year after assignment by DA, officer retention rose by 16.7%, although the effect faded out by the second year. They also find evidence of strategic communication between officers and assignment owners which may explain the absence of more intense effects. This paper differs theirs in that first, the DAF has many fewer instances of "first choice"-to-"first choice" assignment matches, and so offers potentially more room for optimization and second, the introduction of the entire TM system at once is arguably a much larger change than merely introducing the DA algorithm to an already existing system.

In contrast to the matching literature, there is no unified theory of internal labor markets. As noted in Baker and Holmstrom (1995), almost any ILM can be rationalized given "the right combination of uncertainty, asymmetric information and opportunism," of which there are many empirical examples. These issues can each be linked to any number of fundamental models, such as Roy (1951) comparative advantages, differences in human capital (Becker 1964), unobservable differences in worker ability (Spence 1973; Lazear and Rosen 1981), efficiency wages (Shapiro and Stiglitz 1984), and ordinal performance rank-

9. The Army had been experimenting with systems similar to TM prior to the DAF, but had yet to add the DA algorithm into their assignment process

ing (Akerlof 1976; Malcomson 1984).[10]

The models that are particularly relevant to the military are those which explain some of its distinctive internal labor market features, such as its strict job hierarchy, up-or-out policy, and its heavy reliance on retirement vesting as a long term incentive.[11] While some aspects of these policies simply implement the requirements of US law, others can be seen as solutions to ambiguities in worker quality or to principal-agent problems. The Talent Marketplace system has to potential to add a new element to these policies for the DAF by improving the quality of person-job matches as in Sattinger (1993). This obviously matters to workers in the short run by raising their contemporaneous utility, although a better job match can also improve human capital acquisition, which can raise their future utility as well (Fredriksson, Hensvik, and Skans 2018; Guvenen et al. 2020).

Looking beyond direct effects on workers, happiness seems to have positive spillovers on firms' overall productivity (Oswald, Proto, and Sgroi 2015) and job quality can also be a form of non-monetary incentive which can lower the monetary cost of labor (Cassar and Meier 2018; Khan, Khwaja, and Olken 2019).[12] Other benefits to the firm include the alleviation of talent hoarding within divisions by increasing cross-divisional job movement (Friebel and Raith 2022) and the avoidance of the "Peter principle" by shifting the internal hiring focus from current to future performance (Benson, Li, and Shue 2019).[13]

Of course, match quality can simply lead to a direct increase in productivity as well. A randomized controlled trial of the optimal assignment of tax collection personnel in the

10. For reviews, see Lazear and Oyer (2013) and Waldman (2013)

11. While distinctive (Asch and Warner 2001), these are not necessarily limited to the military context: see Bertrand et al. (2020)

12. Cowgill et al. (2021) find that there can be important tradeoffs between match-specific productivity and job satisfaction, which is a potentially mitigating factor

13. The Peter principle is the tendency of individuals to be promoted as long as current performance is above some threshold, which only terminates once current performance falls below this threshold. Focusing on future performance for internal hiring decisions will be productivity enhancing to the extent that current and future performance are not perfectly correlated.

Congo was able increase tax collections by 26% from baseline (Bergeron et al. 2022). In structural work, the optimal assignment of police officers to neighborhoods in Chicago has been shown capable of both improving officer welfare and significantly reducing crime (Ba et al. 2022) and in an urban area of the US midwest, model estimates suggest that a centralized system designed to maximize teacher-school match productivity could raise average student test scores by 7% of a standard deviation (Laverde et al. 2023).

Finally, although dynamic discrete choice, dynamic spatial trade, and dynamic personnel retention models each have large associated literatures, they also have significant areas of overlap.[14] This intersection, describing individuals' time-consistent optimal choices among (internal job) options that are distributed across space, is critical to understanding the structure of the problem with which TM interacts.

The first models of this type that were applied to military personnel retention suffered from a lack of computing power, although this constraint quickly diminished over time (Gotz and McCall 1983; Black, Moffitt, and Warner 1990; Daula and Moffitt 1995).[15] The binary stay/leave decision has always been the main area of focus, but the importance and value of location choice in military service has also been a common area for research (see, e.g. Christensen, Golding, and Houck 2002; Carrell and West 2005; Coughlan, Gates, and Myung 2014). In order to formally incorporate geography into the military members' decision model however, much more structure is required.

Such structure is arguably to be found in models of trade and geography. Coen-Pirani (2010) answers the puzzle of why there would be simultaneous gross flows of workers both into and out of a single location by using idiosyncratic, random match qualities between workers and locations.[16] Caliendo, Dvorkin, and Parro (2019) then build on this intuition

14. Nesting roughly in that order
15. It is now the standard retention modeling technique: see Asch (2019) for a review
16. The Roback (1982) model would seem to imply that workers only ever move from low to high utility

to add sub-national locations and sectoral choices into the venerable Eaton and Kortum (2002) general equilibrium trade model. Among their many other important innovations, most useful to this paper is their elegant derivation of gross migration flows which will help to clarify the mechanics behind the introduction of TM.[17]

1.3. Theory

Suppose as in Caliendo, Dvorkin, and Parro (2019) that there is an infinitely-lived representative agent who, in my application, lives in a world with N discrete locations and begins her career in the military, indicated by a capital M, at the entry-level rank, in time 0. Her flow utility in this state, $v_t^{M,njk}$, at time, t, location, n, and specialty, jk, is the sum of her military wages, $w_t^{M,njk}$, a subjective amenity value of the location, $\zeta_t^{M,njk}$, and a term representing her future discounted expected value, given optimal decision-making.[18] Because of military requirements, there is a fixed probability, $\bar{p}^{njk,ijk}$, that an individual in specialty jk must be relocated from n to i.[19][20] Given a realization of the reassignment location, i, the agent then has the choice to either accept the contract, remain in the military and move to i, or separate from the military in location n, become a civilian, C, and join the civilian-equivalent sector, j.[21] β is a discount factor, $\eta^{r,s}$ is a fixed adjustment cost for moving from state r to state s, and $\nu\varepsilon_t^s$ is an ideosyncratic, i.i.d., mean zero shock with scale factor, ν.

locations (and stay there), but empirically, simultaneous inflows and outflows are nearly uniformly observed across locations.

17. See Aguirregabiria and Mira (2010) and Redding (2022) for surveys of the dynamic discrete choice and trade and geography literatures, respectively

18. I abstract from any particular job to focus on the *location* of these jobs, but in principle an additional index could be added to account for the presence of multiple jobs in each location

19. Specialties in the military are not substitutable and are rarely changed, e.g. a shortfall among pilots cannot be solved by assigning more maintenance personnel to that location

20. Note that due to the structure of DAF operations, many specialties have locations for which there is zero probability of assignment. This has no impact on identification, but may help to explain heterogeneous TM effects by specialty.

21. I assume that military specialties, jk, can be partitioned such that each nests within one associated civilian sector, j

$$v_t^{M,njk} = w_t^{M,njk} + \zeta_t^{M,njk} + \sum_{i=1}^{N} \bar{p}^{njk,ijk} \max_{s \in \{(M,ijk),(C,nj)\}} \left\{ \beta E[v_{t+1}^{s}] - \eta^{(M,njk),s} + \nu \varepsilon_t^{s} \right\}$$

Once the agent decides to become a civilian, due to the lack of lateral entry into the military, they must remain a civilian permanently.[22] Their flow utility has the same general form except that they now have the choice to move wherever they like. As before, they still choose the optimal location from their choice set, given the transition costs and moving shocks that they face.

$$v_t^{C,nj} = w_t^{C,nj} + \zeta_t^{C,nj} + \max_{\{i\}_{i=1}^{N}} \left\{ \beta E[v_{t+1}^{C,ij}] - \eta^{(C,nj),(C,ij)} + \nu \varepsilon_t^{C,ij} \right\}$$

Assuming a Type-I Extreme Value distribution for the shocks allows a closed form expression for the expected value of the maximum among all choices of location, yielding

$$\begin{aligned} E[v_t^{M,njk}] \equiv V_t^{M,njk} = w_t^{M,njk} &+ \zeta_t^{M,njk} \\ &+ \nu \sum_{i=1}^{N} \bar{p}^{njk,ijk} \ln \left[\exp\left(\beta V_{t+1}^{M,ijk} - \eta^{(M,njk),(M,ijk)}\right)^{1/\nu} + \exp\left(\beta V_{t+1}^{C,nj} - \eta^{(M,njk),(C,nj)}\right)^{1/\nu} \right] \end{aligned}$$

and

$$E[v_t^{C,nj}] \equiv V_t^{C,nj} = w_t^{C,nj} + \zeta_t^{C,nj} + \nu \ln \left[\sum_{i=1}^{N} \exp\left(\beta V_{t+1}^{C,ij} - \eta^{(C,nj),(C,ij)}\right)^{1/\nu} \right]$$

Caliendo, Dvorkin, and Parro (2019) then show how this multinomial logit-like structure

22. This makes the civilian sector an absorbing state

can be used to derive the gross migration flows (equivalently, the probability of movement), $y_t^{s,r}$, between any two states, s and r. In this context,

$$y_t^{(M,njk),(M,ijk)} = \bar{p}^{njk,ijk} \left[\frac{\exp\left(\beta V_{t+1}^{M,ijk} - \eta^{(M,njk),(M,ijk)}\right)^{1/\nu}}{\exp\left(\beta V_{t+1}^{M,ijk} - \eta^{(M,njk),(M,ijk)}\right)^{1/\nu} + \exp\left(\beta V_{t+1}^{C,nj} - \eta^{(M,njk),(C,nj)}\right)^{1/\nu}} \right]$$

$$y_t^{(C,nj),(C,ij)} = \frac{\exp\left(\beta V_{t+1}^{C,ij} - \eta^{(C,nj),(C,ij)}\right)^{1/\nu}}{\sum_{m=1}^{N} \exp\left(\beta V_{t+1}^{C,mj} - \eta^{(C,nj),(C,mj)}\right)^{1/\nu}}$$

$$\begin{aligned}
y_t^{(M,njk),(C,nj)} &= \sum_{m=1}^{N} \left(\bar{p}^{njk,mjk} - y_t^{(M,njk),(M,mjk)}\right) \\
&= \sum_{m=1}^{N} \bar{p}^{njk,ijk} \left[\frac{\exp\left(\beta V_{t+1}^{C,nj} - \eta^{(M,njk),(C,nj)}\right)^{1/\nu}}{\exp\left(\beta V_{t+1}^{M,ijk} - \eta^{(M,njk),(M,ijk)}\right)^{1/\nu} + \exp\left(\beta V_{t+1}^{C,nj} - \eta^{(M,njk),(C,nj)}\right)^{1/\nu}} \right] \\
&= \sum_{m=1}^{N} \bar{p}^{njk,ijk} \left\{ \frac{1}{1 + \exp\left[\beta V_{t+1}^{M,ijk} - \eta^{(M,njk),(M,ijk)} - \left(\beta V_{t+1}^{C,nj} - \eta^{(M,njk),(C,nj)}\right)\right]^{1/\nu}} \right\}
\end{aligned} \tag{1.1}$$

Equation (1.1) analytically describes the mean military separation rate for specialty jk in location n at time t. It is a weighted average of the probability, expressed in a power-transformed conditional logit form, that the civilian sector is chosen over each military location to which it is possible to be reassigned. To the extent that manning requirements for any specialty and experience level are independent of the source of the manning (i.e., to fill a jkt shortfall in location i, a jkt worker from location n would be just as acceptable as one from location m), the separation rate varies primarily with the compensation available in the relevant civilian sector, j.[23] Aggregating over all locations gives us the mean separation rate by specialty.

At issue is effect of the introduction of a person-job matching algorithm on this flow of workers leaving the military. The only parameters that this could affect are the military location amenity values, $\{\zeta_t^{M,njk}\}_{n=1}^{N}$.[24] If these values increase (decrease) overall, then the expected value of military service will increase (decrease), and the mean separation rate will fall (rise). A priori, it is not possible to make an unambiguous prediction about how these values will change. Even if the DA algorithm is followed exactly, there is no guarantee that it is definitely more or less efficient at preference satisfaction from the military members' perspective than the prior system. That said, because DA always achieves the most efficient matching among all matchings in the core of the market, the old system would need to have been *more* efficient than the core in order for retention to subsequently fall in response to TM. This suggests that retention would likely rise.

1.4. Empirical Methods

I use the Gardner (2022) 2-step event study method to calculate the causal effects of various categories of exposure to TM using military ranks crossed with specialties as the units of interest.

Assumption 1. *SUTVA-a: Treatment effects are constant, conditional on the time since becoming treated.*

Assumption 2. *SUTVA-b: No interactions or spillovers between units.*

23. Recall that military wages are fixed by law. All other parameters are constant by assumption.

24. The collection of individuals that are represented by our representative agent likely have amenity values that are constant and probabilities of assignment that vary with the implementation of the algorithm. Given fixed manning requirements however, aggregating from individuals to a representative agent yields assignment probabilities that are constant and an *average* of amenity values in each location which vary as the algorithm re-sorts individuals across locations.

Both of these follow directly from the structural model. Under these assumptions, we have the treatment assignment matrix (Arkhangelsky and Imbens 2023):

$$\Omega = \begin{bmatrix} \omega_{111} & \dots & \omega_{JK1} \\ \vdots & \ddots & \vdots \\ \omega_{11T} & \dots & \omega_{JKT} \end{bmatrix}$$

where $\omega_{jkt} \in \mathbb{N}_0 \;\; \forall jk, t$ and $\omega_{jkt} = \omega_{jk,t-1} + 1$ if $\omega_{jk,t-1} > 0$. I.e. units are untreated ($\omega_{jkt} = 0$) until some time, τ, at which point $\omega_{jk\tau} = 1$ indicates initial treatment and in all subsequent periods the treatment assignment is defined by the number of periods since initial treatment.

Assumption 3. *Parallel trends: For any two specialties, jk and jk', associated with civilian sector, j, the difference in mean separation rates at time t, minus any treatment effects, is a constant.*

The structural model suggests that trends are parallel after applying a link function that is the weighted average of power-transformed conditional logits. Both the averaging and the power transformation have the effect of flattening the standard logit sigmoid shape.[25] Thus the trends will be approximately linear within a small enough neighborhood. This assumption gives us potential outcomes in terms of unit, μ_{jk}, and time, λ_{jt}, fixed effects, plus treatment effects, $\gamma_{\omega_{jkt}}$:

$$Y_{jkt}(0) = \mu_{jk} + \lambda_{jt} + \varepsilon_{jkt}$$

$$Y_{jkt}(\omega_{jkt}) = \mu_{jk} + \lambda_{jt} + \gamma_{\omega_{jkt}} + \varepsilon_{jkt}$$

25. Assuming ν is greater than one in accordance with the literature.

Assumption 4. *Unanticipated treatment timing: Potential outcomes are only realized for the actual treatment assigned (there is no treatment anticipation).*

These four assumptions allow identification of the average treatment effect on the treated:

$$
\begin{aligned}
ATT_{\omega_{jkt}} &= E[Y_{jkt}(\omega_{jkt}) - Y_{jkt}(0)|D_{\omega_{jkt}} = 1] \\
&= E[Y_{jkt}^{obs}|D_{\omega_{jkt}} = 1] - \mu_{jk} - \lambda_{jt} = \gamma_{\omega_{jjt}}
\end{aligned}
$$

for observed treatment status $D_{\omega_{jjt}} \in \{0, 1\}$.

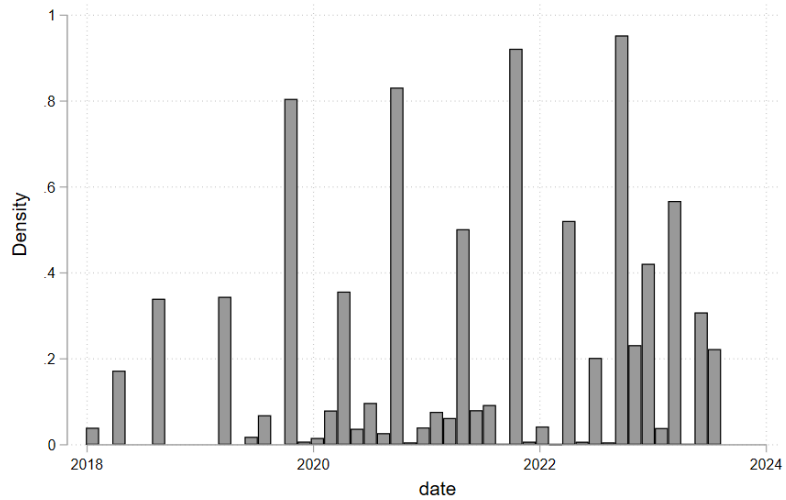
I therefore run the following two regressions, restricting (1.2) to the untreated observations only. I use the fixed effect estimates from (1.2) to generate $\tilde{y}_{jkt} = y_{jkt} - \hat{\mu}_{jk} - \hat{\lambda}_{jt}$ which is the dependent variable in (1.3):

$$y_{jkt} = \mu_{jk} + \lambda_{jt} + \xi_{jkt} \tag{1.2}$$

$$\tilde{y}_{jkt} = \sum_{\omega_{jkt}} \gamma_{\omega_{jkt}} D_{\omega_{jkt}} + u_{jkt} \tag{1.3}$$

As noted in Gardner (2022) this method is robust to heterogeneity and dynamics in the treatment effects when properly specified. It will capture the overall average effect within the designated category, sidestepping the possibility that treated units are ever compared to other treated units and without any need for reweighting. Inference is accomplished via GMM standard errors due to the implicit presence of the fixed effects as generated regressors.

Figure 2: Move Cycle Dates



1.5. Data

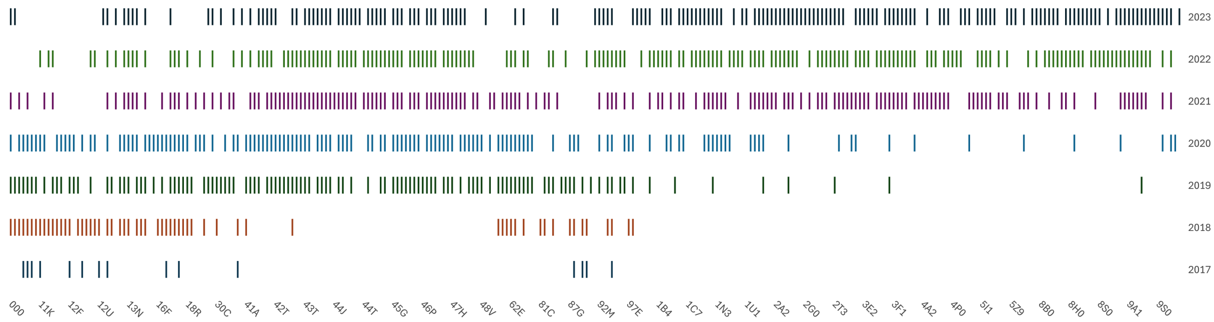
I received data from the Office of Labor and Economic Analysis at the US Air Force Academy which includes an anonymized monthly administrative panel of every DAF officer at or below the rank of colonel from 2016-2024 and every DAF enlisted member from 2019-2024. Paired with this are nearly all preferences input and nearly all assignment matches generated by TM.[26] Importantly, I can see where each individual is assigned in each month and whether they have indicated that they wish to separate, but I cannot see any communications that might occur between individuals and their assignment managers. This means that while I can infer assignment offers whenever they are accepted (since the individual subsequently appears at that location), assignment offers are unknown whenever an individual opts to separate in lieu of accepting an assignment.[27]

Figure 2 is a histogram of the reassignment cycles using TM over time, showing both the

26. There are 3,546 preference lists and 7,155 matches that cannot be merged into the panel, most likely attributable to beta testing, given the timing of the observations

27. This is colloquially known as the "7-day option," since by regulation the decision must be made within 7 days of receiving the assignment offer.

Figure 3: Treatment Timing



Each vertical line indicates the year of the first observed instance of treatment for some rank within the corresponding specialty on the x axis. Officer specialties are sorted alphabetically on the left side and enlisted specialties are sorted alphabetically on the right. Air Force Specialty Codes (AFSC) are taxonomic, with alphanumeric characters to the left side of each code indicating broader categories and each character to its right indicating subcategories thereof. Not all AFSCs are labeled due to space considerations.

usual strong periodicity in assignments and an increase in the frequency of usage over time (as expected, given the roll-out). Figure 3 highlights the variation in the year of first treatment (indicated by a vertical line) by rank and specialty over these cycles. We can see that the earliest treatments were in (late) 2017 and took about 3 years per specialty to complete.[28]

Note that the significant disruption of the COVID-19 pandemic occurred during the roll-out of the program. This does not affect identification in general as long as assumptions 1 through 6 hold, since the changes in the macro economy induced by the pandemic will all be differenced away. One potential threat to identification would be if choice sets were to change non-randomly (due to movement restrictions in certain locations). Movement restrictions did in fact occur during the pandemic, although they were lifted after only 3 months, which was not enough time to substantially change assignment matches, after the delay (Department of Defense 2024).

28. There are multiple instances of first treatment in this figure because there are 6 officer ranks and 9 enlisted ranks per specialty, each of which may become treated at a different time.

Summary statistics appear in Tables 1 and 2. Although the officer sample does not include the executive force (the General ranks), it is still apparent that officers are older and have more military experience on average than the enlisted force. They are also more likely to be white, married, and hold a bachelors degree.[29] In the bottom section of each table, the key TM variables appear. Note that for officers, only 57% of the preference submissions to TM resulted in a match and, of those instances, 76% were manually reassigned to a job different than that match. Few enlisted members have been given the opportunity to input preferences so far, but of those who have, only 6% of the resulting assignments were the result of an algorithmic match and 87% of those were manually reassigned. Despite this, the average list length submitted is near 20 for both groups, indicating high levels of personnel engagement with the system.[30]

What is clear from these summary statistics that the DA algorithm was not a point of emphasis in the rollout of TM. If there were constraints that were not easily coded into the system (leading to many preferences submitted, and matches generated, between agents that turned out to be incompatible), this would explain the high percentage of manual overrides.[31][32] Preference lists submitted by assignment owners were also significantly shorter than for individuals, which could be another reason why the match generated by the algorithm was under-utilized.[33] In any case, even without the algorithm, there could still be benefits from automation and/or information dissemination that were more highly valued by the participants in the market than the matching functionality per se.

29. A BA is currently a requirement for commissioning as an officer

30. Some individuals submitted over 100 preferences

31. I.e. people could be requesting assignments that would require substantial retraining that the military is unwilling to provide. In other words, the system may be incorrectly presenting job options that are outside of the true feasible choice sets.

32. Problems with the mechanism interface, code, and/or confusion as to its theoretical benefits could also potentially explain this.

33. It is much harder for assignment owners to learn useful information about all of the many individuals who could be assigned to them than it is for individuals to learn about the assignments.

Table 1: Summary Statistics: DAF Officers

	Obs.	Mean	Std. Dev.	Min.	Max.
Date of obs.	6,593,699	2020	2.3	2016	2024
Rank	6,593,631	3.3	1.3	1	6
Months of service	6,593,662	123	86	0	526
Age	6,593,690	34	7.5	19	69
White	6,593,699	0.78	0.41		
Male	6,593,699	0.78	0.41		
Married	6,593,699	0.69	0.46		
Dependents	4,207,250	2.6	1.4	1	14
BA+	6,593,699	0.95	0.21		
Officer Training Sch. grad.	6,593,699	0.2	0.4		
Academy grad.	6,593,699	0.23	0.42		
Spouse is military	6,593,699	0.11	0.32		
Operations specialty	6,593,699	0.46	0.5		
Years in location	6,556,233	1.9	1.6	0	38
List length	610,263	21	20	1	294
Rank of algorithm-assigned job	18,674	7.5	8.7	1	151
Rank of observed job	32,524	8.3	9.9	1	139
Rank if algorithm over-ridden	10,210	6.1	7.1	1	103
Assignment improves match	18,674	0.10	0.30		
Assignment equal to match	18,674	0.24	0.43		
Assignment worse than match	18,674	0.66	0.47		
Separation rate	6,593,699	0.0049	0.07		

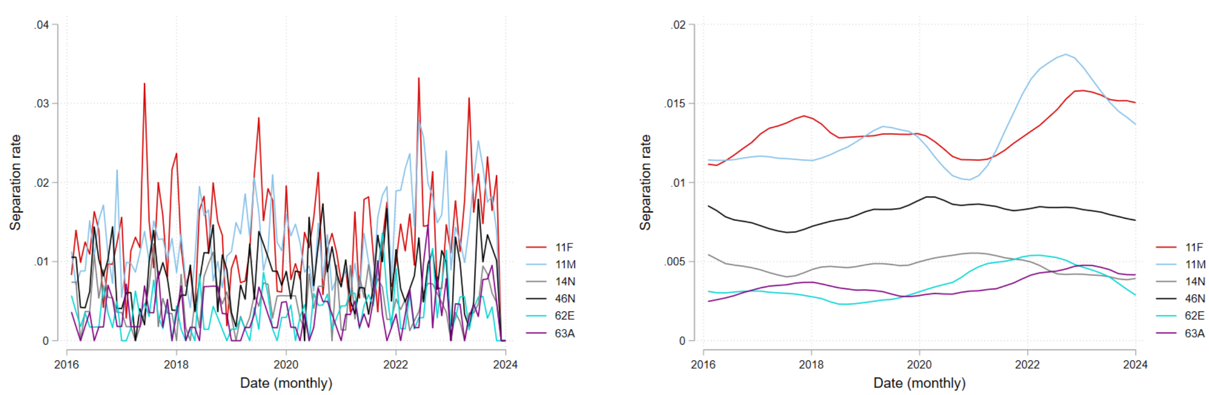
97,763 unique individuals. The rank of an assignment received after an algorithm override is only available for cases where the assignment appeared on the individual's preference list.

Table 2: Summary Statistics: DAF Enlisted

	Obs.	Mean	Std. Dev.	Min.	Max.
Date of obs.	15,954,024	2022	1.4	2019	2024
Rank	15,953,445	4.6	1.6	1	9
Months of service	15,953,810	90	75	0	670
Age	15,953,989	28	6.6	17	68
White	15,954,024	0.69	0.46		
Male	15,954,024	0.79	0.41		
Married	15,954,024	0.5	0.5		
Dependents	7,507,259	2.2	1.2	1	15
AFQT %	15,733,869	68	17	0	99
BA+	15,954,024	0.12	0.33		
Spouse is military	15,954,024	0.11	0.31		
Operations specialty	15,954,024	0.21	0.41		
Years in location	15,670,176	2.3	2.1	0	51
List length	155,885	17	18	1	155
Rank of algorithm-assigned job	583	4.2	5.5	1	49
Rank of observed job	9,821	7	8.1	1	71
Rank if algorithm over-ridden	156	2.7	3.2	1	26
Assignment improves match	583	0.03	0.18		
Assignment equal to match	583	0.13	0.33		
Assignment worse than match	583	0.84	0.37		
Separation rate	15,954,024	0.0058	0.076		

394,557 unique individuals. The rank of an assignment received after an algorithm override is only available for cases where the assignment appeared on the individual's preference list.

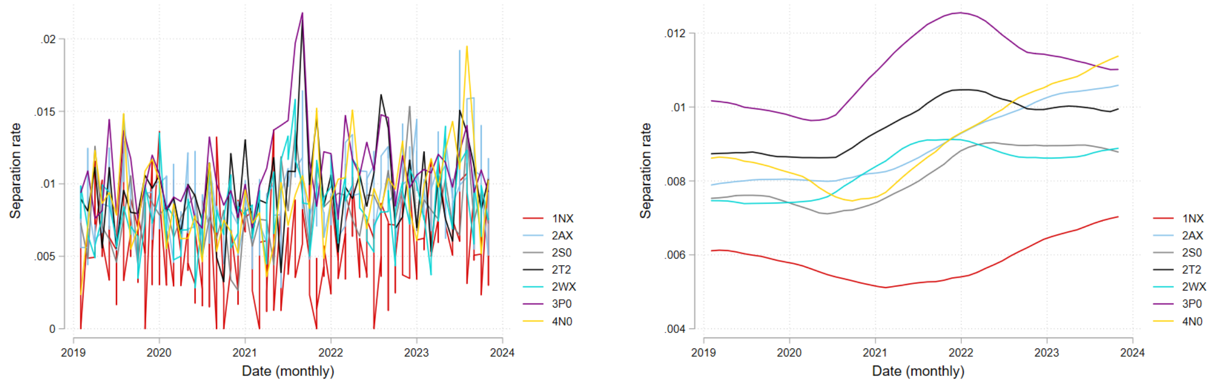
Figure 4: Parallel Trends: Officers



(a) Raw data

(b) Local linear smoothed

Figure 5: Parallel Trends: Enlisted



(a) Raw data (b) Local linear smoothed

Figures 4 and 5 show the separation rates for some of the largest specialties among officers and enlisted, respectively. White noise appears to be several times larger than the average separation rates in both figures. Additionally, there are two groups of specialties within each for which trends appear to track especially closely. These groups correspond to pilots, medical personnel, intelligence specialists, and all others, which is not surprising given the different outside options for these groups.[34]

1.6. Results

Results appear in Figures 6 through 10 and in Table 3. I define four treatment types of interest. First is "exposure," which initially occurs for all individuals of a given rank and specialty whenever any individual in that category is observed with preferences submitted to TM. This baseline treatment also defines the cutoff for the control groups that are used to estimate fixed effects since this is the broadest measure of treatment. Next is the "actual use" of TM which requires an individual to personally submit preferences to the system. The last two are defined by being matched to a job that is anywhere on an individual's preference list, "ranked," or being matched to a job that is one of the top three

34. These groups are compared separately for this reason (implicitly, with a different civilian sector, j)

ranks on the list, "top 3."

As part of the event study results, we can also perform another assessment of the event study assumptions by examining pre-trends. In Figure 6, the difference in pre-trends between treatment and control are all statistically indistinguishable from zero except for the point two periods prior to treatment for officers in panel (a). It is plausible that rumor-based information would be available at this point, which could introduce an opportunity for anticipation of the treatment. In panels (b) and (c) however, no statistically significant pre trends are seen. In order to anticipate treatment by the amount of treatment offset in these panels, individuals would need to be aware of the exact timing of their move much earlier than seems plausible. I therefore redefine all individuals as exposed to TM 6 months prior to the actual instance in the data in order to ensure that the no anticipation assumption holds.

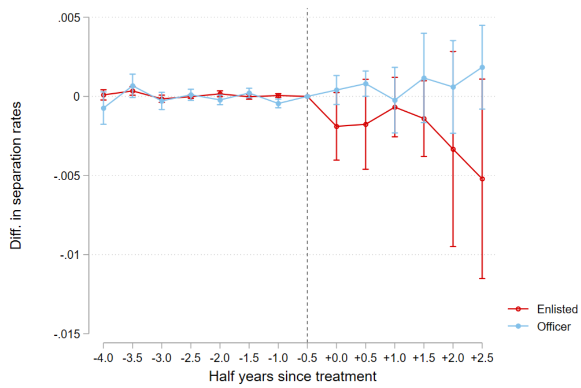
Having addressed parallel trends and anticipation as well as is possible, I now turn to the effects portion of the event studies in Figure 7. Panel (a) shows an increase in separations within the first year for officers exposed to TM and statistically insignificant effects for enlisted. Panels (b) through (d) show nearly identical effects of actual use, ranked match, and top 3 match for officers, with a slight anticipatory increase in separations followed by sharp decrease, which fades over time (but not to the point of insignificance). The enlisted effects begin insignificant but actually grow over time, becoming significant by year 2.[35] Effects actually appear to be smaller for ranked or top 3 outcomes than for actual use, although this is not a statistically significant difference.[36]

Overall average effects for the first two years, as well as heterogeneity by race and gender are shown in Table 3. Averaging over the two years produces very precise average treat-

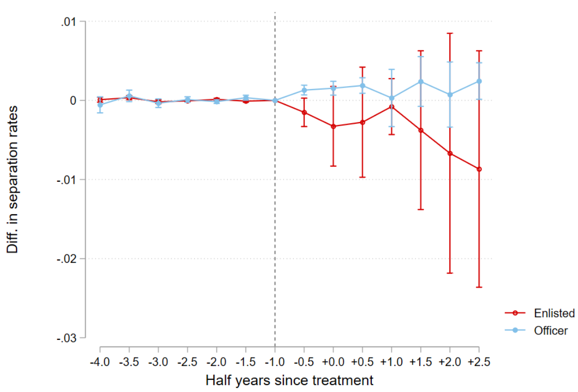
35. Due to the especially small pool of treated enlisted members at the end of the observation period, some caution is in order

36. The sample size for this treated group is even smaller

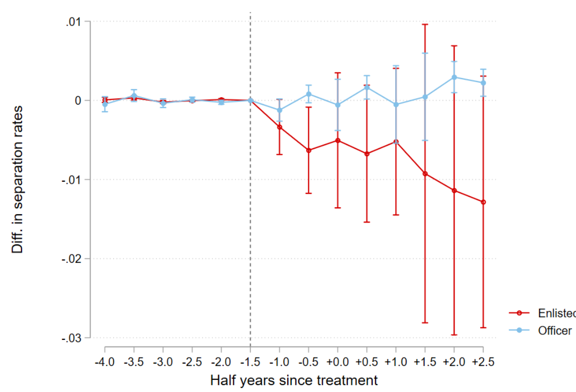
Figure 6: Anticipation Effects in Exposure?



(a) No treatment offset

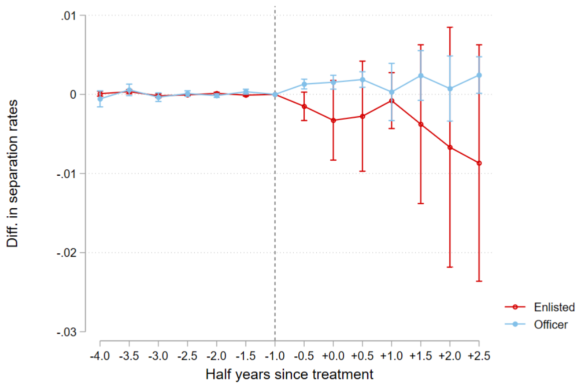


(b) 6 month offset

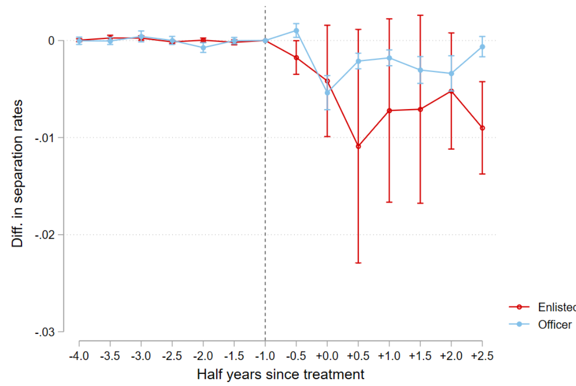


(c) 12 month offset

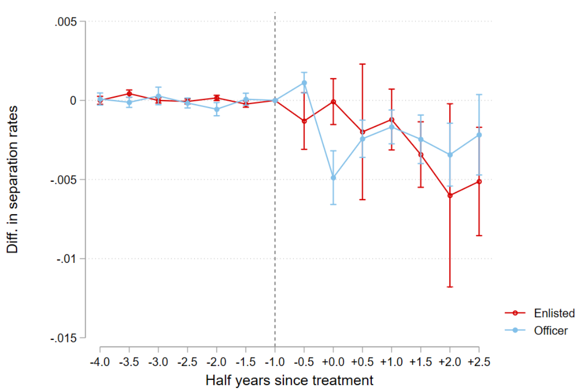
Figure 7: 6 Month Offset Treatment Effects



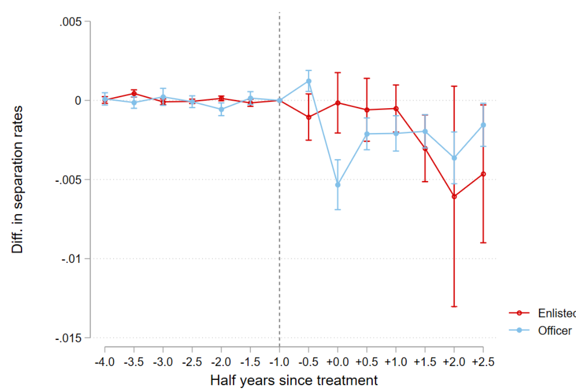
(a) Exposure



(b) Actual Use



(c) Received Ranked Match



(d) Recieved Top 3 Match

Table 3: AF Talent Marketplace Effects - Gardner DiD2S Results

	Eligible	Using	Ranked	Top 3
Officer				
Overall	0.0012*	-0.0018**	-0.0015*	-0.002***
	(0.00053)	(0.00056)	(0.00063)	(0.00058)
Female × Non-white	0.00085	-0.0025**	-0.002*	-.0023*
	(0.00061)	(0.00095)	(0.00085)	(0.001)
Female × White	0.0013*	-0.0015	-0.00091	-0.0011
	(0.00055)	(0.00087)	(0.00081)	(0.00089)
Male × Non-white	0.00098	-0.0017**	-0.0015*	-0.00085
	(0.00055)	(0.00063)	(0.00069)	(0.00079)
Male × White	0.0013*	-0.0021***	-0.0018***	-0.0024***
	(0.00062)	(0.00052)	(0.00055)	(0.00053)
Enlisted				
Overall	-0.000049	-0.0044***	-0.0054***	-0.0055***
	(0.00027)	(0.00041)	(0.00059)	(0.0011)
Female × Non-white	-0.00055**	-0.0046***	-0.0078***	-0.008***
	(0.0002)	(0.00038)	(0.00068)	(0.00049)
Female × White	0.00035	-0.0047***	-0.0074***	-0.008***
	(0.00019)	(0.00041)	(0.00037)	(0.00043)
Male × Non-white	-0.00039	-0.0042***	-0.0043*	-0.0013
	(0.00041)	(0.00044)	(0.0017)	(0.0026)
Male × White	0.00008	-0.0043***	-0.0056***	-0.0059***
	(0.00029)	(0.00047)	(0.00057)	(0.0012)
Observations	21,838,787	21,825,316	21,829,251	21,829,527

Standard errors in parentheses

Estimates for average treatment effect on the treated

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ment effect estimates, including the top-line numbers of -0.18 percentage points (0.056) separation rate for officers and -0.44 percentage points (0.041) separation rate for enlisted. This is a difference of 37% and 76% from baseline, respectively, representing approximately 16,000 additional DAF personnel remaining per year.[37] The differences between the three outcomes nested under "actual use" are not significant for either officers or enlisted overall, although female enlisted members seem to respond particularly strongly to receiving a ranked job match. No other demographic-based effect heterogeneity stands out in the table.

Next, I look at heterogeneity in actual use by specialty, with officer specialties in Figure 8 and enlisted specialties in Figure 9. Officers' results are remarkably consistent, with the majority of specialties tightly clustered near 0, and most of these statistically significantly negative. Commander specialties see to have especially increased rates of separation while special duties see the most decrease. On the enlisted side, there is much more variation and much less precision, although there are also many fewer instances of increased separations, which may help to explain the overall average effects.

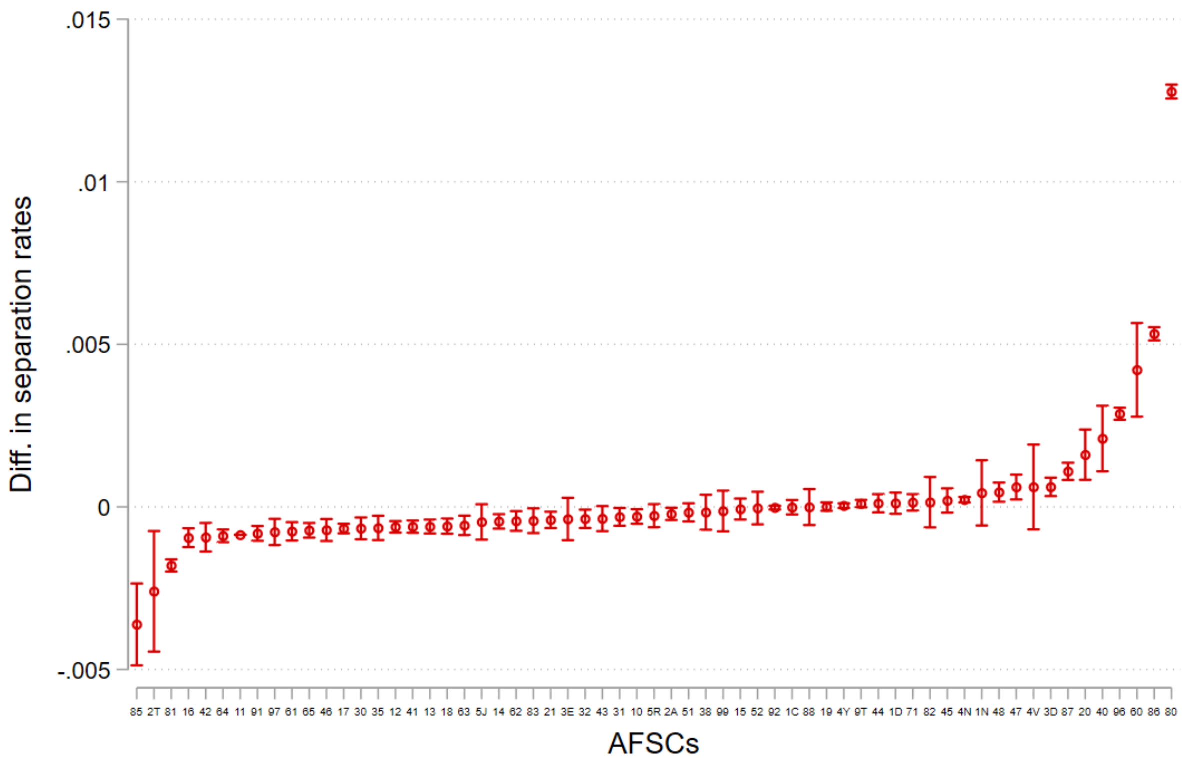
Finally, in Figure 10, we see heterogeneity in the effect of actual use by rank. Here there are clear patterns, with the initial ranks for both enlisted and officers having insignificant effects.[38] Following this, the largest decreases in separations for both groups generally track with the ranks for which there is the highest baseline separation rate prior to retirement vesting: E3 for enlisted and O4 for officers. Enlisted also show a large decrease in separations in ranks E9, which is the top of the enlisted payscale and well past retirement vesting, so the baseline separation rate is quite high here too.

1.7. Discussion

37. Assuming 65,000 officers and 270,000 enlisted on average

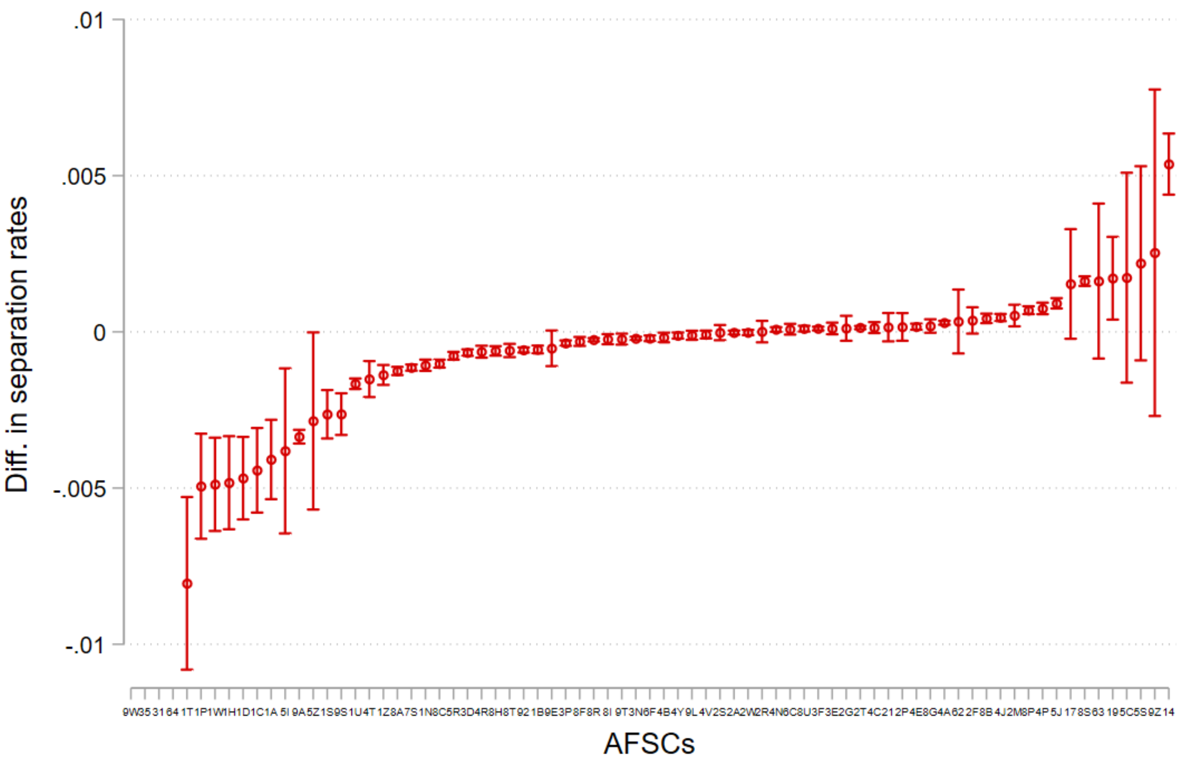
38. These individuals are almost all still under an initial contract, so they would be unable to voluntarily separate

Figure 8: Officer Specialty Heterogeneity



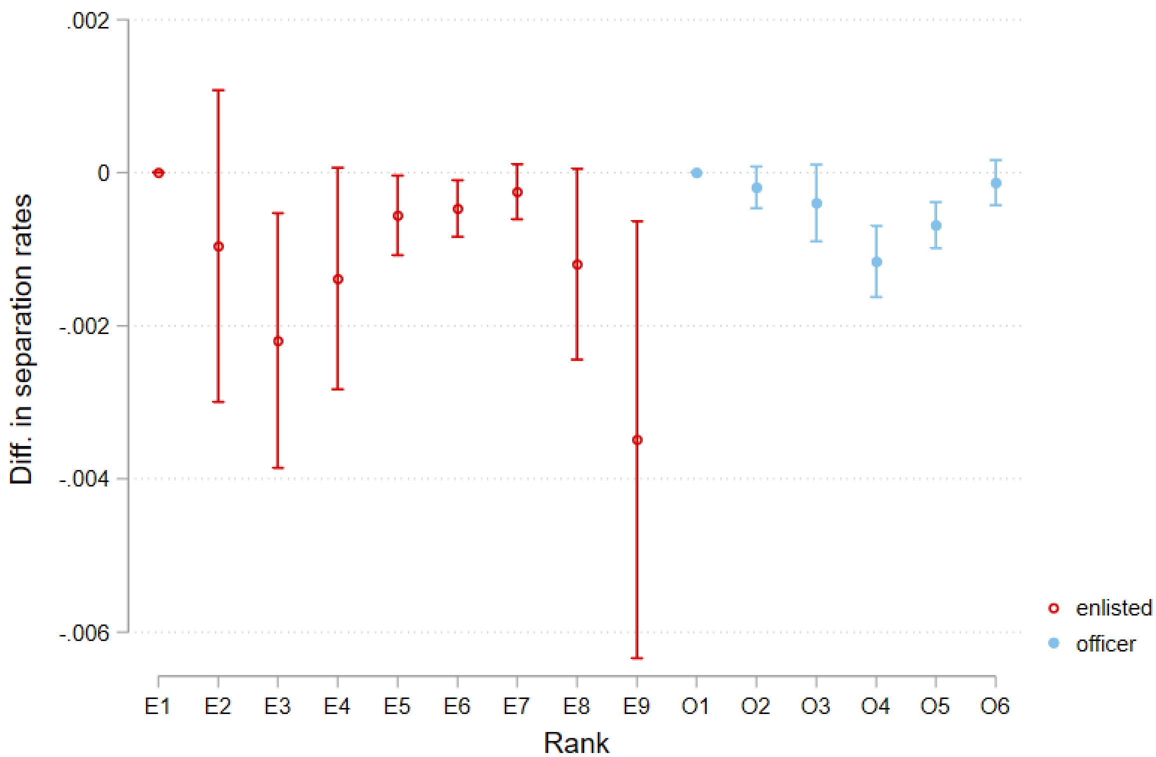
"AFSC" is the Air Force Specialty Code which defines each job specialty using a series of alphanumeric characters which indicates the job's position in the overall taxonomy. Sorted by effect size.

Figure 9: Enlisted Specialty Heterogeneity



"AFSC" is the Air Force Specialty Code which defines each job specialty using a series of alphanumeric characters which indicates the job's position in the overall taxonomy. Sorted by effect size.

Figure 10: Rank Heterogeneity



1.7.1. Mechanisms

The key findings so far are that, 1) exposure to TM without actively using the system increases separations for officers and 2) while the actual use of TM had a relatively large impact on retention, this effect did not seem to operate via the DA algorithm as expected - being matched to a higher ranked assignment did not statistically significantly impact retention.[39] To get a sense of what the mechanism behind these effects could be, I use the preference data from TM to rerun each match cycle using different algorithms and compare them to the actual match and the actual realized assignments.[40]

Figure 11 and Table 4 display the results of these matches. DAp refers to the person-proposing DA algorithm, which produces the maximally efficient stable (core, or no-"envy") match for personnel, DAa is the assignment-proposing DA algorithm, TTCp refers to the person-optimal two-sided Top Trading Cycle algorithm, which produces the envy minimal efficient match for personnel (Abdulkadiroğlu and Sönmez 2003), and TTCa is the assignment-optimal TTC algorithm. Throughout, I assume that unranked people are tied on the assignment-owners' lists and that unranked assignments are unacceptable on the military members' lists. Percent envy is defined as the percent of agents on the shorter side of the market for whom there exists at least one agent on the other side who is ranked higher than the current assignment and who ranks the reference agent higher than their own current assignment (i.e. the two would be willing to leave their current partners for each other). Percent improvable is the percent of agents who can be improved from their current assignment using the one-sided, or "house-allocation" TTC algorithm (Shapley and Scarf 1974). Lastly, pseudo utility is defined as the average of $\left(\frac{max\ rank_i - matched\ rank_i}{max\ rank_i}\right)$

39. Note that the distinction between a "match" and an "assignment" is especially important here. There is a large chance that a TM-generated match will be overridden, yielding an assignment offer that is substantially different from the match.

40. For the 14 largest assignment cycles (with greater than 8,000 participants) the DA algorithms could not be computed due to computer memory issues

over all agents, i, of a given type.[41] Note that a pseudo utility closer to 1 is more desirable, in contrast to the other measures for which values closest to 0 are most desirable.

Immediately, it is clear that if there is no missing data issue (e.g. the potential assignment constraints and choice set mistakes discussed above), both DA algorithm variants vastly outperform the other algorithms. They also achieve what appears to be a more equitable allocation between the two sides of the market than TTCp, which is slightly more efficient than DA but at the cost of significant amounts of envy. Additionally, the given match and realized assignments appear to be highly inefficient. Put more starkly, if there is even a single instance of envy based on legitimate (compatible) preferences, then the given match cannot have been generated by DA, and yet this occurs for nearly every agent, nearly every time.[42] The realized assignments, for all their inefficiency, actually improve on the given matches. This is a potential explanation for the pattern in estimated causal effects - that the preference information elicited in TM improves the assignment managers' manual matching performance even though the algorithm's match is routinely overridden for reasons that are unclear. It also potentially explains the increase in separations due to exposure-only, since out-of cycle assignments must go through the assignment managers, who now have fewer "good" assignments left over between cycles.

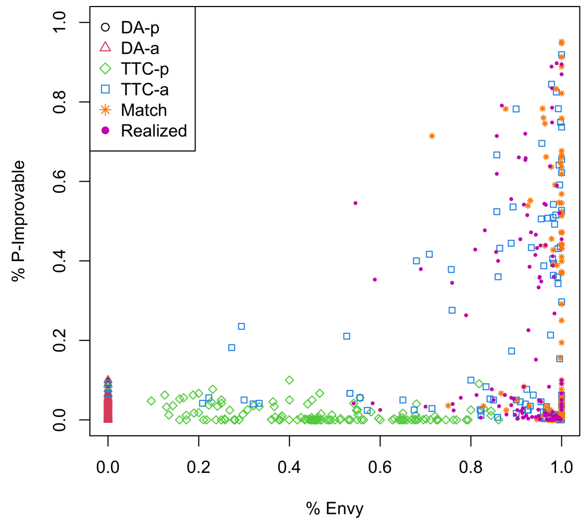
1.7.2. Implications

If these results are accurate, what does this mean for the DAF and for US national security? Existing estimates of the retention elasticity of pay center around 2.0 for enlisted members and 1.5 for officers (Asch and Warner 2018). The observed average regular military compensation in 2020 was $62,891.14 for enlisted and $108,372.78 for officers (De-

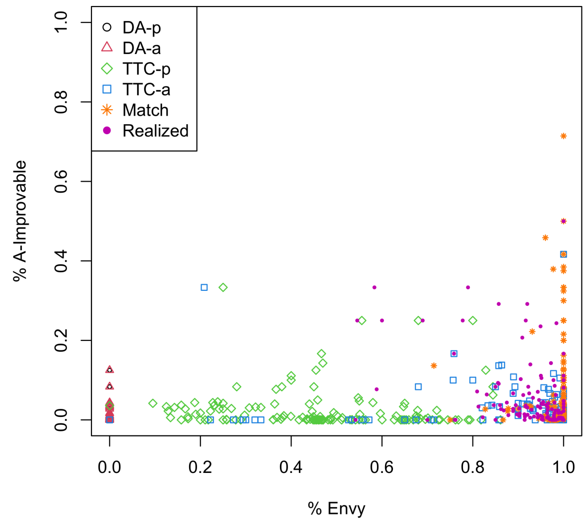
41. This is obviously not actual utility for many reasons, so the cardinal distance between any two points with respect to pseudo utility has little meaning. That said, the relative ordering of points, while still somewhat arbitrary, is at least consistent across matches, even with different numbers of agents participating.

42. I am currently following up on a request for the exact algorithm code, but this will take some time to process

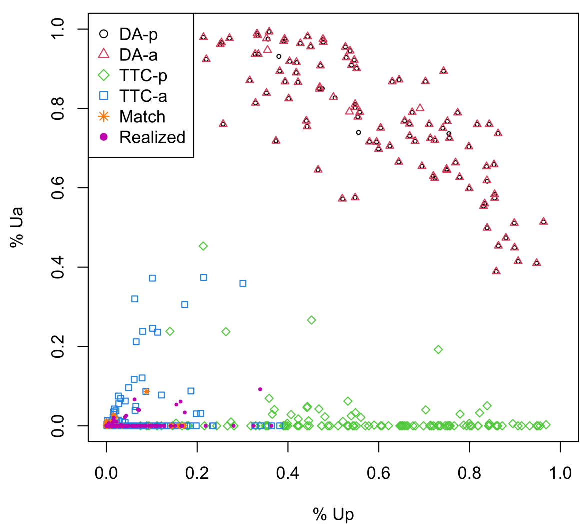
Figure 11: Matching Effectiveness



(a) Envy vs. Person-Improvable



(b) Envy vs. Assignment-Improvable



(c) Pseudo Utilities

Table 4: Matching Summary Statistics

	DAp	DAa	TTCp	TTCa	Given Match	Assignment
Envy	0.000	0.000	0.462	0.871	0.981	0.918
	(0.000)	(0.000)	(0.198)	(0.221)	(0.044)	(0.097)
Person improvable	0.014	0.014	0.016	0.200	0.250	0.223
	(0.022)	(0.022)	(0.023)	(0.254)	(0.295)	(0.270)
Assignment improvable	0.004	0.005	0.028	0.031	0.085	0.061
	(0.016)	(0.016)	(0.055)	(0.057)	(0.125)	(0.088)
Unmatched	0.124	0.124	0.124	0.816	0.872	0.499
	(0.100)	(0.100)	(0.104)	(0.224)	(0.255)	(0.258)
Person top 3	0.481	0.477	0.524	0.058	0.007	0.030
	(0.256)	(0.254)	(0.235)	(0.074)	(0.028)	(0.046)
Assignment top 3	0.743	0.746	0.015	0.040	0.001	0.012
	(0.186)	(0.187)	(0.059)	(0.104)	(0.008)	(0.026)
Person pseudo-utility	0.553	0.552	0.555	0.076	0.010	0.052
	(0.231)	(0.231)	(0.240)	(0.081)	(0.036)	(0.069)
Assignment pseudo-utility	0.786	0.788	0.016	0.039	0.001	0.004
	(0.159)	(0.159)	(0.057)	(0.101)	(0.008)	(0.014)
N	111	111	128	119	122	125

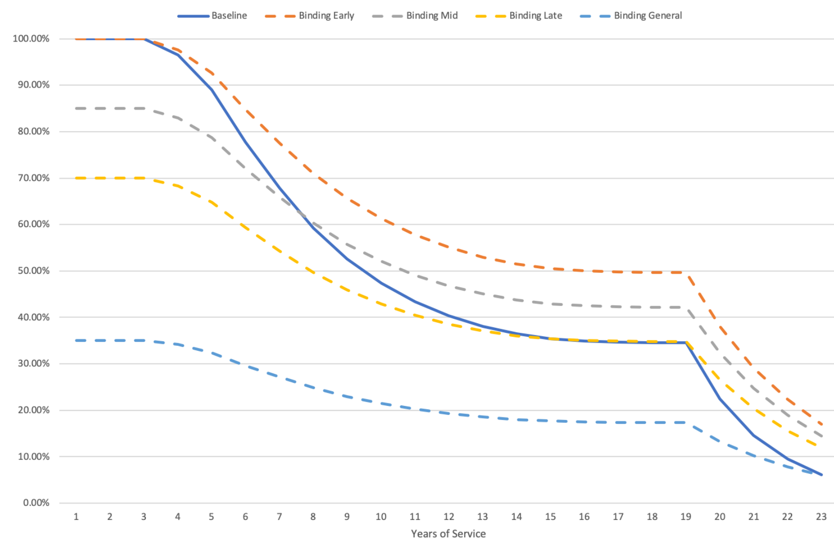
All metrics are percentages. Standard deviations in parentheses partment of Defense 2020). These numbers imply that the use of TM was equivalent in its retention impact to an average increase in compensation of $26,551.33 for officers and $23,835.74 for enlisted. Needless to say, this would be a massive expense if carried out with cash payments, but in this instance it was achieved at a marginal cost of $0, which preserves scarce government resources for more pressing uses and is a short-run net benefit.

The long run impacts are more mixed, but also more speculative. Consider that the constraints on military personnel management mean that effectively there is only a "gas pedal" (recruitment) and a "brake" (separation) available for tailoring the force structure. This metaphor should make clear that "removing the brakes" need not be a positive change in the long run. The optimal stationary structure depends on an unknown minimal manning requirement across the ranks, but we can examine how the force structure could change depending on the point where this unknown requirement binds.

Figure 12 overlays several alternative force structures (dashed lines) with 37% lower separation rates on the typically existing current structure for officers (in solid blue).[43] If the binding point occurs in the early ranks, implying currently unneeded labor at the later ranks, then the reduction in the separation rate will only worsen this imbalance. Alternately, if the binding point occurs at the General officer level, then the TM-related slowdown in separations allows for a more than proportionate slowdown in recruitment, yielding a smaller, older, but in this example more efficient force. Realistically, the binding point is somewhere in the middle, which, depending on the tradeoff in productivity and wage bills across ranks, as well as the tradeoff between the costs and benefits of additional separation incentives, may or may not be beneficial in the long run.[44]

43. Since this is speculative, I keep the focus on only the officer ranks at an abstract level
44. So far, no changes in recruiting flows are apparent in the data - see Figure 13 in the appendix

Figure 12: Long Run Impacts

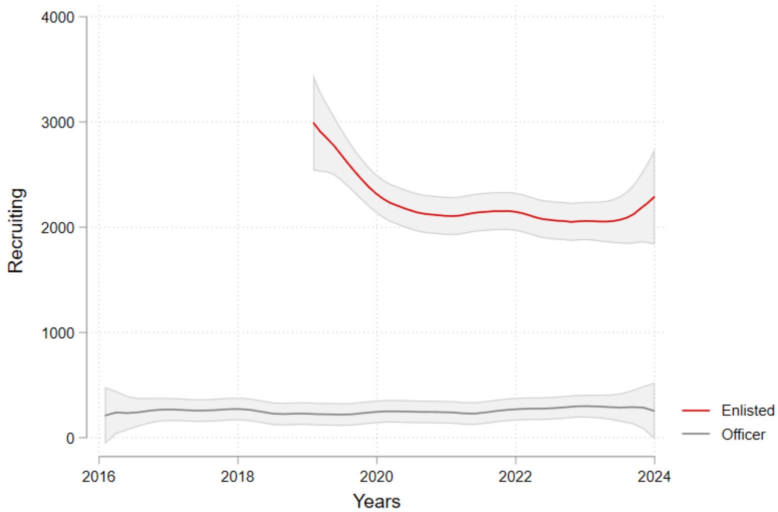


1.8. Conclusion

I investigated the causal effects of the DAF Talent Marketplace assignment matching system. I found that it had economically and statistically significant positive effects on the retention of personnel, both on the officer force for whom the system has been completely implemented, and for the initial cohort of the enlisted force. I also found that exposure, without actual usage of TM, weakly increased the separation rate for officers and that there was no retention effect of increased match rank. My best explanation for these findings is that the preference elicitation function of TM increased the performance of the assignment managers, which increased the preference satisfaction of the military members who used the system. Whether due to programming errors or other mistakes, the DA algorithm itself seemed to play little role, although there is suggestive evidence that fully implementing it could further improve the retention impact. In the short run, these effects are large net benefits. The long run impacts are less clear.

1.9. Appendix

Figure 13: Smoothed Recruiting Rates



Data extend one year prior to first treatment for each category.

CHAPTER 2

Gender differences in the returns to a double major

with Alfonso Flores-Lagunes and Maria Zhu

Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at the Cornell Federal Statistical Research Data Center (supported by the Cornell Center for Social Sciences) under FSRDC Project Number 2985. (CBDRB-FY24-P2985-R11338) (CBDRB-FY24-P2985-R11339)

2.1. Introduction

A substantial body of research indicates that there are sizable returns to education and that the returns to higher education in particular have been increasing in recent years, both in absolute and relative terms (Goldin and Katz 2007; Binder and Bound 2019; Deming 2022). This trend has coincided with a significant rise in college attainment rates over the past century in the U.S. (Lovenheim and Turner 2019). Several studies have focused on the returns to different college majors, generally finding large differences in earnings returns across fields.[45] However, much less is known about the returns to double majoring, even though over 15 percent of recent college graduates in the U.S. have a degree with multiple majors.

This paper evaluates the returns to double majoring on several later-life outcomes, including earnings, employment, marital status, fertility, and graduate education. We use

45. Altonji, Blom, and Meghir (2012) and Lovenheim and Smith (2022) provide reviews of the literature on returns to college major.

restricted-access data from six waves the National Survey of College Graduates (NSCG) spanning from 2010 to 2021. These surveys provide a repeated cross sectional random sample of U.S college graduates and contain detailed information on labor market outcomes, educational attainment, and demographic characteristics. Additionally, the restricted-access NSCG data contain university codes, which allow us to identify individuals who graduated from the same institutions.

Measuring the causal effects double majoring is challenging due to non-random student selection into double majoring. The decision to double major is likely influenced by unobservable factors, leading to omitted variables bias concerns when attempting to measuring the causal relationship between double majoring and later life outcomes, even when controlling for observed characteristics. First, students sort into colleges based on unobserved factors such as ability, preferences, and ambition, which affect later life outcomes. This poses a challenge to inference since policies and norms around double majoring likely vary across institutions, leading unobserved factors to influence both the propensity to double major and future outcomes. Second, even within institutions, there is likely significant sorting into decisions to double major along characteristics that affect later outcomes. For instance, students with more ambition may be more likely to pursue a double major, and ambition likely affects future outcomes independently of double majoring as well.

We tackle these sorting concerns using multiple strategies. First, to address concerns about non-random sorting across colleges and universities, we include institution fixed effects in our estimations. Second, to address concerns about non-random sorting within institutions, we provide bounds on our estimates using the coefficient stability method introduced by Oster (2019). Intuitively, this method assesses the robustness of estimates to selection on unobserved characteristics by using information on the stability of coefficients to the inclusion of observed control variables, in conjunction with information on the degree to which these observed variables contribute to predicting the outcome.

Results indicate significant gender differences in the labor market returns to double majoring. The earnings return to double majoring for women is between two percent and five percent, in line with previous results, but the return for men is statistically indistinguishable from zero. Notably, double majoring does not statistically affect employment for either gender, suggesting that the earnings results are not driven by selection into employment. Additionally, we find that double majoring increases the propensity for women to obtain graduate degrees at just under twice the rate for men. Double majoring does not perceptibly increase the job-degree match quality for men or women, defined by the NSCG as having a "principal job closely related to highest degree." Double majoring decreases the propensity of being married for both men and women and decreases the propensity of having children in the household for women, but not men.

Conceptually, the returns to double majoring could be explained by many competing theories, foremost among them, the acquisition of human capital and from the role of a double major as a signal of ability. We assess that the returns to double majoring for women in particular are most consistent with a model of labor market signaling. Specifically, women may be using the double major as a signal of their labor market ambition, both practically, in terms of career orientation, and academically, in terms of the propensity to pursue education beyond a bachelor's degree. In both cases, for women, double majors' decreased propensity to have children is especially salient. Pure human capital theory appears to be less relevant, especially given the null effects for men.[46]

This paper contributes to a growing literature investigating the causal effects of college

46. Given that men tend to choose majors (e.g. engineering) that carry high observed returns while women are more likely to choose majors (e.g. education) that have low observed returns, it would be natural to expect men who double major to have *higher* returns via the composition of their degrees. It seems very hard to explain why the opposite would be true using only a human capital explanation.

majors on various post-college outcomes. Several papers investigate the earnings returns to single majors, generally finding significant heterogeneity in returns across majors (Arcidiacono 2004; Hamermesh and Donald 2008; Webber 2014; Hastings, Neilson, and Zimmerman 2013; Kirkeboen, Leuven, and Mogstad 2016). More recent papers build on prior work to provide further nuance on the subject, investigating the effects of major choice on earnings growth and variability, mechanisms behind the returns, and interaction effects between degree choice and university selectivity (Andrews et al. 2022; Bleemer and Mehta 2022; Britton et al. 2022).

In comparison to the literature on single majors, much less is known about the returns to a double major, even though a significant number of undergraduate students, approximately 15 percent in the most recent cohorts of our data, graduate with more than one major. Zafar (2012) finds evidence that students are strategic in their double major choices and choose majors that differ in terms of difficulty, likelihood of completion, and chances of finding a job after graduating. In line with this, Hanks et al. (2024) find that a double major may be used as a diversification tool to hedge against income risk, with double majors trading off lower average earnings for more consistency in their earnings. Existing studies looking at the relationship between double majoring and earnings primarily rely on OLS estimation with control variables. Del Rossi and Hersch (2008) take this approach, finding that having a second major is related to 2.3 percent higher earnings on average, compared to a single major. Similarly, Hemelt (2010) finds a 3.2 percent average relationship, and Del Rossi and Hersch (2016) estimate an imprecise zero relationship. Zhu and Zhang (2021) use propensity score weighting and find that double majors initially earn less than their single major peers with the same higher-paying major, but earnings converge four years after graduation. They also find that students who double major have higher graduation rates, work more hours after graduation, and are more likely to attend graduate school compared to single major peers.

This study builds on prior work in several ways. First, we incorporate novel information from restricted use data to address selection across institution by incorporating institution fixed effects. Second, we use recently developed tools to assess the relevance of selection on unobservables within institutions. These additions allow us to estimate causal effects of double majors that address concerns about selection on unobservable characteristics. Finally, this study has a larger sample size relative to prior work, allowing us to examine heterogeneity by gender and provide a nuanced exploration of mechanisms underlying our results.

Additionally, our findings speak to the large literature on the gender wage gap.[47] In particular, our results can be interpreted in light of the salience of gender differences in industry, occupation, and hours worked (Blau and Kahn 2017), a phenomenon popularly known as "greedy jobs" (Goldin 2021).[48] Additionally, we find some evidence in line with Wiswall and Zafar (2015), who find that the observed differences in major choice between genders are mostly explained by "black box" taste factors. While a large portion of the gender gap among single majors is explained by major choice, we provide novel findings suggesting that double majors play an important role in labor market signaling for women.

In the remainder of the paper, Section 2.2 discusses our empirical strategy for assessing the returns to double majoring. Section 2.3 provides information on the data used and descriptive statistics. Results and analysis are shown in Section 2.4 and Section 2.5 concludes the paper.

47. For a review, see Goldin, Kerr, and Olivetti (2022).

48. I.e. if certain particularly remunerative jobs demand especially high levels of commitment and accessibility that mothers cannot provide (due to their other commitments), then these individuals will be at a disadvantage in the labor market. Likely, they will also self-select out of these industries and/or occupations before becoming mothers.

2.2. Empirical Methods

2.2.1. Overview

We estimate a series of regressions of the the following form to assess the effects of double majoring on later life outcomes:

$$Y_{isnat} = \beta D_{isnat} + X'_{isnat}\gamma + \eta_a + \pi_s + \tau_t + \theta_n + \left(\tilde{w}_{isnat} + \epsilon_{isnat}\right) \quad (2.1)$$

where Y_{isnat} denotes the outcome of interest for individual i born in state s graduating from institution n who is age a in survey year t. The outcome is a function of D_{isnat}, an indicator variable that takes a value of one if individual i has a double major and zero otherwise. β represents the causal returns to double majoring under some assumptions. To assert that an estimate of β is causal is challenging because individuals are not randomly assigned to single versus double majors. Conditional on receiving a bachelor's degree, selection into double majoring is likely driven by a combination of observed and unobserved factors. To address sorting on observable characteristics, we control for a vector of variables, X_{isnat}, which includes race and ethnicity, gender, and parental education. Additionally we control for age, state of birth, and year fixed effects, denoted by η_a, π_s, and τ_t, respectively. We discuss the composite error term $\left(\tilde{w}_{isnat} + \epsilon_{isnat}\right)$ in the next section.

To obtain an unbiased estimate of β, we need to address sorting along unobservable characteristics on two dimensions: First, policies around double majoring vary significantly across institutions, and the non-random sorting of students into colleges on factors such as ability and preferences that may also affect later-life outcomes. Second, even within institutions, there is likely significant sorting into decisions to double major along characteristics that affect later-life outcomes. We control for a large component of unobserved ability and preferences through the inclusion institutional fixed effects, θ_n. Then, to assess the role of within-institution sorting on unobservable characteristics, we provide bounds on our estimates using the coefficient stability method from Oster (2019). Altogether, this empirical strategy allows us to obtain estimates of the causal returns to double majoring on later-life outcomes by accounting for the role of selection on unobservable characteristics across and within institutions. We provide more information on the implementation of Oster (2019)'s method in the next section.

2.2.2. Addressing within-institution sorting on unobservable characteristics

The error term in Equation (2.1) is a composite of a traditional independent and identically distributed error, ϵ_{isnat}, and an index, $\tilde{w}_{isnat}$, representing the influence of all other factors (such as within-institution differences in ability) that affect the outcome but are unobserved. The ordinary least squares (OLS) estimate, $\hat{\beta}$, will be equal to the causal effect, β, only if $\tilde{w}_{isnat}$ is uncorrelated with selection into double majoring, which is unlikely. Depending on the magnitude of selection based on unobservables, however, the resulting bias may or may not be economically significant. To formally assess this, we apply the method developed in Oster (2019).

For expositional simplicity, in what follows, the fixed effects in Equation (2.1) have been partialled out of all other variables via auxiliary regressions.

Assumption 5. *Relevance: The variances of the observables, X, and unobservables, $\tilde{w}$, as well as their covariances with treatment, D, are all nonzero. $\sigma^2_X \neq 0$, $\sigma^2_{\tilde{w}} \neq 0$, $\sigma_{XD} \neq 0$, and $\sigma_{\tilde{w}D} \neq 0$, where σ_{AB} indicates covariance between A and B and σ^2_A is the variance of A.*

In other words, the covariates must be capable of explaining selection into treatment. In the context of this study, Assumption 5 requires that observed student characteristics (race and ethnicity, gender, parental education) are related to the propensity to double major, net of institution and other fixed effects.

Assumption 6. *Factor of proportionality: Define δ to be the factor of proportionality in the degrees of selection on observables relative to unobservables, such that $\delta \frac{\sigma_{XD}}{\sigma_X^2} = \frac{\sigma_{\tilde{w}D}}{\sigma_{\tilde{w}}^2}$.*

For this study, Assumption 6 means that higher values of δ indicate greater ability of the observable student characteristics, X, to explain selection into double majoring, D, relative to unobservable student characteristics, $\tilde{w}$.

Assumption 7. *Exogenous controls: $\sigma_{X\tilde{w}} = 0$*

We assume that the two sets of student control variables, X and $\tilde{w}$, are orthogonal. Assumption 7 is non-standard (since focus more often lies with the relationship between the main explanatory variable, in this case D, and the error term) however, as noted in Diegert, Masten, and Poirier (2023), this assumption is required for the omitted variable bias equation to hold.[49] Let $\hat{\beta}$ be the OLS estimate of β in Equation (2.1). Then under assumptions 5 through 7 and using standard OLS omitted variable bias formulas (from the omission of $\tilde{w}$), Oster (2019) shows that the bias $(\hat{\beta} - \beta)$ can be expressed as:

$$\hat{\beta} - \beta = \frac{\sigma_{\tilde{w}D}}{\sigma_{\tilde{D}}^2} = \frac{\delta \sigma_{XD} \sigma_{\tilde{w}}^2}{\sigma_X^2 \sigma_{\tilde{D}}^2}$$

where $\tilde{D}$ represents the residuals from an auxiliary regression of D on X. Let $\mathring{\beta}$ represent the coefficient of a regression of Y on D (omitting both X and $\tilde{w}$). Then,

$$\hat{\beta} - \beta \approx \delta \left(\mathring{\beta} - \hat{\beta} \right) \frac{R_{max}^2 - R^2}{R^2 - \mathring{R}^2} \tag{2.2}$$

where R^2, $\mathring{R}^2$, and R_{max}^2 correspond to coefficients of determination of the OLS regression of Y on D and X, the regression of Y on D, and the infeasible regression of Y on D, X,

49. To the extent that this assumption fails, our estimated bounds will be too tight

and $\tilde{w}$.[50]

In other words, the bias resulting from the omission of $\tilde{w}$ can be approximated by the product of the factor of proportionality between the selection due to observables and unobservables, the difference between two estimable coefficients, and a ratio involving the R^2s of the two same estimable regressions and one corresponding to the infeasible complete regression model.[51] The unknown quantities in Equation (2.2) are β, δ, and R^2_{max}. However, since R^2_{max} is bounded from above by 1, Equation (2.2) allows making assumptions about either β or δ to yield implications for the other.

Assumption 8. *Bounded δ: There is a known constant $\bar{\delta} \geq 0$ such that $|\delta| \leq \bar{\delta}$ (Masten and Poirier 2022, Assumption 7). In particular, we will assume that $\bar{\delta}$ is small enough to rule out changes in the sign of β across different values of δ.*

Using assumption 8, we will bound the true causal effect of double majoring, β, between $\hat{\beta}$ and the estimate in the case where there is equal selection of observable and unobservable student characteristics (i.e., when $\delta = 1$).[52] Note that fixed effects, which have been partialled out of all of the above, should have the effect of tightening the bounds to the extend that they reduce the impact of unobservables and make $\hat{\beta}$ less biased. We will also estimate the minimum level of δ that would be required in order for the causal return to double majoring to be zero (i.e., when $\beta = 0$). Therefore, we will have increasing confidence of our identification of the causal effect of double majoring if the estimated bias under the equal selection assumption is small (yielding tight bounds) and/or if the estimated δ required for the causal effect to be zero is large (i.e., considerably greater than 1).

50. This equation holds with equality only when $\delta = 1$.

51. Oster (2019) offers a precise result (not an approximation, as in Equation (2.2)). We abstract from additional details here because they are not central to convey the intuition of the approach.

52. This assumption ensures that the identified set is convex, bounded by $\hat{\beta}$ on one end and the equal selection β_{Oster} on the other.

2.3. Data

Data for this project come from the 2010, 2013, 2015, 2017, 2019, and 2021 waves of the National Survey of College Graduates (NSCG), conducted by the U.S. Census Bureau. These surveys form a repeated cross sectional random sample of all non-institutionalized US college graduates who hold at least a bachelor's degree, live in the United States, and are younger than 76 years old. Individuals are selected to participate in the NSCG from the sample of American Community Survey participants, and the NSCG collects information on various labor market outcomes, additional educational attainment, and demographic characteristics. This paper uses restricted-use NSCG data, which additionally provides us with university codes that allow us to identify which individuals graduated from the same institutions. A key benefit of the NSCG dataset is that it contains detailed information about each of the majors a student earns. An individual is classified as having a double major if they list a second major for their first bachelor's degree.

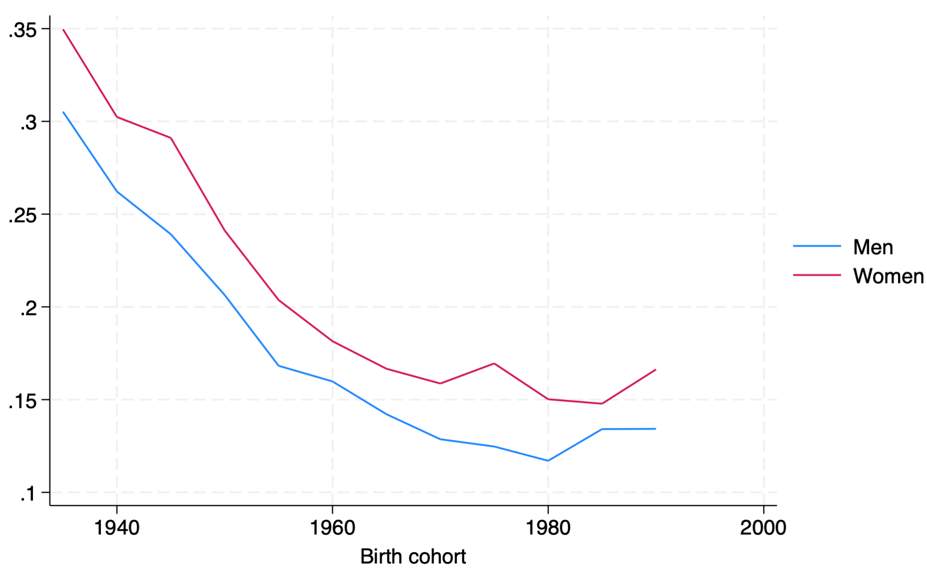
Table 5 displays summary statistics by gender for the pooled sample of 527,599 observations. Double majors overall are fairly similar to single majors in terms of racial and ethnic composition and parental education for both men and women. On average, double majors are older than single major counterparts and received their first bachelor's degree earlier as a result. They are more likely to have obtained their bachelor's degree from a liberal arts college or comprehensive college and less likely to have obtained their bachelor's degree from a research university.[53] Our outcome variables of interest include primary labor market indicators, earnings and employment status, as well as a number of other outcomes that are of interest in their own right but also help to shed light on potential mechanisms: marital status, children, job match, and graduate education. Double majors are less likely to be employed, have fewer children, and have higher levels of graduate edu-

53. Comprehensive colleges are institutions that offer graduate education through a master's degree.

cation compared to single major counterparts.

Figure 14 shows trends in double majoring over time. Rates of double majoring have been consistently about five percent higher for women than for men in all the birth cohorts we observe in our sample. The overall rate of double majoring for later birth cohorts has declined significantly for both men and women by about half from double majoring rates of the cohorts born in 1935-1940, with double majoring rates becoming fairly constant at around 15 percent starting with birth cohorts in the 1970s to the most recent birth cohorts in 1990.

Figure 14: Proportion of Double Majors by Cohort



Next, Table 6 displays distributions of majors by area of study for men and women, for both single majors and double majors. The table shows that there are sizeable differences by gender in major choice. For single majors, the starkest differences can be seen in a 3:1 female preference for education majors and 7:1 male preference for engineering majors. There is also a female preference for arts and social science and a male preference for business. The patterns for single majors generally also apply to double majors, although many

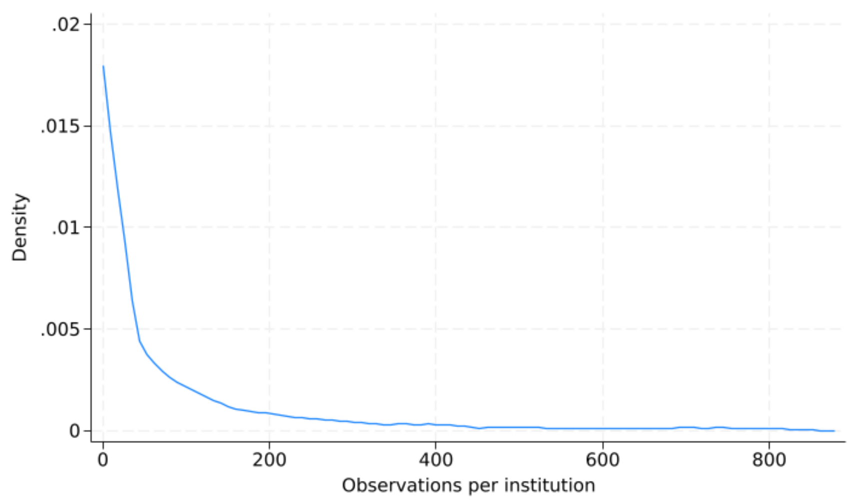
Table 5: Summary Statistics by Gender and Double Major Status

	Men		Women	
	Single major	Double major	Single major	Double major
Control variables				
Race/Ethnicity				
White	0.75	0.76	0.71	0.75
Black	0.06	0.07	0.09	0.08
Hispanic	0.08	0.07	0.09	0.08
Asian	0.09	0.08	0.09	0.07
American Indian	0.00	0.00	0.00	0.00
Pacific Islander	0.00	0.00	0.00	0.00
Multiple	0.02	0.02	0.02	0.02
Mother has BA	0.33	0.32	0.33	0.32
Father has BA	0.42	0.40	0.41	0.40
Carnegie class.: first BA inst.				
Research	0.34	0.31	0.28	0.27
PhD-granting	0.12	0.12	0.12	0.11
Comprehensive	0.27	0.28	0.32	0.34
Liberal arts	0.10	0.14	0.13	0.17
Other	0.16	0.14	0.15	0.12
Age	47.44	50.94	45.21	48.28
	(14.14)	(14.89)	(13.70)	(14.55)
Year of first BA	1993	1988	1995	1991
	(14.62)	(15.38)	(13.84)	(15.00)
Survey year	2017	2016	2017	2016
	(3.62)	(3.74)	(3.59)	(3.71)
Outcome variables				
Earnings	85,956.80	83,147.41	46,407.32	46,334.43
	(139,529.32)	(144,973.23)	(73,869.52)	(71,324.50)
Employed	0.75	0.68	0.63	0.58
Married	0.74	0.74	0.68	0.67
Number of children in household	0.68	0.58	0.73	0.59
	(1.07)	(1.02)	(1.07)	(0.99)
Good job match	0.35	0.31	0.33	0.31
Greater than BA	0.33	0.40	0.33	0.41
N	240,619	46,212	191,324	49,444

"Hispanic" includes any hispanic identification; other race/ethnicity categories are all non-hispanic. Job match defined by the NSCG as "principal job closely related to highest degree," restricted to individuals who have no degrees higher than a single BA. Observations for this variable: 129,111, 22,800, 94,322, and 22,345 of the major combinations are quite rare.[54] A large share of students who double major choose two majors in the same field, with two arts/social science, two business, and two science/math double majors making up over half of the observed double major combinations for both men and women.

Finally, to get a sense of the variation in our institution fixed effects, Figure 15 plots a kernel density of the distribution of individuals across institutions, with 5 percent of each tail trimmed off according to Census disclosure rules. The figure indicates that there is a wide range of institution sizes represented. Additionally, there are generally many individuals per institution, which facilitates making comparisons within institution.[55]

Figure 15: Distribution of Fixed Effect Sizes



FSRDC Project Number 2985; Disclosure Clearance Number CBDRB-FY24-P2985-R11339. Data trimmed according to Census disclosure rules. Default bandwidth used.

2.4. Results

54. The double major combinations are defined the same as in Del Rossi and Hersch (2008) for ease of comparability.

55. There are very few institutions with only one individual in the data—these observations are dropped from the analysis.

Table 6: Major Combinations by Gender

	Men	Women
Single major categories		
Arts/social science	0.30	0.41
Business	0.27	0.18
Education	0.05	0.15
Engineering	0.14	0.02
Science/math	0.24	0.23
Double major categories		
Two arts/social science	0.28	0.34
Arts/social science and business	0.09	0.08
Arts/social science and education	0.04	0.12
Arts/social science and engineering	0.01	0.00
Arts/social science and science/math	0.07	0.07
Two business	0.19	0.11
Business and education	0.01	0.01
Business and engineering	0.01	0.00
Business and science/math	0.06	0.03
Two education	0.03	0.12
Education and engineering	0.00	0.00
Education and science/math	0.02	0.03
Two engineering	0.03	0.00
Engineering and science/math	0.03	0.00
Two science/math	0.13	0.08

2.4.1. Main Results

The main results for all six of our outcomes are presented in Table 7. Note that the fixed effects seem to absorb quite a bit of selection, with many of the δ_{Oster} values rising an order of magnitude from their initial OLS results. The marriage outcome in particular becomes much more stable. Overall, the results are in the same direction in both tables however.[56]

The "Full" horizontal panel implements Equation (2.1) using the full sample and interacting double major with gender. The "Men only" and "Women only" horizontal panels implement Equation (2.1) separately by gender and are our preferred specifications. Column 1 indicates that, accounting for all control variables and fixed effects, there appears to be no earnings effect of double majoring for men and a marginally statistically significant effect for women of 3.4 percent. In the estimates using women only, those who double major have a statistically significant earnings boost of 5.2 percent. When considering men only, the estimated effect of double majoring is close to zero and statistically insignificant.

The rows denoted β_{Oster} and δ_{Oster} are related to Oster (2019)'s strategy to assess the potential impact of remaining selection based on unobservables. The β_{Oster} row indicates that when assuming equal ($\delta = 1$) or lesser selection on unobservables relative to observables (given the bounding nature of the exercise), for women only, the causal effect is no less than $\beta_{Oster} = 0.0204$, or 2 percent. Next, the δ_{Oster} row suggests that this estimate is also quite stable, requiring *at least* a $\delta_{Oster} = 3$ or a 3:1 unobserved to observed degree of selection for the causal effect for women only to be zero.

Despite the null effects for employment across the board, column 2 is nevertheless notable, since selection into employment is a major potential category of gender disparity.

56. Table 7 is reproduced without the restricted fixed effects in Table 8 in the appendix for comparison.

Table 7: Main Results

	(1) Log Earnings	(2) Employed	(3) Married	(4) Children	(5) Job Match	(6) Grad. Ed.
Full						
Double major	0.0103	-0.0050	-0.0076	0.0079	-0.0041	0.04307***
	(0.01343)	(0.00509)	(0.00505)	(0.00487)	(0.00766)	(0.00528)
Double major × Female	0.0337*	0.0069	-0.0167**	-0.0364***	0.0031	0.0155*
	(0.01885)	(0.00738)	(0.00711)	(0.00685)	(0.01065)	(0.00730)
Men only						
Double major	-0.0059	-0.0029	-0.0192***	0.0038	-0.0104	0.0369***
	(0.01287)	(0.00497)	(0.00483)	(0.00476)	(0.00745)	(0.00516)
β_{Oster}	-0.0478	0.0129	-0.0206	0.0180	0.0178	-0.0082
δ_{Oster}	5.980	0.487	30.810	0.038	0.156	0.788
Women only						
Double major	0.0518***	0.0014	-0.0172***	-0.0258***	-0.0051	0.0613***
	(0.01345)	(0.00538)	(0.00506)	(0.00486)	(0.00750)	(0.00509)
β_{Oster}	0.0204	0.0541	-0.0270	-0.0193	0.0087	0.0608
δ_{Oster}	3.000	1.221	29.740	1.899	0.279	2.682
Full						
N	464,000	527,000	527,000	527,000	268,000	527,000
R^2	0.2118	0.2088	0.1790	0.3061	0.1302	0.1266
$R^2{}_{within}$	0.0552	0.0276	0.0030	0.0007	0.0011	0.0022
Men only						
N	257,000	287,000	287,000	287,000	151,000	287,000
R^2	0.2479	0.2707	0.2301	0.3273	0.1720	0.1696
$R^2{}_{within}$	0.0000	0.0000	0.0003	0.0000	0.0001	0.0008
Women only						
N	206,000	240,000	240,000	240,000	116,000	240,000
R^2	0.1705	0.1893	0.2031	0.3395	0.1745	0.1566
$R^2{}_{within}$	0.0004	0.0000	0.0002	0.0005	0.0000	0.0025

FSRDC Project Number 2985; Disclosure Clearance Number CBDRB-FY24-P2985-R11339. Results rounded according to Census disclosure rules. Job match column restricted to individuals whose highest education is a single BA. β_{Oster} is the bound on the double major coefficient assuming "equal selection," i.e. a selection ratio of 1. δ_{Oster} is the (absolute value) selection ratio required for the true effect to be zero. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

It seems that the earnings effect of double majoring from column 1 does not operate via the extensive margin.[57] In column 3, we see that the gender-specific specifications point to fairly similar negative effects of double majoring on marital status. Oster bounds posit the causal effect between -1.9 percentage points and -2.1 percentage points for men and between -1.72 percentage points and -2.70 percentage points for women. Remarkably, these estimates are extremely stable, with a δ_{Oster} of over 29.

Column 4 indicates another stark gender difference in the effect of double majoring, this time on the presence of children in the household. There appears to be no impact from double majoring on the presence of children in the household for men, but women who double major are between -1.93 percentage points and -2.58 percentage points less likely to have them. The stability of this estimate is strong, but not overly so, with a δ_{Oster} of 1.9.

Finally, while there is no discernible effect of double majoring on the quality of job-degree matches in column 5, there is a large effect from double majoring for all samples on the propensity to attain graduate education in column 6.[58] The effect for men is positive and statistically significant, but the Oster bounds cross zero and δ_{Oster} is less than one, strongly suggesting a lack of robustness to selection based on unobservables for this outcome. The corresponding effect for women is about 6.1 percentage points and is very stable, with a δ_{Oster} of 2.7.

2.4.2. Mechanisms

Theoretically, a double major could be viewed through many lenses: an investment in general human capital (Becker 1964; Ben-Porath 1967; Card 1999), a signal of ability or aptitude (Spence 1973; Weiss 1983), a method of improving a comparative advantage (Roy

57. Which is reassuring, since there are approximately 63,000 $0 earnings which are automatically dropped due to the log specification.

58. A potentially contributing factor to this are the smaller sample sizes that result from the way that the "job match" variable is recorded in the NSCG. Since the question only asks about the "highest" degree, we restrict this sample to those whose highest degree is their first BA.

1951; Lazear 2005; Altonji, Arcidiacono, and Maurel 2016), an affinity for an academic subject which yields non-pecuniary returns (Rosen 1986), or, as in Hanks et al. (2024), as insurance against income risk. These theories do not, in general, provide clear a priori predictions for the effect of a double major on each of our outcomes.

We therefore focus on human capital/comparative advantage on the one hand and signaling theory on the other as our primary competing explanations. By "human capital theory," we mean the accumulation of productive knowledge, gained via education in a formal school setting, while by "signaling theory" we mean a primarily instrumental use of educational credentials as a way to indicate innate ability. Since a labor market signal reveals pre-existing dispositions, to the extent that these dispositions are linked to labor market outcomes, we would expect these variables to move together (e.g. ambition and earnings). This sets up our main contrast with human capital and comparative advantage explanations, since in this case we would expect more uniform labor market effects that are unassociated with variables outside of the labor market.[59]

What we observe is broadly consistent with the signaling theory, particularly for women. While double majors of both genders are less likely to be married, only women who double major are less likely to have children and only they have an earnings return to double majoring. This suggests a fertility connection to earnings for double majors. If the labor market penalizes women due to the chance of a future maternity leave, then those women who are less likely to have kids due to their career focus would be incentivized to pursue costly differentiation strategies. A double major may be such a costly, and thus credible, signal of intent.

This same evidence tends to cast doubt on the human capital story. Even if a double ma-

59. As a second order effect, an increase in the opportunity cost of time could impact these non-labor market variables, however.

jor had a unique signaling value for women, its human capital content should still be valuable for men. Despite this, it seems that there is essentially no labor market value to a double major for men. This provides a potential answer to the debate over whether double majors have "extra" skills or are lacking in deep knowledge–our evidence suggests that the answer is neither. A double major bachelor's degree appears to carry the same human capital as that of a single major.

Finally, although more speculative, there is a story to be told about preferences for academics *overall* as a signaling device. Double majors are much more likely to pursue graduate education. This makes sense since a choice to double major represents a higher level of academic achievement, as are degrees beyond BA. Those with stronger preferences for academics would thus naturally be more likely to have double majors and higher degrees. At the same time, we do not see any compensating wage differentials at an aggregate level, as would be expected if preferences were for specific majors. Further, the graduate education effect for women, who have strong earnings effects, is much more stable than for men, who do not. While we cannot rule out a similar effect for men, our evidence is at least consistent with this preference for overall education, as revealed through a double major, being an important mechanism through which women are signaling their labor market intent to employers.

2.5. Conclusion

This study provides novel evidence of the causal effects of double majoring in college on several later life outcomes. Using a combination of new data and new techniques, we show that, while our top line numbers are in line with prior studies, we differ from these studies in that we find a large difference in labor market returns to double majoring by gender. Specifically, there is a notable earnings return to double majoring for women, while we find no evidence of a return for men. This effect is not driven by selection into the labor market.

The lower propensity to have children among female double majors suggests that this effect is likely due to the signaling value that a double major provides to employers, indicating labor market ambition and thus commanding higher wages. At the same time, the gender split in returns suggests that the overall human capital associated with a double major is likely the same as that for single majors. Finally, double majors of both genders, perhaps surprisingly, are about equally less likely to be married, and, less surprisingly, are much more likely to have graduate education, presumably due to their preference for academics.

Nothing about our estimates suggests that these labor market effects should be limited to double majoring, a phenomenon that is unique, but not sui generis. If women are motivated in this instance to pursue costly signaling strategies, they will likely make similar use of other similar devices. More research is needed in order to find such additional instances of gender-based signaling elsewhere in the labor market.

2.6. Appendix

In Tables 9 and 10, we explore additional heterogeneity in double major effects for each outcome.[60] Table 9 displays heterogeneity results for men and Table 10 displays results for women. First, we compare double majors whose majors are in the same field ("2x –"), which we refer to as "Close," to double majors whose degrees are in different categories, which we refer to as "Far." These fields are classified using the categories shown in Table 6. The only apparent difference between genders is that men are less likely to be employed when they have a dissimilar major combination and women are less likely to be married

60. We only have "sign and significance" results for these in order to facilitate Census disclosure review.

Table 8: Public Use Results

	(1) Log Earnings	(2) Employed	(3) Married	(4) Children	(5) Job Match	(6) Grad. Ed.
Full						
Double major	0.00328	-0.00802	0.0199	-0.00520	-0.00995	0.0537***
	(0.817)	(0.103)	(0.061)	(0.319)	(0.206)	(0.000)
Double major $\times$ female	0.0423*	0.00731	-0.0760***	-0.0143	0.00927	0.0106
	(0.032)	(0.319)	(0.000)	(0.055)	(0.405)	(0.174)
Men only						
Double major	-0.00536	-0.00553	0.0121	-0.0171***	-0.00661	0.0504***
	(0.702)	(0.261)	(0.253)	(0.001)	(0.402)	(0.000)
β_{Oster}	0.2487	0.2013	0.2930	-0.0986	0.5370	-0.2979
δ_{Oster}	0.023	0.024	0.047	0.256	0.015	0.190
Women only						
Double major	0.0601***	-0.000719	-0.0520***	-0.0101	-0.00287	0.0668***
	(0.000)	(0.896)	(0.000)	(0.058)	(0.719)	(0.000)
β_{Oster}	0.5028	0.2908	0.1369	-0.0209	0.3606	-0.2255
δ_{Oster}	0.149	0.003	0.278	1.095	0.008	0.268
Full						
N	464145	527596	527596	527596	268577	527596
R^2	0.1528	0.1850	0.3048	0.1188	0.0471	0.0489
R^2_{within}	0.0578	0.0289	0.0004	0.0037	0.0008	0.0026
Men only						
N	257446	286829	286829	286829	151910	286829
R^2	0.1522	0.2340	0.3009	0.1453	0.0569	0.0577
R^2_{within}	0.0000	0.0000	0.0000	0.0002	0.0000	0.0016
Women only						
N	206699	240766	240766	240766	116667	240766
R^2	0.0809	0.1331	0.3175	0.1109	0.0450	0.0497
R^2_{within}	0.0005	0.0000	0.0005	0.0001	0.0000	0.0030

Job match column restricted to individuals whose highest education is a single BA. β_{Oster} is the bound on the double major coefficient assuming "equal selection," i.e. a selection ratio of 1. δ_{Oster} is the (absolute value) selection ratio required for the true effect to be zero. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Double Major Heterogeneity (Men) - Sign and Significance

	(1) Log Earnings	(2) Employed	(3) Married	(4) Children	(5) Job Match	(6) Grad. Ed.
Major similarity						
Close	ns	ns	-**	ns	ns	+***
Far	ns	-**	-**	ns	ns	+*
Major category combination						
2x Art/Sci	-***	-*	-***	-***	-***	+***
Art/Sci + Bus	+*	ns	-**	ns	-***	-*
Art/Sci + Edu	-***	-***	ns	ns	ns	+***
Art/Sci + Engr	ns	ns	ns	ns	ns	-**
Art/Sci + Sci/Math	ns	ns	-***	ns	ns	+***
2x Bus	+***	+***	ns	+**	+**	-***
Bus + Edu	-*	ns	ns	ns	ns	ns
Bus + Engr	+***	ns	ns	ns	ns	ns
Bus + Sci/Math	+***	ns	+*	+***	+**	-**
2x Edu	-***	-***	ns	ns	+***	+***
Edu + Engr	ns	ns	ns	ns	ns	ns
Edu + Sci/Math	-**	-**	ns	ns	ns	+***
2x Engr	+***	ns	ns	ns	+***	ns
Engr + Sci/Math	+***	ns	ns	ns	ns	-*
2x Sci/Math	+***	+*	ns	+***	+***	+***
Ivy league						
Non-Ivy Plus	ns	ns	-***	ns	ns	+***
Ivy Plus	+**	ns	-**	-*	ns	+*
Average SAT quintile						
1st	ns	-*	-***	-**	ns	+***
2nd	ns	ns	ns	ns	ns	ns
3rd	-*	ns	-*	ns	ns	+***
4th	ns	ns	-*	ns	-**	+***
5th	+**	ns	ns	ns	ns	ns
Admit rate quintile						
1st	+***	+*	-*	ns	ns	+***
2nd	ns	ns	ns	ns	ns	+**
3rd	ns	ns	-**	ns	ns	+***
4th	ns	ns	ns	ns	ns	+*
5th	ns	-*	-***	ns	ns	+***

FSRDC Project Number 2985; Disclosure Clearance Number CBDRB-FY24-P2985-R11338. Quintiles are ordered numerically, from smallest to greatest (the greatest average SAT score is in the 5th quintile and the lowest average admissions rate is in the 1st quintile)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, *ns* $p \geq 0.05$

Table 10: Double Major Heterogeneity (Women) - Sign and Significance

	(1) Log Earnings	(2) Employed	(3) Married	(4) Children	(5) Job Match	(6) Grad. Ed.
Major similarity						
Close	+**	ns	-***	-***	ns	+***
Far	+*	ns	ns	-*	ns	+***
Major category combination						
2x Art/Sci	ns	ns	-***	-***	-***	+***
Art/Sci + Bus	+*	ns	-*	-***	-*	-**
Art/Sci + Edu	ns	-***	+*	ns	ns	+***
Art/Sci + Engr	ns	+**	ns	-**	ns	ns
Art/Sci + Sci/Math	+*	ns	-*	ns	ns	+***
2x Bus	+***	+***	ns	-**	+*	-***
Bus + Edu	ns	-**	ns	ns	-***	ns
Bus + Engr	+***	ns	+*	ns	ns	ns
Bus + Sci/Math	+***	+***	ns	+**	ns	ns
2x Edu	ns	-***	ns	ns	+***	+***
Edu + Engr	+***	ns	-***	-*	-**	ns
Edu + Sci/Math	ns	ns	ns	ns	+***	+***
2x Engr	+***	ns	ns	ns	ns	+*
Engr + Sci/Math	+***	+**	+*	-*	ns	+*
2x Sci/Math	+***	+***	-*	-**	+*	+***
Ivy league						
Non-Ivy Plus	+***	ns	-**	-***	ns	+***
Ivy Plus	ns	ns	ns	-*	ns	ns
Average SAT quintile						
1st	+*	ns	ns	ns	+*	+***
2nd	ns	ns	ns	-***	ns	+***
3rd	ns	ns	-*	ns	ns	+***
4th	+**	ns	ns	-*	ns	+***
5th	+***	ns	ns	ns	ns	+***
Admit rate quintile						
1st	+***	+*	ns	-**	ns	+***
2nd	ns	ns	-***	ns	ns	+***
3rd	ns	ns	ns	ns	ns	+***
4th	ns	-**	ns	-**	ns	+***
5th	+*	ns	ns	-***	ns	+***

FSRDC Project Number 2985; Disclosure Clearance Number CBDRB-FY24-P2985-R11338. Quintiles are ordered numerically, from smallest to greatest (the greatest average SAT score is in the 5th quintile and the lowest average admissions rate is in the 1st quintile)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, *ns* $p \geq 0.05$

when they have a similar combination.[61]

Next are the major categories themselves. The most striking feature here is the similarity between men and women who double major with a double business degree. This is the one of the few instances where employment, children, and job match indicators are all positive for double major men, and it is the only instance where earnings, employment, job match, and graduate education effects are the same across genders. The effect on children is positive for men and negative for women, but it is similarly negative for both genders on graduate education. This suggests that the proposed signaling effect of a double major for women need not exclusively operate via an academic channel. These women seem to be less academically inclined than other double major women but are still receiving an earnings boost.

Other cases where genders show some similarity by categories are positive earnings effects for engineering and science/math combinations, negative employment effects for double education and education/arts and science combinations, and negative fertility and job match effects for combinations involving arts and science degrees. Business and science/math combinations, like for double business majors, have opposite fertility effects, with double major men more likely to have children and double major women less likely to have them. Overall, there are no clear patterns here, suggesting that aggregate effects are unlikely to be driven by major composition.

Finally, we look at several categories of institutional selectivity. Earnings returns to double majoring for men are only positive for Ivy Plus graduates, but earnings effects for women are only positive for non-Ivy Plus. This pattern is similar across SAT and admissions rate quintiles, with effects for men positive at the most selective schools and the effects for

61. Thus we do not have enough evidence to assess the argument that double majors have a labor market insurance value.

women positive at either end of the selectivity ranking.[62] For women, there is also a negative effect of double majoring on children at either end of the admissions rate ranking, but not for average SAT. There is no particular pattern by selectivity for the other outcomes.

62. The most selective schools are in the 1^{st} admission rate quintile.

CHAPTER 3

Paying by waiting in line: Public sector queuing and the public sector wage gap

with Hugo Jales and Felipe Araujo

3.1. Introduction

Government employees make up a large portion of the labor market. Hiring, firing, promotion, and wage setting in government jobs operate in a specific manner that is usually unique to those jobs. Government jobs are usually characterized by low unemployment risk, stronger unions, and somewhat predictable career progression. Employment in the public sector is a-cyclical, meaning that it does not grow much during the boom of the business cycle, but it also does not shrink during the bust.

In developing countries, there is some evidence that public sector jobs have a wage premium. This is somewhat puzzling since the lower unemployment risk should suggest that those jobs would be typically priced at a discount in a standard Hedonic equilibrium model. In this paper, we argue that the combination of wage posting – a form of a price control with a subsidy – from the employer perspective (there is no bargaining of job conditions at the point of hiring); combined with a quantity restriction – the government sets the quantity to be demanded in a way that is independent of the actual supply of laborers to the position – yields a market that is characterized by large surpluses of labor supply to government jobs.

The assignment of workers to these jobs is set by the outcomes of admission exams. These exams are designed to test workers in some of the abilities required to perform the jobs – such as reading, writing, law, accounting, etc. These exams are graded in a double-blinded manner, and candidates are by and large ranked solely on the outcomes of these tests. Employment contracts are offered to those with the best scores in the admission exams.

We argue in this paper that the combination of characteristics of public sector jobs (externally set wages, positive wage premium, and quantity restrictions) leads to an oversupply of workers to the public sector career. Given that the entry to this career is decided according to the rankings in a high-stakes admission exam, workers spend real time and effort preparing for these exams, competing with others for the shot of supplying labor to the public sector. The entrance point of the public sector gets crowded, and the tightness (the ratio of vacancies to applicants) shrinks until the labor market reaches an equilibrium. This equilibrium is characterized by an approximate equalization between the monetary net present value of supplying labor to the private sector and the monetary net present value of supplying labor to the public sector only after paying the equilibrium price: time spent waiting in line to access the public sector jobs.

We use an unique dataset of public sector admission exams that includes data on the wages of thousands of admission exams administered in Brazil from 2007 to 2016. The dataset includes data on the educational requirements of the job, the number of vacancies, and the scores of each individual who took the test. The panel nature of the dataset allows us to see whether individuals took multiple tests over the course of a large number of years, which allows us to see how long individuals usually take to enter the public sector career.

In our empirical analysis, we estimate a series of regression models that are derived from our theoretical work. Our theory predicts that the tightness should have a unitary elasticity with the value of the job. In the simplest form of the model in which workers are risk neutral and do not value the other amenities of public sector employment, this implies that the coefficient of a regression of the logarithm of the number of candidates on the posted logarithm of the wage should be one. We find that even the simplest version of the model provides an excellent fit to the data.

Our results also allow us to calculate how much of the nominal differential between the private sector value of the career and the value of the public sector career remains after accounting for the queue at the point of entrance in the public sector. Our results show that likely all of the potential career benefits of supplying labor to the public sector are dissipated in the queue, leading the value of public sector jobs to be not that different from private sector jobs. This value dissipation process comes from workers taking advantage of obvious arbitrage opportunities in the labor market. The queue length increases for jobs that pay relatively more, making them proportionally harder to access, up to the point where value is equalized across jobs.

3.2. Literature Review

The existence of a wage gap between the public and private sectors is well documented in many countries.[63] As noted in Schager (1993), these gaps often feature a "double imbalance," in which the lowest wages are greater in the public sector while the highest wages are greater in the private sector . Although countries in the former Eastern bloc are prominent exceptions (Lausev 2014; Danzer 2019), in general, average wages are found to be much higher in the public sector (e.g. Bender 2003). In particular, Araujo (2020) finds that the average public sector premium in Brazil (the focus of this paper) is approximately 48% and is decreasing in educational attainment.[64]

If a country's public sector overpays for its labor (relative to comparable private sector positions) then it will face multiple problems related to resource misallocation. Quadrini and Trigari (2007) find theoretically that misallocated public sector labor can increase the

63. See Gregory and Borland (1999) for a review

64. Evidence for negative selection bias is also found, with OLS specifications only picking up about half of this premium

volatility of both employment and output at a macro level. In Brazil, Glomm, Jung, and Tran (2009) estimate that the generosity of public pensions cost nearly 3% of GDP annually through early retirements. Albrecht, Robayo-Abril, and Vroman (2019) and Pousada and Ulyssea (2017) each calibrate models with heterogeneous agents (using Colombian and Brazilian data, respectively) and find that in each case misallocation arises from sorting based on education, skills, and risk preferences. In a similar model, using Brazilian data, Cavalcanti and Santos (2021) find that adverse sorting across sectors specifically costs 11.2% of annual output. While some effects are estimated near zero (e.g. Dos Reis and Zilberman 2013), since the public sectors of many countries are quite large (17.9 % average in OECD countries) even small deviations from efficiency in their labor markets can be of first order importance (OECD 2021).[65]

Any employer, public or private, would seem to have an incentive to minimize costs. Why then might public sector labor markets have inefficiently high wages? Some of the oldest accounts favored rent seeking by bureaucrats (Barro 1973), efficiency wages (Stiglitz 1984), or unionization (Gregory and Borland 1999) as explanations. While undoubtedly possible, each has faced both theoretical and empirical challenges.[66] More recent explanations emphasize the insurance value of a (presumably more stable) government job (Rodrik 2000), search frictions (Montgomery 1991), and the potential for Roy (1951) sorting across skill levels or (Weiss 1980) ability discrimination between the public and private sectors (Depalo 2018).

If a gap exists in total compensation between the public and private sectors, then a cor-

65. For an overview of the macroeconomic misallocation literature, see Restuccia and Rogerson (2017), who note that government wage policy is an important source of such misallocation which can significantly slow macroeconomic growth.

66. The range of the observed gaps, the potential for Rosen (1986) compensating differentials through both soft factors such as "mission-oriented" motivation (Besley and Ghatak 2005) and fringe benefits (Danzer 2019), as well as the varying degree of unionization are all make it difficult to explain the public wage gaps through these lenses alone.

responding excess of labor supply should be induced as workers attempt to capture these rents. This will be observable as a queue, or a persistent ratio of applicants per job greater than one (Krueger 1988; Holzer, Katz, and Krueger 1991).[67] Mohanty (1992) finds such a queue for unionized jobs, both public and private, in the U.S. Mengistae (1999) finds evidence of public job queues in Ethiopia and Hyder (2007) finds similar evidence in Pakistan. In a government recruiting experiment in Mexico, Bó, Finan, and Rossi (2013) are actually able to observe the increasing relationship between queue length and the posted wage for a randomized set of public jobs, confirming the theoretical prediction.[68] Finally, Mangal (2021) finds that a partial public sector job freeze in India caused a 30% increase in unemployment among likely test-takers which was not associated with an increase in general human capital (suggesting that studying for public sector job applications is an economically unproductive activity).[69]

3.3. Model

3.3.1. Sector Choice

We will assume that workers take market wages as given and choose where to supply labor. There are two sectors: public and private. Private sector wages are denoted by w_0 and public sector wages are denoted by $w_1 \equiv (1+\delta)w_0$, where $\delta > 0$ is the public sector wage premium. Workers have at their disposal only the choice of sector $S \in \{0,1\}$. Their goal is to maximize utility:

$$S^* = \arg\max_{S\in\{0,1\}} E[SU(S=1) + (1-S)U(S=0)]$$

67. Note: this is the inverse of "tightness"

68. A 33% increase in wages led to a 26% increase in applications, which yields an elasticity estimate of 0.787, quite close to our estimates in this paper.

69. India has an exam-based public sector job allocation system that is quite similar to Brazil's

The solution to this problem is given by:

$$S^* = \mathbb{1}\{E[U(S=1)] > E[U(S=0)]\}$$

That is, workers will choose the public sector if, and only if, the expected utility of working in the public sector is larger than the expected utility of working in the private sector. We also assume that workers are risk-neutral and care only about the wage and employment prospects of each choice. Thus:

$$E[U(S)] = p_s w_s$$

where p_s is the probability of finding a job when choosing sector s to supply labor.

If both sectors have employment in equilibrium, then it must be the case that $p_1 < p_0$. Furthermore, the higher the public sector wage premium, the lower must be the chances of finding a job there. Note that in equilibrium $E[U(S=1)] = E[U(S=0)]$, so workers are indifferent between supplying labor to the public and of the private sectors. Using the equilibrium condition, we obtain:

$$p_1 w_1 = p_0 w_0$$

$$\frac{p_1}{p_0} = \frac{w_0}{w_0(1+\delta)}$$

$$\log(p_1) - \log(p_0) = \log(1) - \log(1+\delta)$$

$$\textit{\%Difference in employment probabilities} = -\textit{\% Difference in Wages}$$

3.3.2. Asset pricing

We can also calculate how many years of earnings workers are willing to sacrifice in exchange for a public-sector job. Assume that workers discount time at rate r (and thus have a discount factor $\beta = 1/(1+r)$. Assume further that private and public-sector wages are constant at, respectively, w_0 and $w_1 = (1+\delta)w_0$. Workers are paid at the end of every period, are perpetually young (live forever), and do not place any value in non-wage features of the job. Thus, the lifetime utility of taking a private-sector job is equal to:

$$V_0 = \sum_{t=1}^{\infty} \beta^t U(w_{0,t}) = \sum_{t=1}^{\infty} \beta^t w_{0,t} = \sum_{t=1}^{\infty} \beta^t w_0 = w_0 \left(\sum_{t=0}^{\infty} \beta^t - 1 \right)$$

$$= w_0 \frac{1}{1-\beta} - w_0 = w_0 + \frac{w_0}{r} - w_0 = \frac{w_0}{r}$$

Similarly:

$$V_1 = \frac{w_1}{r} = \frac{(1+\delta)w_0}{r} = (1+\delta)V_0$$

Thus, the value of a public sector job is the value of the private sector job multiplied by the public sector wage differential.

Now, the question we seek to answer is how many years of a private-sector job a worker would be willing to sacrifice to secure entrance to a public sector career. One approach to the problem is to look at the worker's willingness to pay for a public sector job, and then translate that number from dollars to time (using the worker's private sector wage as the conversion factor). A worker is willing to pay to enter the public sector career at most:

$$\textit{Willingness to pay} = V_1 - V_0 = (1+\delta)V_0 - V_0 = \delta V_0 = \delta \frac{w_0}{r}$$

We next ask how many years of work does it take a worker to obtain $\delta w_0/r$. This value is found by finding the period T such that:

$$\delta \frac{w_0}{r} = \sum_{t=1}^{T} \beta^t w_0 = w_0 \left(\sum_{t=0}^{T-1} \beta^t - 1 + \beta^T \right)$$

$$\Rightarrow \frac{\delta}{r} = \left(\frac{1-\beta^T}{1-\beta} - 1 + \beta^T \right) = \left(\frac{\beta - \beta^{T+1}}{1-\beta} \right) = \frac{1}{r}(1-\beta^T)$$

$$\Rightarrow \beta^T = (1-\delta) \Rightarrow T \log(\beta) = \log(1-\delta)$$

$$\Rightarrow -Tr \approx -\delta \Rightarrow T \approx \frac{\delta}{r}$$

Hence a worker is willing to sacrifice a number of years proportional to the public sector wage gap and inversely proportional to the discount factor.

One way to interpret this result is that if there were a literal queue to enter the public sector, and workers were to get a job there on a first-come, first-served basis, then workers would be willing to enter the queue for the public sector job as long as the length of time queuing was lower than δ/r years. In other words, whenever the queue length was lower than δ/r, workers in the private sector would start queuing and the length would increase. Conversely, whenever the queue was found to be higher than δ/r, workers at the end of the queue would stop waiting for a public job and take jobs in the private sector. As a result δ/r is the only queue length that can prevail in equilibrium.

3.3.3. Combining these two

Workers can, in every period, decide whether or not to supply labor to the private or public sectors. A worker can always find a job in the private sector, but can only find a job in the public sector with probability p (determined endogenously). Assume further that wages are fixed over the course of the worker's career, that there are no job separations, that workers care only about salary and that workers are perpetually young.

A worker's choice set is simply the sector in which he decides to supply labor at every period. If the worker decides to supply labor in the private sector, he gets:

$$V_0 = \frac{w_0}{r}$$

If the worker decides to supply labor in the public sector, he gets a value of:

$$V_s = p\beta V_1 + (1-p)(0 + \beta V_s)$$

$$rV_s = 0 + p(V_1 - V_s)$$

where V_s is the value of *searching* for a job in the public sector, and V_1 is the value of *obtaining* a job in the public sector. Here we use the fact that while studying/waiting to get a public sector job the worker gets no wage and that the chance that the worker finds a job in every period is given by p.

The worker's decision at every point is whether or not to move to the public sector. In equilibrium, if both sectors have positive labor supply, it must be the case that:

$$V_s = V_0$$

Now, we have the following system of equations that determine p:

$$V_s = V_0$$

$$V_1 = (1 + \delta)V_0$$

$$(r + p)V_s = pV_1$$

Solving for p, we obtain:

$$(r + p)V_0 = pV_0(1 + \delta) \Rightarrow r + p = p + p\delta$$

$$\Rightarrow p = \frac{r}{\delta} \tag{3.1}$$

At every period some workers will be lucky and find a job, while others won't. The distribution of the time it takes to get a job will be geometric, with a probability of success equal to r/δ. The expected duration of the unemployment while queuing for a public sector job is given by the inverse of the chance of success. Thus:

$$\textit{Expected unemployment duration} = E[T] = \frac{\delta}{r} \tag{3.2}$$

where T is the random variable that denotes the unemployment duration, or "waiting time." This expression coincides exactly with the formula for the waiting time based on the asset pricing equations. The only difference is that, here, it does not hold deterministically. Instead, it holds in expectation: Workers expect in equilibrium to wait for a public sector job *precisely* the exact amount of time they would be willing to sacrifice if they were asked to do so. Thus, the queue acts as a compensating wage differential, establishing the ex-ante equality of utilities across different career options.

3.3.4. The value of employment insurance

Public and private sector jobs differ not only in terms of their monetary compensation. On top of wage differentials, public jobs also have a different package of job amenities. The most salient of them is essentially guaranteed job safety.[70] Private enterprises can fire workers more or less freely, which diminishes the expected value of a private-sector job.[71]

In this section, we characterize the market value of public-sector employment insurance. This allows us to place a monetary value on the most salient job amenity that differentiates public and private sector jobs.

The setting is the same as before. However, now at every period, private-sector workers have a chance s of being separated from their jobs. When a job is destroyed, a private-

70. Public-sector workers can be fired without cause in the first 3 years on the job—which very rarely happens—and can only be fired after that period under specific circumstances as described in the law.

71. By that we mean, they might have to pay firing cost fee, but firing is an option that is still often exercised.

sector worker moves to the pool of unemployed, where he starts searching for a job, which he finds with a probability p. The value of employment and unemployment in the private sector are then given by:

$$V_{e,0} = \frac{w_0}{1+r} + \frac{s}{1+r}V_{u,0} + \frac{1}{1+r}(1-s)V_{e,0}$$

$$V_{u,0} = \frac{b}{1+r} + \frac{p}{1+r}V_{e,0} + \frac{1}{1+r}(1-p)V_{u,0}$$

Thus, we have that:

$$rV_{e,0} = w_0 + s(V_{u,0} - V_{e,0})$$

$$rV_{u,0} = b + p(V_{e,0} - V_{u,0})$$

After some algebra, it can be shown that:

$$rV_{e,0} = \omega_e w_0 + (1-\omega_e)b$$

$$rV_{u,0} = \omega_u w_0 + (1-\omega_u)b$$

where $\omega_e = \frac{p+r}{p+r+s}$ – thus $(1-\omega_e) = \frac{s}{p+r+s}$ and $\omega_u = \frac{p}{p+r+s}$ – thus $(1-\omega_u) = \frac{r+s}{p+r+s}$.

These expressions show that the value of a private-sector job $V_{e,0}$ and the value of searching for a job in the private sector market $V_{u,0}$ are a weighted average of the flow value of a job in the private sector w_0 and the flow value of unemployment in the private-sector market, which is given by the value of time at home/unemployment benefits b.

The weights depend on how often the worker is expected to stay in each of the states of the world (employed and unemployed). The larger is the job separation rate s, and the lower is the job-finding rate p, the higher is the weight put on the unemployment benefit b, and the lower is the weight placed on the private sector wage w_0. In other words, the harder it is to find or to keep a job in the private sector, the higher it will be the discount associated with the wage in that job. This is perhaps easier to see when b is equal to zero. In that case, workers perceive in expectation that a private sector employment contract displays a wage times a discount factor, which marks down the wage due to the risk of unemployment. Another useful special case to note is that when r is very small relative to p and s, the weights reduce to the fraction of time the worker is expected to stay in each state since in this model the fraction of periods the worker is expected to find himself employed is given by $\frac{p}{p+s}$ and the fraction of periods that the worker is expected to find himself unemployed is given by $\frac{s}{s+p}$.

It is immediate from these results that, given knowledge of b, s, and p, one can immediately find the value of the public sector's employment insurance. One way is to look at a worker's willingness to pay for such an amenity. That is, how much would a worker be willing to spend on setting s to zero, which is essentially inducing employment insurance on the private sector job. The answer to this question is identical to the difference between the value of a private-sector job when ω_e is set to be equal to one. That difference is going to be larger when s is large and when p is small.

3.3.5. Accounting for differences in returns to tenure

The public sector wage differential isn't necessarily constant over the course of a worker's career. In this section we show how to account for such differences in our analysis.

Let $w_{0,t}$ be the wage a worker earns in the private sector at time t, and let $w_{1,t}$ be the wage a public sector worker earns at time t. Let g_0 be the per period growth rate of wages in the private sector and g_1 be the growth rate of wages in the public sector. Let $w_{1,1}/w_{0,1} = (1+\delta)$ be the baseline difference in wages at the beginning of the worker's career. Then:

$$V_0 = \sum \beta^t U(w_{0,t}) = \sum \beta^t w_{0,t} = \sum \beta^t w_0 (1+g_0)^t = \frac{w_0}{1 - \frac{1+g_0}{1+r}} = \frac{w_0(1+r)}{r - g_0}$$

Thus, as usual, wage growth over the course of a workers career will manifest itself as a lower "effective rate of time discount." Similarly, for workers in the public-sector, we have that:

$$V_1 = \frac{w_1(1+r)}{r - g_1}$$

As a result, the difference between the value of a job in the public sector when compared to the private sector is given by:

$$\frac{V_1}{V_0} = \frac{w_1}{w_0} \frac{r - g_0}{r - g_1}$$

$$\frac{V_1}{V_0} = (1+\delta) \frac{r - g_0}{r - g_1}$$

The equation above shows that, as long as $g_1 = g_0$, the difference between the value of a job in the public sector when compared to a job in the private sector is still given by the wage differential at the outset of the worker's career $(1 + \delta)$.

However, in the general case in which the rates g_1 and g_0 differ, then the public sector premium will have one component associated with differences in level (δ) and another one associated with the difference in the slope $((r - g_0)/(r - g_1))$.

Using a Taylor approximation, we obtain:

$$\log \frac{V_1}{V_0} = \delta + \frac{g_1 - g_0}{r}$$

Thus, the difference between the value of a public sector job is, in percentage terms, given by the difference in levels δ, plus the difference in wage growth, normalized by the worker's impatience r.

3.3.6. Finite Careers

Assume all workers enter the labor market at time zero, and retire at $\bar{T}$. Here, we analyse the effects of a finite career on the results we derived thus far. For simplicity, we go back to the setting with no job destruction and no wage growth over the life-cycle.

$$V_0 = \sum_{t=1}^{\bar{T}} \beta^t U(w_{o,t}) = \sum_{t=1}^{\bar{T}} \beta^t w_0 = w_0 \sum_{t=1}^{\bar{T}} \beta^t = w_0 \left[\left(\sum_{t=0}^{\bar{T}-1} \beta^t \right) + \beta^{\bar{T}} - 1 \right]$$

$$= w_0 \left[\frac{1 - \beta^{\bar{T}}}{1 - \beta} + \beta^{\bar{T}} - 1 \right] = w_0 \frac{1}{r} (1 - \beta^{\bar{T}})$$

Similarly, for the public sector job, we have:

$$V_1 = w_1 \frac{1}{r}(1 - \beta^{\bar{T}})$$

Thus,

$$V_1 = w_0(1+\delta)\frac{1}{r}(1 - \beta^{\bar{T}})$$

This implies that:

$$\frac{V_1}{V_0} = (1+\delta)$$

Thus, whether or not the worker's career is finite plays no role in the relative value of public versus private jobs. It is, in both cases, given by $(1+\delta)$, the public sector wage differential. However, in absolute terms, it matters. Note that:

$$V_1 - V_0 = w_0(1+\delta)\frac{1}{r}(1 - \beta^{\bar{T}}) - w_0\frac{1}{r}(1 - \beta^{\bar{T}})$$

$$V_1 - V_0 = \delta\frac{1}{r}(1 - \beta^{\bar{T}})$$

It is not quite straightforward to derive how close a worker must be to the end of his career so to be not worthwhile to enter the queue to join the public sector.

It pays to simplify the model a little and assume that workers do not discount time, so $r = 0$ and $\beta = 1$. In this case, the worker lifetime utility is the product of the number of years working times the wage in the chosen sector. Thus:

$$V_1 = n_1 w_1$$

$$V_0 = n_0 w_0$$

Thus, the worker will be better off by joining the queue to enter the public sector if, and only if $V_1 > V_0$, which implies:

$$n_1 w_1 > n_0 w_0$$

Or, alternatively:

$$\frac{w_1}{w_0} > \frac{n_0}{n_1}$$

Thus, defining ζ to be the percentage decrease in the length of the worker's career associated with queuing for the public sector job, we have that:

$$\textit{Percentage increase in Wages} > \textit{Percentage Decline in career length}$$

Or, in other words, it must be the case that $\delta > \zeta$ for the worker to choose the public sector. It is immediate from this expression that workers closer to retirement will perceive a greater decline in their career lengths with the same amount of expected wait to enter the public sector. Thus, the older is the worker, *ceteris paribus*, the less likely it is that he will find investing in entering the public sector a worthwhile enterprise.

3.3.7. The price of anarchy

As long as public sector workers are paid at a premium, there is an economic surplus to be fought for between workers in this labor market. However, part of this surplus is lost due to the time workers spend attempting to get into the public sector. In this section we discuss how much of this surplus is lost, and what would be the workers' welfare if they could coordinate their actions. In the decentralized equilibrium, a fraction θ of workers end up in the private sector, whereas the remaining fraction $(1-\theta)$ end up in the public sector. Thus, the average expected welfare of workers is given by:

$$\textit{Expected Welfare} = \theta V_0 + (1-\theta)V_s = \theta V_0 + (1-\theta)\frac{1}{r}p(V_1 - V_s)$$
$$= \theta V_0 + (1-\theta)\frac{1}{r}p(V_1 - V_0) = \theta V_0 + (1-\theta)\frac{1}{r}p\delta V_0 = V_0$$

where in the second-to-last equation we use the fact that, in equilibrium, p is equal to $\frac{r}{\delta}$.

This implies that, in the decentralized equilibrium, the expected welfare of workers is equal to the welfare in the private sector. Thus, all the surplus associated with the presence of the public sector premium is dissipated by the congestion externalities workers impose in one another when queuing to enter the public career.

How much surplus is lost? To answer this question, we must find the maximum of workers' welfare that can be obtained in the presence of the public sector premium. One simple way to look at this is to think that workers could coordinate their actions through a chain of contracts. It is straightforward to see that the maximum welfare of workers that can be obtained is given by, where η is the share of total jobs in the public sector:

$$\textit{Centralized Welfare} = (1-\eta)V_0 + \eta V_0 + \eta\delta V_0 = (1-\eta)V_0 + \eta V_1 = (1+\eta\delta)V_0$$

Comparing workers' welfare in the decentralized equilibrium and the one that could be obtained if worker's were able to coordinate their actions, we get the price of anarchy. The decentralized equilibrium costs workers an amount that is proportional to the size of the public sector (relative to the number of workers) and to the public sector wage premium. In other words, all of the potential surplus from the public sector premium is lost due to the workers' inability to coordinate their actions to limit the queue's length.

3.3.8. Roy Heterogeneity - Wages

So far, we have assumed away heterogeneity in wages in both the public and the private sectors. The unique price for labor in the public sector is appropriate since the wages are set regardless of which worker happens to take the job. However, the same assumption is unappealing for the case of private jobs. Here, we study the model's equilibrium in the presence of wage heterogeneity in the private sector.

Workers are characterized by a public sector wage w_1 and a private sector wage $w_0 = we^{\epsilon}$, where ϵ is a mean-zero wage heterogeneity component in the private sector – which can be thought of as a combination of luck, human capital investments, and innate ability–, and w is a baseline private sector wage. Note that workers with ϵ greater than zero earn more than w and workers with ϵ smaller than zero are less than w. Now, let $\gamma \equiv log(w_1) - log(w)$, that is, γ measures the strength of the *average* public sector premium.

In the presence of wage heterogeneity in the private sector, not all workers will find it worthwhile to search or wait for a job in the public sector. It is then useful to consider the fraction of workers for which the public sector is worth considering, depending on the size of the queue. In the presence of equal probabilities of finding a job in both sectors, that is, in the absence of a queue, a worker will choose the public sector if, and only if:

$$\log(w_1) > \log(w_0)$$

$$\log(w_1) > \log(w) + \epsilon$$

$$\epsilon < \gamma$$

Thus, the fraction of workers that would choose the public sector in the absence of a queue is given by $Pr[\epsilon < \gamma] = F_e(\gamma)$. Under the assumption that unobserved heterogeneity in log-wages in the private sector is normally distributed with mean zero and variance σ^2, we have that $Pr[\epsilon < \gamma] = \Phi(\frac{\gamma}{\sigma})$. Thus, a worker will consider joining the public sector only if his employment prospects in the private sector are below a threshold. Moreover, we can see that there are two key components that determine the fraction of workers that might choose to enter the public sector: The first is the average public sector premium γ, and the second is the size of wage heterogeneity σ. The higher wage heterogeneity in the private sector, the lower the fraction of workers that may choose to enter the public sector.

In the discussion that follows, we assume that the mass of workers for which this is the case is larger than the number of jobs in the public sector, so that in equilibrium there is rationing of jobs in the public sector. Now, in the presence of a queue, workers need to consider the trade-off between finding a job immediately in the private sector, versus wasting time but finding a better job in the public sector.

Before we look at equilibrium objects, it is worthwhile to consider the worker's willingness to wait for a public sector job. Recall from our previous discussion that the worker's willingness to wait for a public sector job is the number of years a worker is willing to queue to secure employment in the public sector. In the presence of wage heterogeneity, this object is going to be different for different workers. The worker's willingness to wait for a public sector job is the value of T_i that solves:

$$\beta^{T_i}(1+\gamma)\frac{w}{r} = \frac{w_i}{r}$$

$$T_i log(\beta) + \gamma + log(w) = log(w) + \epsilon_i$$

$$T_i = \frac{\gamma - \epsilon_i}{r}$$

Thus, a worker's idiosyncratic willingness to wait for a public sector job is increasing in the average public sector premium, decreasing in the worker's impatience, and decreasing in his private sector earnings potential ϵ. Note that the expression above is identical to the willingness to wait we derive in the absence of wage heterogeneity in the private sector, except for the ϵ_i term. Thus, it follows that the expected willingness to wait across the population of all workers is:

$$E[T_i] = \frac{\gamma}{r},$$

which is identical to the expression we obtained before.

A worker will decide to enter the queue for a public sector job if, and only if, the expected wait for a public sector job is lower than $\frac{\gamma-\epsilon_i}{r}$. That is, if the expected wait for a public sector job is lower than the maximum wait that he would consider acceptable to secure public employment.

The equilibrium in this model is characterized by the following conditions: (i) Given the (equilibrium) probability of finding a job in the public sector p and each worker's wage heterogeneity component ϵ, all workers choose the sector that yields the highest expected utility. Given the number of jobs in the public sector and the number of workers that choose the public sector, the probability of finding a job in the public sector is equal to p.

Now, we are going find the expressions that characterize the equilibrium. It is useful to note that if, in equilibrium, a worker with a value of ϵ equal to ϵ^* is going to the private sector, then *all* workers with $\epsilon_i > \epsilon^*$ must also choose the private sector. Thus, it is sufficient to search for the marginal worker, the worker with the value of ϵ that makes him indifferent between the two sector choices. The condition that characterizes such worker is:

$$E[U(S=1)] = E[U(S=0)]$$

$$pw_1 = w_0 e^{\epsilon^*} \Rightarrow pw_1 = we^{\epsilon^*}$$

$$\Rightarrow p(1+\gamma) = e^{\epsilon^*} \Rightarrow \log(p) + \gamma = \epsilon^*$$

The expression above relates the equilibrium employment probability in the public sector p with the public sector premium γ. We can remove the endogenous value of p by expressing the employment probability p with the ratio of the number of jobs in the public sector η

and the number of workers that, in equilibrium, attempt to get these jobs $n_1 = \Phi(\frac{\epsilon^*}{\sigma})$. Thus, we obtain:

$$\frac{\eta}{n_1}(1+\gamma) = e^{\epsilon^*}$$

$$\eta(1+\gamma) = e^{\epsilon^*} n_1$$

$$\eta(1+\gamma) = e^{\epsilon^*}\Phi(\frac{\epsilon^*}{\sigma})$$

The expression above implicitly characterizes the equilibrium value of ϵ^*. Although there is no closed-form solution for it, it can be easily seen that there is a unique value of ϵ^* for which the equation above holds.[72] This happens because the left hand side is a constant function of ϵ^*, whereas the right hand side is a monotonically increasing function of ϵ^* which tends to zero as ϵ^* goes to minus infinity and tends to plus infinity when ϵ^* goes to infinity. Thus, the RHS crosses $\eta(1+\gamma)$ only once.

The equilibrium value of waiting time characterizes the willingness to wait for the marginal worker, the worker for which labor market potential in the public sector and on the private sector coincide. As a result, the equilibrium waiting time is a lower bound on the willingness to wait for the infra-marginal workers that end up self-selecting to the public

72. One way to arrive at a closed form expression for ϵ^* is assume that the distribution of ϵ is Gumbel with parameter α. Then, $F(\epsilon^*) = Pr[\epsilon < \epsilon^*] = e^{e^{-\frac{\epsilon^*}{\beta}}}$. Assuming also that private sector wages are given by $w_0 = we^{e^{\epsilon}}$, we find that the equilibrium value of ϵ^* associated with the marginal worker is given by:

$$\epsilon^* = \frac{\beta}{\beta - 1}\log\log\eta(1+\gamma)$$

sector. Moreover, note also that in the homogeneous version of the model all rents are dissipated and, as a result, all workers end up with the same utility regardless of the sector that they work at. Here, only the marginal worker ends up with the same utility in both sectors. Thus, most workers in the public sector still manage to earn a economic rent from the public sector premium, although a fraction of the (potential) public sector employment rent is dissipated by the rationing of jobs (and corresponding queue) to enter the public sector.

3.3.9. Roy Heterogeneity - Skill

Now suppose that there is a second dimension of heterogeneity - "skill." Suppose also that public sector jobs have different wages and possibly different threshold scores that are required to secure admission to them. Skill influences how successful an individual is likely to be on an admissions exam, but does not necessarily determine it. Individuals will therefore choose to compete for public sector exams in order to maximize their expected utility, given that their expected waiting time will depend on both their skill and the wage premia, i.e.

$$\max_{\delta} \beta^{T(u,\delta)}(1+\delta)\frac{w_{00}}{r}$$

where u indicates skill level and w_{00} is a reference private sector wage, a normalization. Test taking skills are also valued in the private sector markets, since some of the productive capacities that make a worker excel at a high-stakes test might also be used in some sectors of production. The problem above simply states that the choice of which exam to take must be made optimally. That is, when the public sector offers a multiplicity of different wages for different positions, individuals must choose not only whether or not to attempt to enter the public sector but also which particular position in the public sector career to aim for.

The function T has two arguments: It depends on skill level u. This captures the fact that there is heterogeneity in terms of test-taking abilities and that will affect how fast a worker can reach the scores associated with successfully securing a public sector job. Individuals with a lower u will take more time to access any job with a given δ; individuals with a higher u will have to wait less to reach any job with a fixed level of δ. The function T also depends on δ since different δ will have different equilibrium score thresholds that would be required to ensure admission to a particular job. In other words, T is decreasing in skill level u and increasing in δ.

The first order condition for the optimal choice of δ is

$$\frac{\partial T}{\partial \delta} ln(1+r) + \frac{1}{1+\delta} = 0$$

$$\frac{\partial T}{\partial \delta} = \frac{1}{(1+\delta)ln(1+r)} \approx \frac{1}{(1+\delta)r}$$

A simple function that satisfies this condition is $T(u,\delta) = -(\theta_0 u\delta - \theta_1\delta^2/2) + ln\big((1+\delta)r\big)/r + m(u)$ for some function $m(u)$ and constants θ_0, θ_1 such that $\theta_0 u = \theta_1\delta^*(u)$ at the optimum. This is a reduced-form representation of the relationship between time-to-access different jobs and the pair of wages associated with the job and skill level of the worker. The key condition that is required for sorting in equilibrium is the interaction term. It ensures that the costs of accessing jobs with higher wages rise for all workers regardless of skill, but it rises slower for high-skilled workers. This can be micro-founded from different concavities in the production technology of test scores of high and low-skilled workers, but for our purposes, we just need to state that T rises with delta for all u, but it has a smaller derivative with respect to delta for higher values of u. In equilibrium workers are indifferent between sectors so it must be the case that

$$\frac{w_0(u)}{r} = \beta^{T(u,\delta^*(u))}\big(1+\delta^*(u)\big)\frac{w_{00}}{r}$$

i.e., that expected net present values are equal. Using the fact that skill is positively associated with the private sector wage, $w_0(u)$, according to some function $g(u)$, we have

$$\frac{w_{00}\big(1+g(u)\big)}{r} = \beta^{T(u,\delta^*(u))}\big(1+\delta^*(u)\big)\frac{w_{00}}{r}$$

$$g(u) = -rT(u,\delta^*(u)) + \delta^*(u)$$

$$T(u,\delta^*(u)) = \frac{\delta^*(u)-g(u)}{r} = \frac{\theta_0 u}{\theta_1 r} - \frac{g(u)}{r}$$

Waiting times can therefore be any function satisfying these conditions. Despite not pinning down exact functional forms, they nevertheless ensure 1) individual rationality in the choice of exam and 2) no arbitrage remaining for any skill level. Note that the observed relationship between waiting times and wages is a lower envelope of the waiting time functions for each skill level. In equilibrium, individuals with higher skill will aim for public sector jobs with higher nominal wage $\delta^*(u) = \frac{\theta_0}{\theta_1}u$.[73] Despite accessing a job with higher pay in equilibrium, neither individuals with high or low skill will are able to obtain any rents, since the competition with others of similar skill level ensures that the waiting times for them will be such that the benefits of trying to secure admission to the jobs that

73. Interestingly, $\theta_0/\theta_1 - g'(u)$ is difference in the marginal returns to greater test-taking skills in the private sector, relative to the (entrance to the) public sector. It measures how much more, or less, the private sector values the abilities that makes an individual capable of securing high test scores (such as dedication, organization, memorization, mathematical reasoning, language skills, etc.).

they find the best to aim for is still such that the value of a private sector career is just as large.[74]

3.3.10. Costs of Admission

Thus far in our analysis of the optimal waiting times, we have only considered the opportunity costs of time that could have been used productively on the private sector. In reality, workers lose more than just foregone private-sector wages when they decide to search for a public sector job.

Public sector jobs admit workers based on the results of an admission exam. As a result, a significant part of the time that workers are queuing for a public sector job, they are deliberately practicing for an admission exam. Often, they pay for training classes specializing in preparing workers for these admission exams. Now, we are going to incorporate these costs, the costs of exam training and preparation, in our analysis.

Assume that during the period that the worker is queuing for a public sector job, he needs to pay a cost $\tilde{c}$ to obtain specialized instruction. Our goal is to derive the equilibrium waiting times, as a function of the public sector premium δ, the rate of time discounting r, and the costs of training $\tilde{c}$.

$$V_0 = \frac{w_0}{r}$$

74. Note that no other public sector job is as good as $\delta^*(u)$, the optimal public sector job that the individual of skill level u might consider in equilibrium, and not even $\delta^*(u)$ yields any rent in equilibrium. That is, if an individual tries to overshoot to a better job he will end up taking too much time to access it relative to the pay, and if he tries to undershoot, he will obtain access faster than those who enter that job in equilibrium, but it will cost him relatively more than then since the same force that led you to be skilled enough to access the job in faster-than equilibrium time makes you pay a opportunity costs that is larger since that skill is somewhat priced in the private sector market as well. That is, his private sector wage $g(u)$ is high enough that the benefits of waiting to enter a job that pays less than δ^* are too low relative to the cost (waiting time) to access it.

$$V_1 = -\sum^{T-1} \beta^t \tilde{c} + \sum \beta^{T+t} w_1$$

In equilibrium, $V_1 = V_0$ and thus:

$$\frac{w_0}{r} = -\frac{\tilde{c}(1-\beta^{T-1})}{r} + \beta^T \frac{w_1}{r} \Rightarrow 1 = -c(1-\beta^{T-1}) + \beta^T(1+\delta)$$

$$\Rightarrow ln(1+c) = ln(\beta^T(1+\delta+\frac{c}{\beta})) \Rightarrow c = -Tr + \delta + \frac{c}{\beta}$$

$$\Rightarrow Tr = \delta + c(\frac{1}{\beta} - 1) \Rightarrow T = \frac{\delta}{r} - c \tag{3.3}$$

Thus, the costs of training will reduce the time the worker is willing to wait in line for a public sector job. The exact form of this relationship is given by the equation 1 above. It is also insightful to look at equation one in a different lens. Note that:

$$T + c = \frac{\delta}{r}$$

The right-hand side is the monetary value of the gains to obtain a job in the public sector. This is, still, precisely how much a worker would be willing to pay – either by sacrificing his time through waiting or by sacrificing his resources through out-of-pocket payments, bribes, or any device to ensure entrance to the public sector.

What our result shows is that the worker will be paying in equilibrium exactly what the public sector job is worth. Before, he would do that by waiting in line. Now that there is a second component to the costs of entrance to the public sector, the *total* amount of resources that the worker will dispose to enter the public sector will still be $\frac{\delta}{r}$. However, a part of it will be going towards the training agencies – out of pocket payments – and a part of it will be the worker will pay with his time. The sum of the costs paid with time and with money will add to the value of the public sector job.

There are a couple of implications of this result. The theoretical one is that we can, just as before, obtain estimates of the willingness to spend time trying to enter the public sector as long as we know both δ and r. Now, some part of this time will be spent actually waiting in line, and others will be spent paying for training resources. The fraction that is spent on training resources is going to depend on both the private sector wage w_0 and the costs of training.

This result has also implications for how to empirically estimate and test this theory. Moving c to the other side of the equation above, we have that:

$$T = \frac{\delta}{r} - c = \frac{\delta}{r} - \frac{\tilde{c}}{w_0}$$

Thus, in the presence of training costs, we will have an extra term in the equation that determines waiting times. Waiting times will be decreasing in the costs of training and increasing in the private sector wage. The reason that they are increasing in the private sector wages – which is a counterintuitive property at first glance – is that higher private sector wages implies that a lower number of hours must be spent to acquire the resources to finance the exam preparation, $\tilde{c}$, leaving a larger number of hours that can be spent waiting in line.

The equations above also show that in the presence of non-trivial admission training costs, there will be a unit elasticity of *total* waiting times and the public sector premium and (minus) the interest rate. When one look at the fraction of time which is spent out of the labor market waiting to get in, which is T and not $T + c$, then the unit elasticity result is gone. The elasticity will, however, still be close to one the smaller is c relative to the magnitude of δ over r.

3.4. Data and Empirical Methods

To test this theory, we collected data from two of the largest non-profit foundations which conduct entrance exams on behalf of the Brazilian government. All exams from 2007 to 2017 administered by these companies are represented, including such items as exam dates, individual IDs, test scores, and the final ranking. As described in Araujo (2020), this information was merged with manually collected public notices (*editais*) of public sector exams which provide additional job-specific contextual data.

Summary statistics for exams are displayed in Table 11. Note that there is wide variation in both wages and competitors per exam, with the maxima both orders of magnitude greater than the respective means. There are more exams requiring a college degree than a high school or no degree and jobs are concentrated at the state or municipal level of government. Figure 16 panel (a) depicts the geographic dispersion of jobs in the dataset across Brazil. These are clustered in the north and south-central, particularly in the state of Sao Paulo (SP).[75] In panel (b) of Figure 16, we can see that, despite the clustering in location of the jobs, applicants for these jobs are distributed all across Brazil. This distribution compares favorably to the unconditional distribution of population across Brazil in 2014, depicted in panel (c).

Table 12 shows summary statistics at the test-taker level. Here we can see that on aver-

75. Exam-administration organizations are generally regionally-focused, which is the case here

age, test-takers are 31, have taken roughly two exams across two different years, and are slightly more likely to be male than female. Note that the average number of competitors is much higher than in Table 11, indicating significant concentration of exam competition. The jobs requiring a high school degree and those at the state level also seem to be the most popular.

Tables 13 through 15 show summary statistics conditional on wage terciles within each educational level. The number of competitors, top exam scores, and average years of testing are all clearly increasing with wages for non-degree jobs. Only the number of competitors and years of testing monotonically increase with wages for high school jobs. College jobs feature an inverse-U relationship with wages and all key metrics. This pattern is likely a consequence of heterogeneity in test-taking skills, where sorting across particular skill sets is more pronounced for higher educated individuals, who also, presumably, have greater skills and thus better options in the private sector.

Our theory predicts that if we could regress the log of the waiting time on the log of the appropriate wage differential for each public sector job, we would get a coefficient of exactly one. Instead, what we observe is the number of competitors, the number of posted vacancies, the posted wage, and the frequency with which each exam type appears over time. Since waiting time should be proportional to tightness, v/y, multiplied by the inverse of the rate of arrival of exams, after taking logs and rearranging, we get that:

$$\ln Y = \ln(w_1) - \ln(w_0) + \ln V + \ln \lambda - \ln r \tag{3.4}$$

That is, we expect the number of test-takers to be increasing in the percentage difference between the posted wage for the position and the private sector wage, increasing in the number of slots, increasing in the arrival rate of tests (or decreasing in the time gap between exams for the same position), and decreasing in the interest rate. Importantly we expect, up to approximation errors, that these relationships have elasticities that are not too far away from one.

We do not observe the private sector wage directly, although we show below that there are several different ways to deal with that problem. Looking across pairs of exams undertaken by the same individuals, we can difference out the unobserved private sector wage. Looking at the difference in the number of test-takers across different exams for the same individual, we have that:

$$\Delta \ln Y = \Delta \ln(w_1) + \Delta \ln V + \Delta \ln \lambda$$

That is, across exams in which we can argue that individuals have similar counterfactual private-sector wages, the term $\ln w_0$ is differenced out and can be ignored (or alternatively, absorbed by the constant).

In general, the term $\ln w_0$ can be treated as an unobservable, individual-specific, fixed-effect. In doing so, we arrive at:

$$\ln Y = \ln(w_1) + \ln V + \ln \lambda - \ln r + \mu_i \tag{3.5}$$

We, therefore run regressions of the following form:

$$\ln Y_{ity} = \alpha_0 + \alpha_1 \ln W_{ity} + \alpha_2 \ln V_{ity} + g(Freq_{ity}) + \mu_i + \nu_y + \xi_{ity} \tag{3.6}$$

where i indicates individuals, t indicates exam periods, and y indicates calendar years. The function $g(\cdot)$ acts to correct for the possibility that exam timing might not be an i.i.d.

process, which we approximate with a second order global polynomial. In the simplest setting in which each each job has the same inter-arrival rate of admission exams, then the number of other test takers is proportional to both the expected number of tests required to be admitted to that job, and the expected time required to be admitted to that job. When jobs with different wages also differ in how frequent admission exams are, then there is a possible important source of confounding. Two jobs might have the same number of test takers, but if one has a test frequency that is half of the other, then the individuals that attempt to access the former will take, on average, twice as long to be able to when compared to the latter. Individual fixed effects control for private wages and idiosyncratic test-prep costs.[76]

Table 11: Summary Statistics: Exams

	Mean	SD	Min	Max
Year of exam	2012	2.7	2007	2016
Number test-takers	1,513	9,486	1	150,337
Hourly wage	18	14	2.2	155
Job requirements				
Education				
College	0.51	0.5		
High school	0.32	0.47		
Elementary	0.15	0.36		
Other				
Professional cert.	0.34	0.47		
Related experience	0.14	0.35		
Level of government				
Federal	0.034	0.18		
State	0.45	0.5		
Municipal	0.51	0.5		
Observations	7,066			

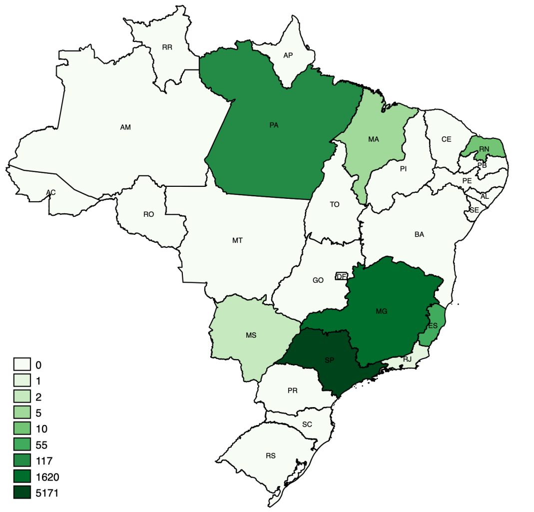
76. Multiple test-taking is extremely common, giving us a lot of within-individual variation

Table 12: Summary Statistics: Test-Takers

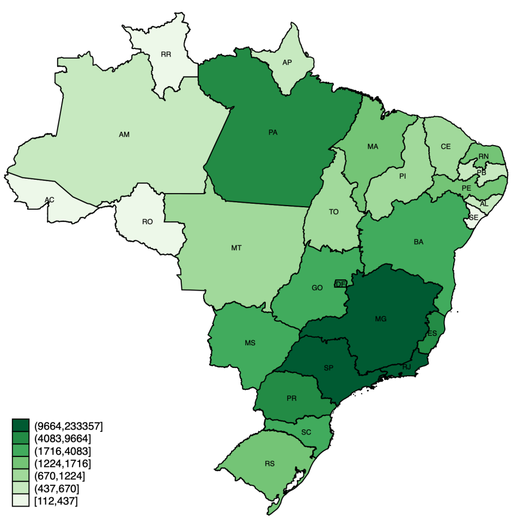
	Mean	SD	Min	Max
Year of exam	2012	2.8	2007	2016
Age	31	9.6	3	79
Num. tests taken	1.8	1.5	1	46
Num. years tested	2.1	2.1	1	10
Competitors	32,688	40,184	1	150,337
Final grade	40	26	0.088	488
Hourly wage	16	13	2.2	155
Classified	0.29	0.46		
Female	0.45	0.5		
Job requirements				
Education				
College	0.27	0.44		
High school	0.59	0.49		
Elementary	0.15	0.35		
Other				
Professional	0.097	0.3		
Relevant experience	0.037	0.19		
Level of government				
Federal	0.014	0.12		
State	0.68	0.47		
Municipal	0.31	0.46		
Observations	3,635,014			

Candidates who score above a job-specific threshold are considered "classified" and are invited for a second round of testing. This may be a demonstration of skills (e.g. driving test) or a second written exam. In either case, the final grade reported is either the sum of both exams if classified or the grade on the first exam if not.

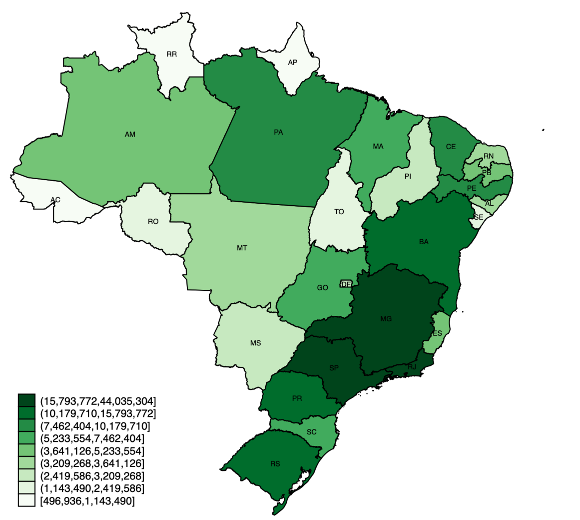
Figure 16: Spatial Distributions



(a) Location of Jobs Available



(b) Location of Test-Takers



(c) Population of Brazil, 2014

Table 13: Summary Statistics by Wage Tercile - Elementary

	1st	2nd	3rd
Competitors	5,430.76	9,174.04	16,128.83
	(5,087.30)	(9,752.71)	(20,176.15)
Tightness	0.03	0.02	0.01
	(0.06)	(0.05)	(0.02)
Score threshold	108.34	93.51	89.12
	(51.64)	(26.76)	(31.83)
Score threshold (adjusted)	9.17	11.04	15.00
	(3.15)	(2.46)	(3.45)
Max. score	117.29	99.41	94.68
	(54.21)	(31.06)	(28.91)
Max. score (adjusted)	10.52	12.19	17.27
	(3.18)	(3.13)	(3.75)
Average years testing	2.76	2.95	3.34
	(0.83)	(0.91)	(0.67)
Observations	178,430	155,130	280,345

"Tightness" defined as the number of jobs advertised for a given exam divided by the number of competitors. This is necessarily an underestimate of the true tightness since the number of jobs actually awarded will be at least the number advertised but possibly more. Adjusted scores account for the facts that 1) each exam has an idiosyncratic grading scale and 2) reported scores are a mixture of two different exam scores for those candidates who are "classified". Assuming that scores are i.i.d. normally distributed, the mean and standard deviation of each test can be inferred to generate the normalized scores reported as "adjusted".

Table 14: Summary Statistics by Wage Tercile - High School

	1^{st}	2^{nd}	3^{rd}
Competitors	4,463.58	23,169.92	44,254.64
	(4,970.28)	(24,743.32)	(43,021.64)
Tightness	0.03	0.02	0.01
	(0.05)	(0.03)	(0.01)
Score threshold	59.92	84.91	41.65
	(17.92)	(23.41)	(41.03)
Score threshold (adjusted)	6.88	10.46	9.09
	(2.21)	(2.61)	(4.13)
Max. score	73.99	96.57	56.63
	(18.85)	(25.05)	(43.30)
Max. score (adjusted)	11.25	13.37	11.84
	(2.77)	(3.12)	(5.14)
Average years testing	3.03	3.38	3.55
	(0.77)	(0.88)	(0.86)
Observations	481,869	824,656	2,357,497

"Tightness" defined as the number of jobs advertised for a given exam divided by the number of competitors. This is necessarily an underestimate of the true tightness since the number of jobs actually awarded will be at least the number advertised but possibly more. Adjusted scores account for the facts that 1) each exam has an idiosyncratic grading scale and 2) reported scores are a mixture of two different exam scores for those candidates who are "classified". Assuming that scores are i.i.d. normally distributed, the mean and standard deviation of each test can be inferred to generate the normalized scores reported as "adjusted".

Table 15: Summary Statistics by Wage Tercile - College

	1st	2nd	3rd
Competitors	2,771.60	18,082.16	5,252.43
	(3,291.53)	(26,213.11)	(5,800.29)
Tightness	0.03	0.01	0.02
	(0.04)	(0.04)	(0.10)
Score threshold	80.39	100.25	88.15
	(24.72)	(39.87)	(82.72)
Score threshold (adjusted)	10.52	12.44	12.18
	(2.15)	(2.43)	(6.04)
Max. score	89.60	106.57	100.02
	(30.71)	(40.95)	(108.93)
Max. score (adjusted)	12.87	14.21	15.33
	(3.00)	(2.63)	(11.07)
Average years testing	3.47	3.55	3.30
	(1.02)	(0.89)	(1.09)
Observations	395,928	601,571	377,484

"Tightness" defined as the number of jobs advertised for a given exam divided by the number of competitors. This is necessarily an underestimate of the true tightness since the number of jobs actually awarded will be at least the number advertised but possibly more. Adjusted scores account for the facts that 1) each exam has an idiosyncratic grading scale and 2) reported scores are a mixture of two different exam scores for those candidates who are "classified". Assuming that scores are i.i.d. normally distributed, the mean and standard deviation of each test can be inferred to generate the normalized scores reported as "adjusted".

3.5. Results

Table 16 displays the main results of our empirical analysis. In the first column, we estimate our model without accounting for frequency or fixed effects (i.e. a random effects model). In the subsequent columns, we first add individual fixed-effect, then we add controls for the frequency of exams, then finally we add year fixed-effects. Individual fixed effects are appropriate here because the theory does not require that all jobs have a tightness-to-wage ratio that is constant; it instead requires that this is true for all jobs for which the worker is willing to take the test. Thus, the within-individual variation in the size of the competition and its relationship with the wage is more informative of the appropriateness of our model than the between-individual variation.[77] The control for test frequency is also justified by our model.

Lastly, we add year fixed-effects. Year fixed-effects are not necessarily required if one believes that the environment is stationary. But they are advisable particularly if different jobs had different wage trajectories over time in unexpected ways. Workers cannot arbitrage back in time (although arbitrage forward, by waiting to begin their test preparation investments should be feasible). Thus whether year fixed effects should be introduced depends on whether workers can accurately forecast the wages that are going to be prevailing in the future. Adding year fixed-effects restricts our variation to be only within-year.

In general, we find strong support for the theory. In column (1), our simplest specification, we find that the elasticity is estimated to be 1.03 (0.0010) In column (2), we add individual fixed-effects and obtain an elasticity of 0.977 (0.0016). In column (3), we add controls for the frequency of admission exams and find the elasticity to be 0.94 (0.0016). In column (4) we add year fixed-effects. We find an estimated elasticity of 1.1 (0.0017), our pre-

77. Note, however, that if one restricts the heterogeneity across workers, then both the within and the between variation became equally useful. Given that there is substantially more information across individuals, there is a real trade-off between bias and precision at play here.

ferred estimate. This specification is overlaid on a binscatter by education level in Figure 17, which visually indicates an excellent fit to the data. In all specifications the estimated elasticity is very close to one.[78]

In Table 17, we investigate how much of the public sector wage differential is lost in the queue. In equilibrium, one should expect the elasticity to be one, and thus, all of the wage differentials should be perfectly offset by longer waiting times. We find that, in our preferred specification, waiting to enter the public sector career dissipates the entire public sector pay differential, plus an additional amount, which varies depending on the discount rates used (less than 10% of the federal minimum wage in Brazil, or about $1.00 USD/hour). The resulting net present value of the career is just below, but very close to the value of the careers found in private-sector positions.[79]

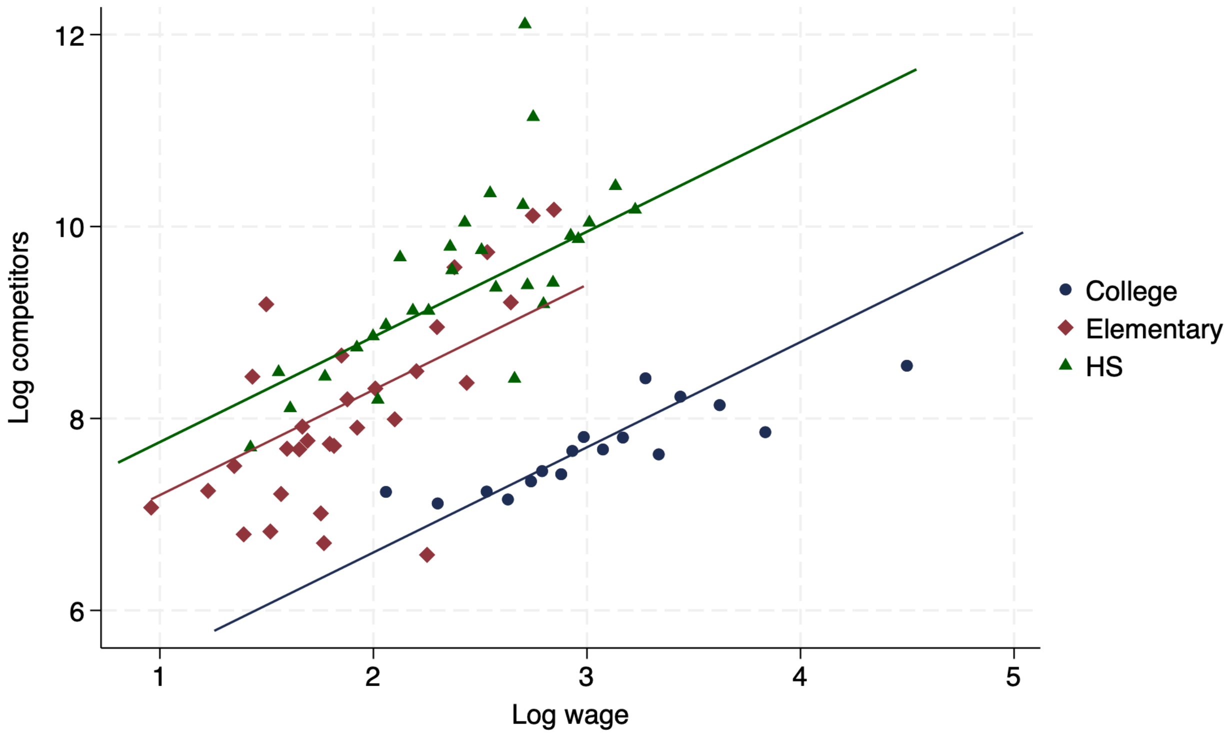
Next, in Table 18 we calculate the expected number of exam attempts it takes to secure a public sector job across wage quintiles using the properties of the geometric distribution (i.e. assuming a constant probability of success). We also calculate the expected waiting times in Table 19 and the variance in waiting times in Table 20 using similar calculations. As expected, in general, our estimates imply more tests and longer waiting times (*much* longer, for the highest wages) on average are required to access public sector jobs as the wage increases.[80] This pattern is not exact however, especially for jobs requiring a college degree, which is similar to the pattern observed in the college summary statistics. As before, skill sorting is the likely confounder here.

78. The theory also predicts that the elasticity of log vacancies should be one. The government must hire at least the number of people as there were jobs initially advertised, but they often hire more. Likely, then, the consistently low coefficient on log vacancies is due to measurement error with respect to the "true," or realized, number of vacancies.

79. This is potentially explained by unobserved amenity values for public sector jobs

80. Since no one is literally waiting millennia to get into these jobs, clearly, the geometric distribution assumption is factually incorrect. That said, these waiting time estimates give a good sense of just how much competition there is for the public sector in some cases.

Figure 17: Binscatter Regression Overlay



Finally, to get a different sense of how well our theory fits our data, in Table 21, we alternately restrict the coefficients on wages and/or vacancies to be their theoretical values (i.e. exactly 1). This is, in a sense, the reverse of the analysis in Table 16. Instead of asking how close our coefficents are to their theoretically expected values, we now set them to these values and ask how well this describes the observed pattern. As it turns out, these constrained regressions fit quite well. In column (1) we reproduce our preferred specification from Table 16, noting the RMSE value of 1.6263. In column (2) we restrict log wages and get an RMSE of 1.6265 (a 0.012% increase from baseline). In column (3) we restrict log vacancies and get RMSE of 1.6979 (a 4.403% increase from baseline). In column (4) we restrict both coefficients and get RMSE 1.6991 (a 4.476% increase from baseline). Especially for our primary explanatory variable, log wages, our theory performs remarkably well.

Table 16: Log Competitors vs. Log Wages

	(1) RE	(2) FE	(3) FE+freq.	(4) 2xFE+freq.
Log hourly wage	1.03***	0.977***	0.94***	1.1***
	(0.000954)	(0.00158)	(0.00155)	(0.00173)
Log vacancies	0.63***	0.627***	0.625***	0.621***
	(0.000245)	(0.000391)	(0.000384)	(0.000374)
High school	-0.057***	-0.236***	0.356***	-0.293***
	(0.00163)	(0.00249)	(0.00319)	(0.0038)
College	-1.8***	-1.96***	-1.02***	-1.9***
	(0.00206)	(0.00324)	(0.00446)	(0.00546)
Test frequency			-0.00936***	0.0000989*
			(0.000036)	(0.0000485)
Test frequency^2			0.000012***	2.42e-07***
			(5.37e-08)	(6.73e-08)
Ind. FE		X	X	X
Year FE				X
Observations	5,584,412	5,584,412	5,584,412	5,584,412
$R^2{}_{within}$	0.60	0.60	0.62	0.66
$R^2{}_{between}$	0.64	0.64	0.66	0.69
$R^2{}_{overall}$	0.64	0.64	0.66	0.69

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Net Public Sector Rents Retained

r =	0.025	0.05	0.075	0.10
Raw fraction	-0.165	-0.122	-0.099	-0.0824
	(0.0034)	(0.0024)	(0.0019)	(0.0016)
% of min. wage (hourly)	-8.10%	-5.99%	-4.86%	-4.04%
	(0.1668)	(0.1177)	(0.0932)	(0.0785)
USD (hourly)	-$0.85	-$0.63	-$0.51	-$0.42
	(0.0175)	(0.0123)	(0.0098)	(0.0082)

Calculated under the assumption that the fraction, θ, of the total public sector rent multiple, δ, remaining after being dissipated in line is determined by the power ϵ, estimated in the main regression: $\frac{\delta-\theta}{r} = (\frac{\delta}{r})^{\epsilon}$. Standard errors calculated via delta method. Minimum wage as of 2012: BRL20.39. 2012 USD/BRL exchange rate: 0.5137

Table 18: Expected Attempts by Wage and Education

	Elementary	High School	College
w_{low}	41.59	64.41	19.41
	(91.64)	(146.89)	(15.23)
$w_{med.low}$	114.2	111.7	56.31
	(175.15)	(220.86)	(71.46)
w_{medium}	538.6	8,407.6	74.18
	(443.59)	(26,444.58)	(88.00)
$w_{med.high}$	836.8	418.3	89.99
	(702.08)	(326.01)	(132.66)
w_{high}		1,087.0	72.01
		(1,416.00)	(155.29)
Observations	931	1,776	3,355

Assuming an exponential distribution of attempts, the mean is the inverse of the probability of success, i.e. c/v

Table 19: Expected Wait Times by Wage and Education

	Elementary	High School	College
w_{low}	0.597	0.807	8.734
	(1.32)	(1.84)	(6.85)
$w_{med.low}$	3.211	1.217	2.293
	(4.93)	(2.41)	(2.91)
w_{medium}	179.5	177.2	0.706
	(147.86)	(557.38)	(0.84)
$w_{med.high}$	1,882.8	15.24	0.746
	(1,579.68)	(11.88)	(1.10)
w_{high}		2,445.8	0.477
		(3,186.00)	(1.03)
Observations	931	1,776	3,355

Measured in years. Assuming an exponential distribution of attempts, the mean waiting time is the inverse of the probability of success divided by the frequency of exams, i.e. $(c/v) \cdot (1/freq.)$

Table 20: Variance of Wait Times by Wage and Education

	Elementary	High School	College
w_{low}	2.084	4.036	120.8
	(18.07)	(48.90)	(200.75)
$w_{med.low}$	34.49	7.264	13.69
	(144.48)	(69.35)	(41.01)
w_{medium}	53,285.6	341,113.6	1.198
	(76,700.56)	(1.59e+06)	(3.50)
$w_{med.high}$	5,416,590.3	372.9	1.767
	(5.96e+06)	(630.81)	(9.38)
w_{high}		13,594,777.5	1.286
		(2.56e+07)	(11.62)
Observations	931	1,776	3,355

Measured in years. Assuming an exponential distribution of attempts, the variance of waiting time is the inverse of the probability of success divided by the frequency of exams squared, i.e. $[(c/v) \cdot (1/freq.)]^2$

3.6. Conclusion

In conclusion, we develop and test a model of queuing for public sector jobs in Brazil. The effective price controls, wage subsidies, and quotas imposed by the test-based public sector job system in Brazil generate the potential for large rents to be captured by its workers. Instead, our model implies that public sector workers actually capture none of these rents. The opportunity cost of the entry process – study time, training fees, and multiple test attempts in the queue – exactly offset these potential gains such that in equilibrium, the welfare of workers is approximately equalized across sectors.

Our empirical analysis bears out this prediction. Our best estimate suggests an average elasticity of approximately 1.1 between wages and applicants for public sector jobs. Since this is above 1, this implies that, after paying the entry cost, public sector workers are

Table 21: Constrained Competitor vs. Wage Regressions

	(1) 2xFE+freq.	(2) Wage Const.	(3) Vac. Const.	(4) Both Const.
Log hourly wage	1.1***	1	1.23***	1
	(0.00318)		(0.00331)	
Log vacancies	0.621***	0.619***	1	1
	(0.000688)	(0.000686)		
High school	-0.293***	-0.247***	-0.775***	-0.67***
	(0.00699)	(0.00682)	(0.00724)	(0.00708)
College	-1.9***	-1.81***	-2.31***	-2.1***
	(0.01)	(0.00962)	(0.0105)	(0.01)
Test frequency	0.0000989	-0.000267**	0.0000986	-0.000774***
	(0.0000893)	(0.0000885)	(0.0000932)	(0.0000924)
Test frequency^2	2.42e-07	8.23e-07***	-3.01e-07*	1.08e-06***
	(1.24e-07)	(1.22e-07)	(1.29e-07)	(1.28e-07)
Ind. FE	X	X	X	X
Year FE	X	X	X	X
RMSE	1.6263	1.6265	1.6979	1.6991
Observations	5,584,412	5,584,412	5,584,412	5,584,412

Regressions compare model fit with constraints on the coefficients of log hourly wage, log vacancies, or both. When a constraint is active, that coefficient is fixed at 1.

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

worse off in terms of observables than their private sector counterparts.[81] Given the years that applicants spend attempting to enter this sector, this should have been no surprise. Nevertheless, it is somewhat counter intuitive based on the discussion surrounding these jobs in popular media.

We thus arrive at practical advice for the aspiring government worker in Brazil. As in almost every other context, here too, there is no free lunch. Accounting for the total benefits *and* the total costs, the value of jobs in either sector is exactly the same despite the large nominal wage differential. Those with comparative advantages or with unique personal situations should, of course, continue to take these factors into account. But for the vast majority of workers, the only choice available is essentially one of timing: lower wages in the private sector now or higher wages in the public sector (potentially) much later.

3.7. Appendix

3.7.1. Alternative Specifications

81. Accounting for unobserved amenities, we expect that they are *exactly* equal

Table 22: Log Competitors vs. Log Wages

	(1) RE	(2) FE	(3) FE+freq.	(4) 2xFE+freq.	(5) 2xFE+freq.
Log hourly wage					
× Elementary	1.4***	1.45***	1.46***	1.85***	
	(0.00266)	(0.00406)	(0.00398)	(0.00396)	
× High school	1.25***	1.14***	1.09***	1.26***	
	(0.00119)	(0.00194)	(0.00191)	(0.00205)	
× College	0.364***	0.446***	0.429***	0.539***	
	(0.00172)	(0.00268)	(0.00263)	(0.00259)	
Constrained					1.1***
					(0.00173)
Log vacancies	0.637***	0.637***	0.635***	0.636***	0.621***
	(0.000242)	(0.000388)	(0.000381)	(0.00037)	(0.000374)
High school	0.0949***	0.335***	1.05***	0.833***	-0.293***
	(0.00609)	(0.00942)	(0.00953)	(0.00918)	(0.0038)
College	0.982***	0.665***	1.64***	1.34***	-1.9***
	(0.00766)	(0.0121)	(0.0122)	(0.0118)	(0.00546)
Test frequency			-0.00962***	0.000138**	0.0000989*
			(0.0000355)	(0.0000475)	(0.0000485)
Test frequency^2			0.0000125***	3.86e-07***	2.42e-07***
			(5.29e-08)	(6.58e-08)	(6.73e-08)
Ind. FE		X	X	X	X
Year FE				X	X
Observations	5,584,412	5,584,412	5,584,412	5,584,412	5,584,412
$R^2{}_{within}$	0.61	0.61	0.63	0.67	0.66
$R^2{}_{between}$	0.66	0.65	0.67	0.70	0.69
$R^2{}_{overall}$	0.65	0.65	0.67	0.71	0.70

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Log Competitors vs. Log Wages

	(1) RE	(2) FE	(3) FE+freq.	(4) 2xFE+freq.	(5) 2xFE+freq. (cons.)
Log hourly wage					
× Elementary	0.839***	0.832***	0.837***	1.03***	
	(0.00402)	(0.00608)	(0.00601)	(0.0061)	
× High school	1.09***	0.968***	0.912***	0.935***	
	(0.00181)	(0.00291)	(0.00289)	(0.00315)	
× College	0.46***	0.675***	0.654***	0.73***	
	(0.0026)	(0.004)	(0.00395)	(0.00397)	
Constrained					0.89***
					(0.00261)
High school	0.0333***	0.133***	0.976***	0.713***	0.516***
	(0.00924)	(0.0142)	(0.0145)	(0.0142)	(0.00571)
College	-0.285***	-0.818***	0.295***	-0.392***	-1.19***
	(0.0116)	(0.018)	(0.0184)	(0.0181)	(0.00823)
Test frequency			-0.0117***	-0.000609***	-0.000254***
			(0.0000536)	(0.0000733)	(0.0000734)
Test frequency^2			0.0000155***	2.05e-06***	1.51e-06***
			(7.98e-08)	(1.01e-07)	(1.02e-07)
Ind. FE		X	X	X	X
Year FE				X	X
Observations	5,657,585	5,657,585	5,657,585	5,657,585	5,657,585
$R^2{}_{within}$	0.14	0.14	0.16	0.23	0.23
$R^2{}_{between}$	0.22	0.21	0.24	0.26	0.26
$R^2{}_{overall}$	0.21	0.21	0.23	0.27	0.27

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Log Competitors vs. Log Wages

	(1) RE	(2) FE	(3) FE+freq.	(4) 2xFE+freq.
Log hourly wage	0.888***	0.872***	0.829***	0.89***
	(0.00143)	(0.00234)	(0.00232)	(0.00261)
High school	0.637***	0.453***	1.16***	0.516***
	(0.0024)	(0.00362)	(0.00471)	(0.00571)
College	-1.52***	-1.35***	-0.274***	-1.19***
	(0.00307)	(0.00475)	(0.00662)	(0.00823)
Test frequency			-0.0115***	-0.000254***
			(0.0000536)	(0.0000734)
Test frequency^2			0.0000153***	1.51e-06***
			(7.98e-08)	(1.02e-07)
Ind. FE		X	X	X
Year FE				X
Observations	5,657,585	5,657,585	5,657,585	5,657,585
$R^2{}_{within}$	0.14	0.14	0.16	0.23
$R^2{}_{between}$	0.21	0.21	0.23	0.26
$R^2{}_{overall}$	0.21	0.20	0.23	0.27

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.7.2. Measurement error

Assuming that individuals make decisions based on actual values of v and δ, but we observe error-ridden measures of v, we have that

$$y = \beta_\delta \delta + \beta_v v + \xi$$

where y is the number of candidates. Our goal is to analyse the effects of regressing y on δ and $(v + u)$, where u is random noise, independent of all other variables in the model. To begin, let's remember how the bivariate ols expression works.

$$\beta = \Sigma^{-1} Cov(y, X),$$

where $X = (\delta, v)$, and Σ is the covariance matrix of X.

Performing the matrix inversion, we obtain that:

$$\beta_\delta = \frac{Cov(y, \delta) - Cov(\delta, v)Cov(y, v)}{Var(\delta)Var(v) - Cov(\delta, v)Cov(\delta, v)}$$

In the special case that δ is uncorrelated with v we obtain the usual univariate regression. It is useful to re-write this expression emphasizing the relationship between δ and v. Let θ be the coefficient of a regression of v on δ, and note that the R squared of such regression is given by $Var(\delta)$ times θ squared. Thus, after some algebra, we have that:

$$\beta_\delta = \frac{\beta_\delta (1 - R^2_{v,\delta})}{1 - R^2_{v,\delta}}$$

When v is measured with error, the same steps yields the following result for the coefficient on δ.

$$\beta_{me} = \frac{A}{B}$$

where the numerator A is

$$A = Var[v+u]Cov(y,\delta) - Cov(\delta, v+u)Cov(y, v+u)$$

$$B = Var[v+u]Var[\delta] - Cov(\delta, v+u)Cov(\delta, v+u)$$

After some algebra, both of them can be written as:

$$A = Var[v+u](\beta_\delta Var[\delta] + \beta_v Cov(\delta, v)) - Cov(\delta, v)(\beta_\delta Cov(\delta, v) + \beta_v Var[v])$$

and

$$B = Var[\delta](Var[v+u](1 - R^2_{v+u,\delta})$$

After some more tedious algebra, we get:

$$\frac{A}{B} = \frac{\beta_\delta(1 - R^2_{v+u,\delta}) - \beta_v \theta_{\delta,v}(1 - \frac{Var[v]}{Var[v+u]})}{1 - R^2_{v+u,\delta}}$$

Note that if measured v is reliable (that is, variance of v+u is close to variance of v) then the last term in the numerator is zero and the ols coefficient coincides with the desired parameter, β_δ.

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Academic Instructor / Director of Operations, Air University, Maxwell AFB, AL 2019 – 2021

- Conducts economic research using Air Force personnel data
- Develops metrics for program assessment/instructional systems design
- Designs long range plans/supervises daily operations/training for 14 instructors
- Taught 116 officers 6 week, hands-on course: leadership/strategic design/joint warfare

Instructor Pilot - U-28A / Chief Resource Advisor, Cannon AFB, NM 2014 – 2019

- Chief financial planner/advisor for $1.3M squadron budget
- Led qualification/requalification/operational flight/classroom instruction for 88 pilots
- Conducted special operations intelligence, surveillance, and reconnaissance (ISR)/high value individual targeting
- Deployed multiple times supporting counter-terror for CENTCOM/AFRICOM commands
- 1,701.5 total flying hours (1,055.2 hours combat/combat support)

Pilot - C-130H / Scheduler, Little Rock AFB, AR 2013 – 2014

- Managed flight scheduling/matched aircrew requirements to sorties available
- Qualified airdrop (personnel and cargo)/short field (assault) takeoff and landing
- 200.1 total flying hours

Pilot - MC-12W, Little Rock AFB, AR 2011 – 2013

- Flew conventional ISR in Afghanistan: counter-Taliban/hostage rescue/overwatch
- 750.2 total flying hours (702.3 hours in combat)

Student Pilot, Undergraduate Pilot Training, Laughlin AFB, TX 2009 – 2011

- Obtained commercial pilot license: single and multiengine/instrument rating
- Completed 275.9 hour syllabus in T-6 (turboprop) and T-1A (jet) trainers

HONORS AND AWARDS

United States Air Force Academy Faculty Pipeline Program 2020

- 26 Air Force officers selected for PhD sponsorship/funding

Field Grade Officer of the Quarter 2020

- 33d Student Squadron: #1/15 officers

Field Grade Officer of the Quarter 2019

- 33d Student Squadron: #1/15 officers

Company Grade Officer of the Month 2017

- (deployed) Joint Special Operations Air Component: #1/58 officers

PUBLICATIONS

Smith, Andrew. 2020. "Convergence within SOCOM – A Bottom-Up Approach to Multi Domain Operations." Over the Horizon Journal, April 9, 2020. https://othjournal.com/2020/04/09/convergence-within-socom-a-bottom-up-approach-to-multi-domain-operations/

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