THE MAPINATOR CLASSIFICATION OF ECONOMICS DEPARTMENTS

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ABSTRACT. The paper provides a classification of economics departments into different tiers based on their graduate placements. The theory is based on a reverse directed search model while the classification into tiers is done using a stochastic block model. We estimate the markets perception of the value of graduates of the different tiers. These estimates suggest that graduates from second 'tier' schools are valued by the market at 86% of the value of graduates of first 'tier' schools.

This paper provides a classification of economics departments based on their graduate placements. It uses placement data collected during the Mapinator project. Departments are placed in a tier when their cross tier placements resemble those of other departments in the tier. This classification was done by James Yu at the University of British Columbia. The approach was suggested by Sam Gyetvay.

The adjacency matrix associated with this classification is given in the following table:

	Tier 1	Tier 2	Tier 3	Tier 4	Totals
Tier 1	568	109	23	10	710
Tier 2	586	258	87	21	952
Tier 3	762	681	350	58	1851
Tier 4	136	197	94	88	515
Teaching Unis	434	587	435	152	1608
Private Sector	460	225	89	11	785
Government	136	197	94	88	515
Totals	3082	2254	1172	428	6936

The rows in the table represent hires and the columns placements. Organizations who belong to each tier hire graduates from each of the other tiers. So, for example, Tier 1 organizations hired 568 gradates from other tier 1 organizations, but only hired 10 graduates from Tier 4 institutions.

The column represents placements. Most Tier 1 graduates are hired by Tier 3 universities for example. Tier 2 graduates are also most likely to be hired by Tier 3 departments. Teaching Universities are institutions that don't graduate Ph'd economists.

This paper explains the theory behind this classification and describes the methods that were used to create it. Our estimates suggest, for example, that graduates

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of Tier 2 universities generate placements that suggest the market assigns them a value that is 85% of the value of tier 1 graduates.[1]

Most theoretical literature on decentralized matching assumes that first best matching is assortative.[2] The basic presumption is that the best types on one side of the market want to match with the best types on the other side. Ideally, models provide enough of a characterization that observations of matching outcomes make it possible estimate the distribution of types that is driving them.

Even when matching is not particularly assortative, market participants are assumed to have distinctive preference types as, for example, Menzel (2015), where asymptotic stable matchings are characterized.

However in labor markets where workers offer complex skill sets, the distribution of types is arguably very coarse. This is true, for example, when graduate ph'd economists are hired. The number of applicants is large enough (around 3000 graduates each year according to econjobmarket.org and data from Fortin, Lemieux and Rehavi) that very fine grained distinctions between all applicants is very costly.

To cope with this departments often focus their search to a small number of departments characterized by top n departments. Letters often recommend applicants with phrases like "all but the top 20". What ranking is supposed to be used is unclear, as it the phrase "top" departments.

However, it seems that there is some agreement on what these phrases mean. This agreement reflects a market perception about where to look for graduates. This paper is an attempt to quantify this perception. Since everyone in economics believes they know what these market tiers are, this paper provides an opportunity to consider how this market perception could materialize in the first place, and to consider its implications.

One part of what we do in this paper is just a standard exercise in structural estimation, uncover the distribution of graduate types from outcomes. What makes this exercise unusual is that we expect this type distribution to be very coarse. Though it is clear the market classifies graduates into a small number of different types, it isn't clear how many of these types there are.

To begin, since this classification is an exercise in reducing evaluation costs, it is likely to be based on very crude and easily identified signals. In this paper we'll use the university that the applicant graduates from to represent this signal. There are other ways to do this. For example, graduates could be filtered by the department where they graduated, rather than the university where they graduated. Alternatively, an applicant's supervisors might provide a filter.

In any case, what we'll do here is to assume that each applicant from the same university has the same type. To find the distribution of types we'll classify universities into different tiers based on their placements. We use a stochastic block algorithm to choose the number of university types.

To explain why types will be revealed by cross-tier placements, we'll use a reverse directed search model borrowed from Peters (2010) to structure the placement process. Reverse directed search means that employers make offers, or apply, to applicants. Applicants may receive many offers, and choose the best one. The

[1]This estimate is based entirely on cross tier placements and has nothing to do with the quality of the research at Tier 2 universities.

[2]See for example, the survey Chade, Eeckhout, and Smith (2017).

coarseness of the type distribution among applicants creates a friction since departments who want to make offers cannot use observable characteristics among graduates to coordinate. This breaks down assortative matching.

The first section in the paper provides a characterization of the equilibrium of the reverse directed search model on the assumption that the tier structure is common knowledge. This characterization shows how cross tier placements are related.

Once we have done that, we try to estimate the values of the graduates in each tier. To do this, we use a kind of reverse directed search. In a standard directed search model, differences in wages paid by firms are used to predict employment rates and profits at different firm. In the academic job market in which hiring firms apply to workers, whatever corresponds to 'wages' isn't observable. So we try to infer what these implicit wages (i.e. values) from observable placement rates.

We use placement data gathered by the Mapinator Project devised by Amedeus D'Souza. This data contains placements of graduates from different departments in the period 2008 to 2021 (at this time of writing). A well known classification method [3] was then used to sort graduates in the data into their corresponding tiers. This process is described in this github repository. The method was suggested to us by Sam Gyetvay from the University of British Columbia.

A preliminary classification of departments can be viewed at this link. If you want to see the tier in which your own department is placed (and see what data is available for your department) you can see it at https://sage.microeconomics.ca/. In the 'Applicant Institution' box at the upper left delete the 'All' selector in the box and type a few letters in your department name until you see it listed. In the 'Placement Year' box at the top right of the display, choose 'All Years'. It will display all the data from your department.

If you scroll to the bottom of the page, you can see the tier in which your department is placed along with summary information.

The next section describes the underlying theoretical model and characterizes its equilibrium.

The Model. We start with a collection of organizations, $D \cup S$. The set D consists of organizations that graduate students who become applicants that can be hired by any organization. The set S consists of organizations that hire applicants but don't graduate their own applicants, for example, government, the private sector and teaching universities. We'll refer to them as sinks. Research universities in D act as both buyers and sellers, organizations in S are buyers only.

Applicants are all graduate from some department in D. Well divide the set of research universities who graduate applicants into k tiers (or types). A graduate from any department has a value v_t that depends on the graduating department's tier. Any organization who hires a graduate of a department from tier t receives a common payoff v_t.

There is a lot of randomness in demand and supply. We will basically ignore this and assume that the number of graduates to be placed each year is $m = \sum_{t=1}^{k} m_t$ where m_t is the number of graduates from tier t.

Offers and matching. Part of the logic in this paper comes from the assumption that academic tiers are related the same way their graduates are. The idea is that

[3] For example Peixoto (2014), or Karrer and Newman (2011).

a job offer from a first tier university will likely be more valuable to a graduate than one from a second tier university.

However, we'll assume that the value of offers is stochastic. Hiring departments from the lowest tier will sometimes have offers that are preferred by applicants to any of the offers available from the higher tier universities. We assume that when an organization of type t decides to make an offer, the value of that offer to applicants is drawn from a distribution F_t that depends on the department's tier. Each of these distributions will be assumed to have full support on $[0,1]$ and to have strictly positive densities.

What binds the academic tiers to its graduates is the the distributions F_t from which the values of its offers are drawn is the same for all organizations in the same tier.

Organizations know their own types, and the value x of any offer they make. However, they don't know the values of the offers of their competitors. This is partly because the offer values are random and privately observed. However, the ultimate point of this paper is to decide if a coarse type characterization is a good one. For this reason, we'll assume that organizations don't know the types of their competitors.[4] For a randomly drawn competitor, there is some prior probability ρ_t with which the competitor has type t. Conditional on this competitor's type being t, the probability this competitor has a value that is no larger than x is given by $F_t(x)$. Since organizations are unsure of the types of their competitors, the probability a randomly drawn competition has an offer whose value is no larger than x is

$$F(x) = \sum_{t \in D \cup S} \rho_t F_t(x).$$

With this preamble, each hiring department sees the graduates from each tier, then chooses one and only one of them, and makes him or her an offer. The applicant accepts the highest offer it receives. If the offer is accepted, the applicant gets x while the department gets v_t where t is the applicant's tier. If the offer isn't accepted, the department who makes the offer gets nothing. Similarly if an applicant receives no offers it gets nothing.

Let $\tilde{\pi}^i_{jt}(x)$ be the probability with which organization j with an offer of value x makes an offer to applicant i in tier t. We'll restrict attention only to symmetric equilibrium outcomes. These have two properties: $\tilde{\pi}^i_{jt}(x) = \tilde{\pi}^i_{j't}(x) \equiv \tilde{\pi}^i_t(x)$ for all pairs j and j' of organizations; and $\tilde{\pi}^i_t(x) = \tilde{\pi}^{i'}_t(x) \equiv \frac{\tilde{\pi}_t(x)}{m_i}$ for every applicant i in tier t. In this notation, $\tilde{\pi}_t(x)$ is the probability with which an organization with an offer of value x makes it to *some* applicant from tier t. The probability the organization makes this offer to any particular applicant in tier t is $\frac{\tilde{\pi}_t(x)}{m_i}$.

A symmetric equilibrium for this game is a vector valued rule $\{\tilde{\pi}_t(x)\}_{t \in T}$ such that $\sum_t \tilde{\pi}_t(x) = 1$ for all x and $\tilde{\pi}_t(x) > 0$ only if

$$v_t \left(1 - \int_x^1 \frac{\tilde{\pi}_t(\tilde{x})}{m_t} dF(\tilde{x})\right)^{n-1} \geq v_{t'} \left(1 - \int_x^1 \frac{\tilde{\pi}_{t'}}{m_{t'}}(\tilde{x})\, dF(\tilde{x})\right)^{n-1}$$

for every $t' \neq t$ for almost every $x \in [0,1]$.

[4]For example, we could assume that organizations are unsure whether or not their competitors are on the market at all.

Equilibrium. The problem is now to characterize the equilibrium. This problem is effectively the same problem as the one discussed in Peters (2010), so a similar theorem applies here, except that the rule has to be adapted because types are coarse.

The different applicants have types t that generated expected payoffs v_t. Order the types so that $v_1 \geq v_2 \geq \dots v_{|T|}$.

Theorem. *There is a finite collection of cutoffs $\{x_0, x_1, \dots, x_K\}$ and a set of constants $\{\pi_j\}_{j=1,k}$ such that $x_0 = 1$, and for each $t > 1$ if $x \in [x_t, x_{t-1})$*

$$\tilde{\pi}_j(x) = \begin{cases} \pi_j \prod_{j<i\leq t} (1-\pi_i) & j \leq t \\ 0 & \textit{otherwise.} \end{cases} \tag{0.1}$$

Any department or institution who has an offer x will randomize when choosing where to make its offer, except when $x \in [x_1, 1)$. In the latter case the department will make its offer for sure to some applicant in the top tier. For offers that whose value exceeds x_t offers are made with positive probability to each tier whose applicants have a value that is at least v_t.

Organizations within the same tier have the same distribution of behavior with respect to offers to all the other tiers. This suggests that types can be identified by looking at the pattern of their placements to all tiers, not just their own.

The next section proves this theorem. One objective is to show how the various probabilities π_j and cutoffs x_j can be computed recursively from the various parameters, including the unobservable values v_j.

Proof:

Lemma 1. *Suppose F is monotonically increasing. There is a type x_1 such that if an organization has an offer of value $x > x_1$, then the only symmetric equilibrium strategy has them making the offer to one of the tier 1 applicants and choosing each applicant with equal probability.*

Proof. The payoff to making an offer to a tier 1 applicant is v_1 times the probability that it is accepted. It is accepted by the candidate if the candidate has no other offers, or if it is the highest value offer the candidate receives. So the payoff when an organization with an offer of value x makes an offer to a top tier applicant is

$$v_1 \left(1 - \int_x^1 \tilde{\pi}_1(\tilde{x})\, dF(\tilde{x})\right)^{n-1} \geq$$

$$v_1 \left(1 - \frac{(1-F(x))}{m_1}\right)^{n-1}.$$

This inequality follows from symmetry. If $\pi(\tilde{x})$ is the probability with which any organization with a value of $\tilde{x}$ makes an offer to *some* tier 1 applicant, and $\frac{1}{m_1}$ is the symmetric probability with which an offer is made to any particular tier 1 applicant, then the left hand side of the equation attains a maximum if $\pi(x)$ is uniformly 1.

Now choose x_1 such that

$$v_2 = v_1 \left(1 - \frac{(1-F(x_1))}{m_1}\right)^{n-1}$$

then any offer whose value exceeds x_1 will earn a strictly higher expected payoff when it is offered to a tier 1 applicant than it would if it were offered to a tier 2 (or lower) applicant. □

An immediate corollary is that for x in $(x_1, 1]$, $\tilde{\pi}(x) = \frac{1}{m_1}$ is the probability with which an organization with an offer of value x makes an offer to any one of the m_1 tier 1 applicants. Note that this mixing probability $\tilde{\pi}(x)$ is independent of x on this interval. Furthermore, x_1 is the solution to

$$1 + m_1 \left(\left(\frac{v_2}{v_1} \right)^{\frac{1}{n-1}} - 1 \right) = F(x_1) \tag{0.2}$$

if a positive solution exists. If no solution exists with x_1 in $[0,1]$ then $x_1 = 0$ and all offers go to candidates in the highest tier.

The next Lemma extends the argument to all other active tiers.

Lemma. *Suppose that there is a tier $t > 1$ and cutoff $x_{t-1} > 0$ such that every symmetric equilibrium has the property that there is a sequence of pairs $\{(x_k, \pi_k)\}_{k=1,t-1}$ with $\pi_1 = 1$, and $0 < \pi_k < 1$ such that for any tier $k \leq t-1$*

- *the probability that any offer x goes to an applicant in tier k conditional on the offer going to an applicant in tier k or higher is π_k ;*
- *the expected payoff associated with making an offer x to any tier $k \geq 1$ is the same for every $x \leq x_{k-1}$;*
- *the expected payoff associated with making an offer to tier k is strictly higher than the expected payoff associated with making an offer to tier $k+1$ for every $x > x_k$.*

Then there is a cutoff $x_t \geq 0$ such that () to () hold when π_t satisfies

$$\pi_t = \frac{\pi_{t-1}}{\pi_{t-1} + \left(\frac{v_t}{v_{t-1}} \right)^{\frac{1}{n-1}} \frac{m_{t-1}}{m_t}} \tag{0.3}$$

and x_t satisfies

$$v_{t+1} = v_t \left(1 - \frac{\pi_t}{m_t} \left(F(x_{t-1}) - F(x_t) \right) \right)^{n-1} \tag{0.4}$$

or

$$F(x_{t-1}) - \frac{m_t}{\pi_t} \left(1 - \left(\frac{v_{t+1}}{v_t} \right)^{\frac{1}{n-1}} \right) = F(x_t)$$

Proof. From Lemma 1, organizations whose offer x lies in $[x_1, 1)$ make an offer to an applicant in tier 1 with probability $\pi_1 = 1$ independent of their type in any symmetric equilibrium because it is a dominant strategy. So (), () and () hold for tier 1 and cutoff x_1.

For $x < x_{t-1}$, let $\tilde{\pi}_t(x)$ be the probability with which the offer is made to a tier t applicant and $1 - \tilde{\pi}_t(x)$ be the probability the offer is made to an applicant from one of the higher tiers. By (), organizations with offers of value $\tilde{x} > x_{t-1}$ do not make offers to any applicants from tier below tier $t-1$, for example, from tier t. Then the payoff associated with an offer to any tier t applicant is

$$v_t \left(1 - \frac{\int_x^{x_{t-1}} \tilde{\pi}_t(\tilde{x})\, dF(\tilde{x})}{m_t} \right)^{n-1}. \tag{0.5}$$

The expected payoff to an offer of value $x < x_{t-1}$ made to any higher tier $k \leq t-1$ is the same by (). the payoff to making the offer to a tier $t-1$ applicant is

$$v_{t-1}\left(1-\frac{\int_{x}^{x_{t-1}}\left(1-\tilde{\pi}_t\left(\tilde{x}\right)\right)\pi_{t-1}dF\left(\tilde{x}\right)}{m_{t-1}}-\frac{\pi_{t-1}\left(F\left(x_{t-1}\right)-F\left(x_{t-2}\right)\right)}{m_{t-1}}\right)^{n-1}. \tag{0.6}$$

If there is an open interval below x_{t-1} where other organizations make their offers to v_t for sure. Let $\underline{x}$ and $\overline{x}$ be the greatest lower and least upper bounds on this region. Then for $x \in (\underline{x}, \overline{x})$, the payoff from making the offer to v_{t-1} is given by

$$v_{t-1}\left(1-\frac{\int_{\overline{x}}^{x_{t-1}}\left(1-\tilde{\pi}_t\left(\tilde{x}\right)\right)\pi_{t-1}dF\left(\tilde{x}\right)}{m_{t-1}}-\frac{\pi_{t-1}\left(F\left(x_{t-1}\right)-F\left(x_{t-2}\right)\right)}{m_{t-1}}\right)^{n-1} \geq$$

$$v_t\left(1-\frac{\int_{\overline{x}}^{x_{t-1}}\tilde{\pi}_t\left(\tilde{x}\right)dF\left(\tilde{x}\right)}{m_t}\right)^{n-1} >$$

$$v_t\left(1-\frac{\int_{x}^{x_{t-1}}\tilde{\pi}_t\left(\tilde{x}\right)dF\left(\tilde{x}\right)}{m_t}\right)^{n-1}.$$

The first inequality follows because $x \geq \overline{x}$ makes an offer to an applicant in tier $t-1$ with positive probability. The second follows since $x < \overline{x}$ and and a set $x' \in (\underline{x}, \overline{x})$ of positive measure make an offer to an applicant in tier t with probability 1.

This gives a profitable deviation.

A similar argument when $\tilde{\pi}_t(x)$ is zero an any open interval, implies that in any symmetric equilibrium

$$(v_t)^{\frac{1}{n-1}}\left(1-\frac{\int_{x}^{x_{t=1}}\tilde{\pi}_t\left(\tilde{x}\right)dF\left(\tilde{x}\right)}{m_1}\right)= \tag{0.7}$$

$$(v_{t-1})^{\frac{1}{n-1}}\left(1-\frac{\int_{x}^{x_{t-1}}\left(1-\tilde{\pi}_t\left(\tilde{x}\right)\right)\pi_{t-1}dF\left(\tilde{x}\right)}{m_{t-1}}-\frac{\pi_{t-1}\left(F\left(x_{t-1}\right)-F\left(x_{t-2}\right)\right)}{m_{t-1}}\right)$$

for almost all x.

Uniform equality requires the derivatives of these two functions to be equal, or

$$(v_t)^{\frac{1}{n-1}}\frac{\tilde{\pi}_t\left(x\right)}{m_1}=(v_{t-1})^{\frac{1}{n-1}}\frac{\left(1-\tilde{\pi}_t\left(x\right)\right)}{m_{t-1}}\pi_{t-1}$$

which gives

$$\left(\frac{v_t}{v_{t-1}}\right)^{\frac{1}{n-1}}\frac{m_{t-1}}{m_t}\tilde{\pi}_t\left(x\right)=\left(1-\tilde{\pi}_t\left(x\right)\right)\pi_{t-1}$$

$$\left(\left(\frac{v_t}{v_{t-1}}\right)^{\frac{1}{n-1}}\frac{m_{t-1}}{m_t}+\pi_{t-1}\right)\tilde{\pi}_t\left(x\right)=\pi_{t-1}$$

or

$$\tilde{\pi}_t\left(x\right)=\frac{\pi_{t-1}}{\pi_{t-1}+\left(\frac{v_t}{v_{t-1}}\right)^{\frac{1}{n-1}}\frac{m_{t-1}}{m_t}}.$$

This verifies properties () for tier t.

Finally, define x_t to be the solution to

$$v_t\left(1-\frac{\pi_t\left(F\left(x_{t-1}\right)-F\left(x\right)\right)}{m_t}\right)^{n-1}=v_{t+1}$$

to get (0.4). □

Corollary 2. *Strategies $\tilde{\pi}$ are defined by*

$$\tilde{\pi}_j\left(x\right)=\begin{cases}\frac{1}{1+\left(\frac{v_j}{v_{j-1}}\right)^{\frac{1}{n-1}}\frac{m_{j-1}}{m_j}}\prod_{j<i\leq t}\left(1-\frac{1}{1+\left(\frac{v_i}{v_{i-1}}\right)^{\frac{1}{n-1}}\frac{m_{i-1}}{m_i}}\right) & j\leq t\\ 0 & \textit{otherwise.}\end{cases}$$

Using the main theorem. The idea is then to use the theoretical framework given by Theorem and Lemma to do two things: (i) use the structure of cross tier placements to place organizations into tiers; then (ii) estimate the values and distributions that fit best the adjacency matrix given by Table .

The probability an organization successfully hires an applicant in tier t

$$\left(1-\int_x^1\frac{\tilde{\pi}_t\left(\tilde{x}\right)}{m_t}dF\left(\tilde{x}\right)\right)^{n-1}. \tag{0.8}$$

The probability that an organization from tier s hires an applicant from tier t is given by the following formula:

$$h_s^t=\int_0^1\tilde{\pi}\left(x'\right)\left(1-\int_x^1\frac{\tilde{\pi}_t\left(\tilde{x}\right)}{m_t}dF\left(\tilde{x}\right)\right)^{n-1}dF_s\left(x'\right) \tag{0.9}$$

The probability that an organization from tier s fails to hire is

$$1-\sum_{t\in D}h_s^t. \tag{0.10}$$

For computational purposes we can rewrite this using theorem .

$$Q_t\left(x\right)=$$

$$\left(1-\int_x^1\frac{\tilde{\pi}_t\left(\tilde{x}\right)}{m_t}dF\left(\tilde{x}\right)\right)^{n-1}=$$

(0.11)

$$\left(1-\left(F\left(x_{s-1}\right)-F\left(x\right)\right)\frac{\pi_t}{m_t}\prod_{i=t+1}^{s}\left(1-\pi_i\right)-\sum_{k=t}^{s-1}\left(F\left(x_{k-1}\right)-F\left(x_k\right)\right)\frac{\pi_t}{m_t}\prod_{i=t+1}^{k}\left(1-\pi_i\right)\right)^{n-1}$$

whenever $x\in[x_s,x_{s-1});s\leq t$, while it is equal to 1 when $x_{t-1}\leq x$.

The probability that an organization from tier i hires an applicant in tier t is then given by

$$h_i^t=\sum_{s=t}^{T}\int_{x_s}^{x_{s-1}}\pi_t\prod_{i=t+1}^{s}\left(1-\pi_i\right)Q_t\left(\tilde{x}\right)dF_i\left(\tilde{x}\right). \tag{0.12}$$

We'll start with the observables. These will include the total number of hiring departments, and the decomposition into the number in each tier, $n=n_1+n_2\ldots+n_T$. This gives the weights $\rho_t=\frac{n_t}{n}$ used to construct F. One major issue comes from the fact that the potential number of hiring departments n and the number of departments who fail to hire is not observed.

To approach this, we calibrate these numbers by using the set of departments who recorded placements over a 5 year period, to approximate the actual number of hiring departments who were active in each year. This data was taken from the mapinator placement data itself.

The number of applicants m_i in each tier is observable in theory by using registration data from econjobmarket. There are two complications with this. The first is that the econjobmarket.org website allowed graduates to record their degree granting distribution by hand prior to 2018. As a consequence only a fraction of all the applicants have been properly assigned to academic departments prior to 2018.

A better measure of the allocation of graduates to tiers is available for the years 2019 to 2021. However there were pandemic years, and registrations look much different in those years than they did previously. As a consequence it is hard to tell how closely these allocations correspond will allocations in prior years.

The second potential difficulty is that not all graduates register with econjobmarket. Data provided by Fortin, Lemieux and Rehavi records the set of graduates from US universities between 2009 and 2017 using public records. Their data suggests that over 90% of all the graduates from US universities during this period had corresponding accounts at econjobmarket. Econjobmarket has registrations from graduates of European Universities. Whether the coverage rate is the same is so far impossible to know.

We use a couple of approaches to deal with this. One uses the allocations from 2019 to 2021 and assumes they apply in previous years. Then we can just use the total number of registrations in each of those previous years, then use the ratios from 2019-2021 to calculate the m_i.

The second approach we tried was to use the data on placement of applicants to different tiers using the data from previous years for which these allocations had been properly recorded. We then assigned the applicants whose affiliations hadn't been recorded using the proportions from the recorded data in the same proportions as was found in the data that had been properly recorded. This didn't work very well in estimation, suggesting that the data collection process isn't random.

Finally we recorded the proportions of applicants in each tier from placement data, then used those proportions to calculate the m_i for the entire market.

Our current estimates use placement data from 2015 to 2020. There were a total of 1909 distinct organizations who were recorded hiring graduates during the 2015 to 2020 period. Organizations who did hire, hired an average of 1.6 applicants in each year. So our calibrated estimates use $n =$3068.

For comparison, an average of 3065 applicants registered on econjobmarket in each of those years.

The unobservables then consist of the payoffs $\{v_t\}_{t \in D}$ and the distributions $\{F_t\}_{t \in T}$ from which offer values are drawn. We used a parametric collection of distributions, all truncated normal on the interval $[0, 1]$. Each distribution F_t is then characterized by it mean α_t^m and variance α_t^v.

Estimation. To estimate the values in v and the distributions that make up F we used placement data from 2015 to 2020. We treated Government, Private Sector and Teaching placements as a single sink organization. The stochastic block assignment of organizations into tiers again yielded four academic tiers. The corresponding adjacency matrix for those years is given below:

	T1	T2	T3	T4
T1	333	79	15	9
T2	346	211	55	20
T3	448	422	238	27
T4	51	76	48	54
Non-Academic	1044	917	548	179

To estimate the number of positions available each year, we took the total number of distinct organizations that hired applicants at some point during the 5 year period. This turned out to be 1909. For organizations that did hire, the average number of positions that they hired for each year was 1.6. Multiplying the two together gives the average number of open position each year at 3054.

The average number of graduates each year who reported to econjobmarket.org that they were completing their phd degrees during the year was 3075, suggesting a rough balance between demand and supply.

From this data, we want to estimate four values $v = (v_1, v_2, v_3, v_4)$ to assign to the graduates of each of the tiers. Since these payoffs are all to be interpreted as cardinal utility values, we normalized the value to tier 1 graduates to 1, leaving the other three values to be determined.

We also want to estimate the distributions of offer values for each of the tiers. For this purpose we assumed that these values had truncated normal distributions with support on $[0, 1]$.

There are 5120 placements of fresh phd graduates in the adjacency matrix above. The assumption here is that each of the individual outcomes that make up the adjacency matrix is the the result of an independent draw that places the outcome in one of the 20 cells in the matrix. So the probability that each such placement is assigned to category (i, j) is $\frac{n_i}{n} h_i^j$, where h_i^j is the probability that an organization in tier i hires from tier j.

This makes the expected number of graduates from tier j hired by some organization in tier i during the sample period $y n_i h_i^j$ where y is the number of years included in the sample.

Since we are basically comparing a realized and actual distribution over a finite number of types, we can use χ-squared test to look for differences. So we choose the 3 value parameters and the 10 parameters that define the offer distributions to minimize

$$\sum_{i,j} \frac{(o_{ij} - y n_i h_{ij})^2}{y n_i h_{ij}}$$

where o_{ij} is the realized outcome in each cell.

The values for h_i^j are given by (0.12), so they are functions of the values and distributions. So minimizing the χ-squared value above will yield estimates of h_{ij}. If the estimation simply involved choosing h_i^j to minimize this, then the minimization would occur when $\hat{h}_{ij} = \frac{o_{ij}}{y n_i}$, at which point the χ^2 value above would be zero. The value and distributional parameters that minimize this sum will not do this because the h_i^j are all restricted by these parameters.

The various estimates are given in the worksheet this worksheet. The parameters that minimize the χ-squared statistic above give the following estimates:

- Tier 1 value 1
- Tier 2 value 0.8635

- Tier 3 value 0.5139
- Tier 4 value 0.2294
- F_1 mean 0.6614 std-dev 0.2329
- F_2 mean 0.5803 std-deviation 0.1851
- F_3 mean 0.3908 std-deviation 0.103
- F_4 mean 0.2832 std-deviation 0.1395
- Sink mean .3712 std-deviation 0.1218

The corresponding χ-squared value is 8.36 = p value .7562.

For completeness, here is the allocation of departments to type:

TYPE 1

Columbia University University of Pennsylvania University of Wisconsin, Madison Boston University New York University Cornell University Northwestern University Ohio State University University of California, Berkeley London School of Economics and Political Science University of Minnesota, Twin Cities Harvard University University of California Los Angeles (UCLA) Yale University Stanford University University of Toronto University of Michigan Duke University University of Maryland Princeton University University of Chicago

TYPE 2

Rice University Massachusetts Institute of Technology University of Rochester Vrije Universiteit Amsterdam London Business School University of Bonn (Rheinische Friedrich-Wilhelms-Universität Bonn) Syracuse University University of Arizona University of California, San Diego Boston College University of Warwick Toulouse School of Economics University of Virginia National University of Singapore University of British Columbia Maastricht University University of Southern California University of Washington Singapore Management University Washington State University Clemson University University of California, Riverside University of Cambridge McGill University University of Oxford Michigan State University University of Texas at Austin University of California, Davis University of Mannheim (Universität Mannheim) Stockholm University Vanderbilt University Erasmus University Rotterdam Tilburg University Bocconi University (Università Bocconi) Universitat Pompeu Fabra Purdue University Washington University in St. Louis Brown University Johns Hopkins University University of Notre Dame Carnegie Mellon University Texas A&M University, College Station Pennsylvania State University University College London University of Connecticut University of Nottingham Stockholm School of Economics George Washington University University of Illinois at Urbana-Champaign Arizona State University Universidad Carlos III de Madrid University of California, Santa Barbara University of Colorado, Boulder

TYPE 3

University of Massachusetts, Amherst Lancaster University Eastern Kentucky University Peking University University of Lausanne (Université de Lausanne) Georgetown University Universidad de los Andes Hong Kong Baptist University Simon Fraser University Colorado State University University of Leicester University of Amsterdam (Universiteit van Amsterdam) Wuhan University George Mason University Drexel University University of Miami Concordia University University of Kentucky National Taiwan University Auburn University University of Kent ETH Zurich (Swiss Federal Institute of Technology; Eidgenössische Technische Hochschule) University of Edinburgh National Research University Higher

School of Economics, Moscow Norwegian School of Economics (NHH) University of St Andrews Western University City University of Hong Kong Australian National University University of Copenhagen (Københavns Universitet) Carleton University Wayne State University University of Groningen (Rijksuniversiteit Groningen) California Institute of Technology (Caltech) Aalto University University of Nebraska, Lincoln Katholieke Universiteit Leuven (KU Leuven) University of North Carolina, Chapel Hill University of Ottawa Rutgers, The State University of New Jersey Georgia Institute of Technology Indiana University Bloomington Copenhagen Business School Miami University University of Vienna (Universität Wien) University of Sydney University of New Mexico University of Utah University of Glasgow Sciences Po University of Hong Kong University of South Carolina University of Missouri, Columbia Queen Mary University of London Iowa State University Aarhus University Koç University University of Calgary Stony Brook University (SUNY) École d'Économie de Paris (Paris School of Economics) Goethe-Universität Frankfurt am Main Monash University Oregon State University Queen's University Fudan University University of Exeter University of Florida Binghamton University (SUNY) Hong Kong University of Science and Technology West Virginia University University of Oklahoma University of New South Wales (UNSW), Sydney Imperial College London Florida International University CERGE-EI (Center for Economic Research and Graduate Education – Economics Institute) University of Essex University of California, Irvine University of Oregon New York University Abu Dhabi University of Tennessee, Knoxville University of Alberta North Carolina State University Georgia State University Southern Methodist University Chinese University of Hong Kong Universíté de Montréal (University of Montreal) Kansas State University University of Cologne (Universität zu Köln) BI Norwegian Business School University of Guelph University of Kansas Nanyang Technological University University of Houston University of Alabama Shanghai University of Finance and Economics University of Bristol University of Sussex University of Melbourne University of California, Santa Cruz INSEAD Texas Tech University Louisiana State University Tulane University University of Gothenburg (Göteborgs Universitet) Baruch College, City University of New York University of Illinois at Chicago University of Pittsburgh Northeastern University Ryerson University University of Arkansas CEMFI University of Georgia Tsinghua University Utrecht University (Universiteit Utrecht) Middle Tennessee State University McMaster University European University Institute Ludwig-Maximilians-Universitat München (LMU) (University of Munich) Oklahoma State University Birkbeck College, University of London University of Delaware Florida State University Uppsala University (Uppsala Universitet) Virginia Tech Università di Bologna (University of Bologna) University of Hawai'i at Mānoa Universidad de Navarra Université Libre de Bruxelles Emory University American University Universitat Autònoma de Barcelona University of Zurich (Universität Zürich) Lund University (Lunds Universitet) Fundação Getulio Vargas (FGV) Temple University

TYPE 4

Indian Statistical Institute, Delhi University of Oslo Bentley University ESMT Berlin (European School of Management and Technology) Insper (Institute of Education and Research) University of Vaasa Korea University LUISS Guido Carli University of Bern (Universität Bern) Université catholique de Louvain Stellenbosch University University of Adelaide Central Michigan University University of Texas at Arlington Cochin University of Science and Technology University of Limerick Kurukshetra University Trinity College Dublin, University of Dublin ESCP Business School (École supérieure de commerce de Paris) Harbin Institute of Technology, Shenzhen University of Liverpool Martin Luther University of Halle-Wittenberg (Martin-Luther-Universität Halle-Wittenberg) Shiv Nadar University Universiteit Antwerpen (University of Antwerp) Freie Universität Berlin International Monetary Fund (IMF) Ecole Polytechnique (IP Paris) University of Nevada, Las Vegas (UNLV) Hebrew University of Jerusalem Université Laval EDHEC Business School (Ecole des Hautes Etudes Commerciales du Nord) University of Innsbruck (Universität Innsbruck) The New School Humboldt University Berlin (Humboldt-Universität zu Berlin) Middle East Technical University Universidad de Alicante (University of Alicante) University of Bath Université de Bordeaux (University of Bordeaux) University of Waterloo Penn State Abington Bharathidasan University Bilkent University (Bilkent Üniversitesi) University of Iowa Brandeis University City University of London Vienna Graduate School of Finance (VGSF) Deakin University Ghent University Heriot Watt University Massey University Universidade Nova de Lisboa Université de Genève (University of Geneva) Kyoto University Sabancı University Delft University of Technology (Technische Universiteit Delft) Royal Melbourne Institute of Technology (RMIT) Suffolk University Royal Holloway, University of London Zhejiang Gongshang University University of South Florida University of Tasmania Indian Institute of Management Bangalore Marquette University Occidental College Clark University Indian Institute of Management Indore IMT School for Advanced Studies Lucca York University SKEMA Business School Technical University of Crete Loyola Marymount University University of Queensland Université de Strasbourg (University of Strasbourg) University of New Orleans Ball State University Northern Illinois University Middle East Technical University - Northern Cyprus Campus St. Thomas University University of East Anglia University of Surrey University of Northern British Columbia Universitat de Barcelona University of Manchester Quaid-i-Azam University Howard University University of Leeds University of Victoria Otto-von-Guericke University Magdeburg Central European University University of Cape Town Towson University National Central University University of Tirana (Universiteti i Tiranës) University of Konstanz (Universität Konstanz) Universiti Malaysia Perlis Universitat de València (University of Valencia) Ca' Foscari University Venice (Università Ca' Foscari) City University of New York Graduate Center Vienna University of Economics and Business Wabash College Università Degli Studi di Milano (University of Milan) Loughborough University University at Albany (SUNY) University of Maine, Orono University College Dublin Universidad de Zaragoza University of South Alabama Sam Houston State University Università della Svizzera Italiana (University of Lugano) University of Wisconsin, Milwaukee Università Cattolica del Sacro Cuore University of Lisbon (Universidade de Lisboa) SOAS (School of Oriental and African Studies), University of London University of Nevada, Reno University of Mississippi California State Polytechnic University, Pomona University of Luxembourg (Université du Luxembourg/Universität Luxemburg) Seoul National University Heidelberg University Frankfurt School of Finance & Management Universitat Rovira i Virgili Indian Institute of Technology, Kanpur Johannes Kepler University Linz University of Saskatchewan Universiti Utara Malaysia MINES ParisTech Kiel Institute for the World Economy Universidad Pontificia Comillas

University of Warsaw (Uniwersytet Warszawski) Università degli Studi di Firenze (University of Florence) University of Tokyo Colorado School of Mines Texas A&M International University Claremont Graduate University Chr. Michelsen Institute (CMI) Federal University of Paraná (Universidade Federal do Paraná) Technische Universität Berlin Bank of Finland University of Strathclyde Academia Sinica University of Colorado, Denver Dalian University of Technology DePauw University University of Texas at Dallas University of Helsinki (Helsingin yliopisto) Université Paris-Dauphine University of Wyoming National Research University Higher School of Economics, St. Petersburg HEC Paris SUNY Buffalo State Hong Kong Polytechnic University ESSEC Business School

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Appendix - Example. The simplest example that contains all the features of the model has 3 academic tiers and one sink. This section just gives the details for computational purposes. The value of applicants in tier 1 is v_1, while $v_3 < v_2 < v_1$ provide the values of the other tiers. The number of hiring organizations in each tier is n_i for $i \in T$. The number of graduates in each tier is m_i for $i \in D$. We'll take these as fixed exogenously here.

By Theorem , we can calculate everything recursively starting with $\pi_1 = 1$. Then

$$\pi_2 = \frac{1}{1 + \left(\frac{v_2}{v_1}\right)^{\frac{1}{n-1}} \frac{m_1}{m_2}}$$

and

$$\pi_3 = \frac{\pi_2}{\pi_2 + \left(\frac{v_3}{v_2}\right)^{\frac{1}{n-1}} \frac{m_2}{m_3}}$$

Similarly, x_1 is given by the solution to

$$v_1 \left(1 - \frac{\int_x^1 dF\left(\tilde{x}\right)}{m_1}\right)^{n-1} = v_2$$

or

$$F\left(x\right) = 1 - m_1 \left(1 - \left(\frac{v_2}{v_1}\right)^{\frac{1}{n-1}}\right).$$

Since there are only three tiers in this example, there is only one other cutoff, x_2, given by the solution to

$$v_2 \left(1 - \frac{\int_x^{x_1} \tilde{\pi}_2 (\tilde{x})\, dF(\tilde{x})}{m_2}\right)^{n-1} = v_3$$

or

$$F(x) = F(x_1) - \frac{m_2}{\pi_2}\left(1 - \left(\frac{v_3}{v_2}\right)^{\left(\frac{1}{n-1}\right)}\right).$$

The 'cutoff' for tier 3, so to speak, is zero.

We can now calculate the various acceptance probabilities. For example, $Q_1(x)$ is

$$\left(1 - (1 - F(x))\frac{1}{m_1}\right)^{n-1}$$

when $x > x_1$;

$$\left(1 - (F(x_1) - F(x))\frac{(1-\pi_2)}{m_1} - (1 - F(x_1))\frac{1}{m_1}\right)^{n-1}$$

when x is between x_2 and x_1; and

$$\left(1 - (F(x_2) - F(x)) - (F(x_1) - F(x_2))\frac{(1-\pi_2)}{m_1} - (1 - F(x_1))\frac{1}{m_1}\right)^{n-1}$$

when $x < x_2$.

Similar formulas apply for $Q_2(x)$ and $Q_3(x)$.

Finally, we can write the formulas for h_1^1,h_2^1 and h_3^1. They are basically all the same except that the distribution that is used to do the integration is different.

$$h_i^1 =$$

$$\sum_{s=t}^{T}\left\{\int_{x_s}^{x_{s-1}} \pi_t \prod_{i=t+1}^{s}(1-\pi_i)\, Q_t(\tilde{x})\, dF_i(\tilde{x})\right\} =$$

$$\int_0^{x_2} (1-\pi_3)(1-\pi_2)\, Q_1(x)\, dF_i(x) +$$

$$\int_{x_2}^{x_1} (1-\pi_2)\, Q_1(x)\, dF_i(x) +$$

$$\int_{x_1}^{1} Q_1(x)\, dF_i(x).$$

At the other extreme, the probability h_i^3 is

$$\int_0^{x_2} \pi_3 Q_3(x)\, dF_i(x)$$

since only offers with values less than x_2 will be directed at tier 3 applicants.