EXECUTIVE SUMMARY

Labor Market Outcomes and Postsecondary Accountability: Are Imperfect Metrics Better than None?

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May 16, 2016

Abstract: Policymakers at the state and federal level are increasingly pushing to hold institutions accountable for the labor market outcomes of their students. There is no consensus, however, on how such measures should be constructed, or how the choice of measure may affect the resulting institutional ratings. Using state administrative data that links postsecondary transcripts and in-state quarterly earnings and unemployment records over more than a decade, we construct a variety of possible institution-level labor market outcome metrics. We then explore how sensitive institutional ratings are to the choice of labor market metric, length of follow-up, and inclusion of adjustments for student characteristics. We also examine how labor market metrics compare to the academic-outcome-based metrics that are more commonly incorporated into state accountability systems. We conclude that labor market data, even when imperfect, *can* provide valuable information distinct from students' academic outcomes. Institutional ratings based on labor market outcomes, however, are quite sensitive to the specific metric. The most obvious labor market metric – average earnings within a year after graduation – proves to be highly unreliable, unduly influenced by incoming student characteristics, and fails to capture other aspects of economic wellbeing that may be valued by both policymakers and students themselves. Our findings suggest a cautious approach: while a mix of feasible labor market metrics may be better than none, reliance on a single unadjusted earnings metric, especially if measured too early, may undermine policymakers' ongoing efforts to accurately quantify institutional performance.

I. Introduction

In his 2013 State of the Union address, President Obama gave voice to growing frustration with the rising costs of college by calling for institutions to be "[held] accountable for cost, value, and quality" and promising to provide students and families with more and better information to evaluate "where you can get the most bang for your educational buck" (U.S. Department of Education, 2013). In September 2015, the Obama administration took a major step towards this goal by releasing an updated version of its College Scorecard, which for the first time provided information not just on college costs and graduation rates, but also on the post-college earnings of students at over 4,000 institutions nationwide.

The postsecondary accountability agenda is even more advanced at the state level. Over the past three decades, numerous states have pushed to improve the effectiveness of higher education systems by aligning funding with student academic outputs rather than to inputs such as student enrollment and credit hours (Dougherty & Reddy, 2011; SRI International, 2012).[1] The idea behind such policies is that reporting and rewarding measures of institutional outputs generates both better information and stronger financial incentives to improve the decision-making processes of prospective consumers, policymakers, and institutions (Dougherty & Reddy, 2013).

As of late 2015, more than half of states were already utilizing some form of performance or "outcomes-based" funding, with another 10 in the process of implementing it (Snyder, 2015). In the context of higher education, "performance funding" typically means funding institutions based on student outcomes such as course completion and/or degree completion, as opposed to simply counting numbers of students enrolled or numbers of credits attempted. While in most states the portion of state funding that is performance-based remains small—typically less than 10 percent—two states (Tennessee and Ohio) now base the majority of institutional funding on performance-based metrics.

Accountability efforts increasingly look beyond just credit and credential completion to what some view as the "holy grail" of student outcomes: measures of post-college labor market success, such as those provided by the most recent federal College Scorecard data. While state higher education agencies cannot access the federal earnings database used to produce the College Scorecard, many have been able to link graduates to in-state quarterly earnings data collected for the administration of state Unemployment Insurance (UI) programs. Taking advantage of such linkages, multiple states now offer interactive data tools enabling students and families to examine employment and earnings of students who graduate from in-state public institutions, by program of study. Nine states incorporate job placement, employment and earnings data into their performance funding formulae, as least for portions of their postsecondary sectors. And the Texas State Technical College System now uses information on students' post-college earnings as the *sole* criteria for making funding recommendations to the Texas legislature (Texas Higher Education Coordinating Board, 2013).

There is no consensus, however, on how such labor market measures should be constructed, nor is there much evidence regarding how the choice of measure may affect the resulting institutional

[1] A cost-plus approach is a traditional budgeting strategy, in which public colleges and universities primarily based their projected budgetary needs on current costs, student enrollments and inflationary increases.

ratings. While the College Scorecard provides earnings for all entrants 10 years after entry, states using labor market data in performance funding formulae typically examine outcomes for graduates less than a year after graduation. Should schools be held accountable for all students, or just those who graduate? Does it matter whether employment/earnings are measured one, two, or ten years post-graduation? What difference does it make if metrics are adjusted to account for the incoming characteristics of the student population? And is it possible to use labor market data to examine more than just average earnings?

In this paper, using administrative data from one state that links postsecondary transcripts to in-state quarterly earnings and unemployment records (from the state's UI database) over more than a decade, we construct a variety of possible institution-level labor market outcome metrics. Our goal is not to identify the "best" metric, but to explore how sensitive institutional ratings may be to the choice of metric, length of follow-up, and inclusion of adjustments for student characteristics. We also examine how labor market metrics compare to the academic-outcome-based metrics that are more commonly incorporated into state accountability systems.

II. Conceptual and practical challenges to using state labor market data

This section describes the challenges and tradeoffs that state policymakers are likely to confront when considering using labor market data for postsecondary accountability. This discussion helps motivate the variety of metrics that we create and compare in the subsequent analysis.

A. Productivity versus student composition

First and foremost, it is one thing to simply measure student outcomes, and another thing entirely to assign all credit (or blame) for those outcomes to the institution. This critical distinction—between simply measuring student outcomes versus measuring institutions' true productivity given equivalent student populations—has helped motivate a small but growing literature using rigorous empirical strategies to measure institutions' true causal effects or "value-added" (Hoekstra, 2009; Dale & Krueger, 2002, 2011; Hoxby, 2015; for a review, see Executive Office of the President, 2015).

Unfortunately, there is no guarantee that state policymakers will have access to both the right data and the right "natural experiment" to rigorously estimate specific institutions' impacts on student outcomes. A more generally feasible strategy is to compute institutional "fixed effects" that use regression analysis to control for any differences in student outcomes that are attributable to observable student characteristics, such as age, race/ethnicity, gender, location of residence at entry, and declared major. In our analysis, we compute both unadjusted institutional mean outcomes as well as adjusted outcomes using an increasingly rich set of controls. Even with our richest model, however, we do not attempt to interpret the resulting institutional fixed effects as causal. Nor are we able to identify the method that most closely approximates a causal analysis. Our modest goal is to evaluate how much these choices actually matter in practice.

B. Measuring outcomes beyond earnings

A fundamental critique that has been leveled against the use of earnings data for post-secondary accountability is that earnings may fail to capture many other positive impacts of education. For example, institutions that send many graduates into teaching or social service jobs will perform worse on earnings-based metrics than those that send many graduates into finance. Even within a given industry, individuals make tradeoffs between wages and other "job amenities" such that wages alone may be a poor summary of overall labor market success. In addition, policymakers (and individuals) may care more about earnings differences at the bottom of the income distribution than in the middle or at the top, but neither average nor median wage metrics will reflect this. Finally, ideally measures of postsecondary accountability would include not just measures of labor market success, but also measures of health and wellbeing.

State UI databases obviously cannot measure all relevant possible institutional effects. Still, even within UI databases it is possible to construct a more diverse range of metrics to capture dimensions beyond earnings. For example, UI data can be used to look at the stability of employment over time (such as whether individuals are employed full-time for the entire year, or how many employers they have had in a given period). Information on industry of employment can also be used to measure employment in "social service" sectors such as teaching or government. Finally, actual unemployment claims can be examined as a measure of job loss. We describe the specific additional measures that we create in Section III below.

C. Outcomes for whom? Graduates versus entrants

While the federal College Scorecard provides median earnings for all entrants, not just those that graduate, most states that examine earnings outcomes do so for graduates only.[2] The argument for looking only at graduates is twofold: first, institutions may have limited influence over the earnings of students who drop out, and second, given the vast differences in earnings of graduates versus non-graduates, averaging across both groups may be a poor summary of either group's typical outcomes. On the other hand, examining the earnings only of graduates may seriously distort institutions' overall productivity if they graduate only a fraction of entrants.

Our resolution to this tradeoff is to examine labor market outcomes for graduates only, but to examine these metrics alongside graduation metrics that *are* measured for all students. This avoids the problem of interpreting labor market metrics that muddles both margins, while still holding institutions accountable for both. One limitation of this strategy is that it will not credit institutions that are particularly effective or ineffective at increasing the earnings of non-graduates relative to graduates. In general, however, it seems reasonable to assume that whatever the earnings payoff to graduating from a given institution, the payoff to attending but not graduating may be proportional to the fraction of the degree that was completed (indeed, empirical evidence on the returns to credits from Kane & Rouse [1999] supports this proportional payoff hypothesis).

D. Interstate mobility

A major challenge in using state UI databases to measure earnings is that such databases typically include information only for individuals who remain in state (though some states do have data sharing agreements with bordering states).[3] Individuals who leave the state are

[2] The Texas State Technical College System is an exception, examining earnings for all students who have either graduated, transferred, or otherwise left the system for at least two years (THECB, 2013).

[3] In addition, UI databases do not include those who are self-employed, some student employees (e.g., work-study students), railroad workers, some agricultural workers, and federal employees. Despite coverage gaps relative to

indistinguishable from those who are in state, but simply not working. Moreover, as mobility accumulates over time, this problem worsens the longer the follow-up period. In part to minimize this issue, the states that provide information on graduates' employment and earnings often do so within a relatively short period of time post-graduation (e.g. three to six months), and condition earnings metrics upon at least some level of observed employment.

Examining earnings conditional on in-state employment has the advantage of avoiding confounds not just from out of state mobility, but also from individual choices regarding labor force participation. On the other hand, such measures will also miss important effects institutions may have on the likelihood of finding and maintaining employment in the first place. Our solution is to look at graduates in four subsequent quarters in a focal year. If they show up in the earnings data at all, we make the assumption that they are part of the in-state labor force. We then construct measures of full-time full-year employment, social service sector employment, and unemployment receipt only for those who appear in the data in that year. For earnings, we further condition on a proxy measure of full-time, full-year employment (described in more detail in the methodology section below).

E. Timing of outcomes measurement

Measures of employment and earnings from relatively early in the life cycle can be not only noisy, but also potentially biased measures of lifetime earnings. Recent graduates may take some time to settle into a good job match, and earnings may grow rapidly as new skills are acquired on the job. It is conceivable that some individuals with the highest long-term earnings potential may have lower-than-expected earnings if measured soon after graduation, because for these individuals it may be worthwhile to take longer to find a good job match and to continue to invest in additional skills/education both on and off the job. Evidence suggests that the optimal time to measure individuals' earnings is not until their early thirties to mid-forties (Haider & Solon, 2006).

From an accountability perspective, such a long lag time is impractical. To be useful, accountability metrics should reflect institutional performance from a relatively recent period. In addition, the longer the lag between graduation and labor market observation, the more serious the interstate mobility problem becomes. But how recent is too recent? Outcomes measured mere months after graduation may reflect mostly noise, or worse—they could be inversely correlated with outcomes over a longer period of time. For our analysis, we measure labor market outcomes four years after graduation, but also test variations from 6 months to 7 years post-graduation.

III. Empirical methodology

A. Data and Sample

De-identified data on students entering public postsecondary institutions within a single state over an eight-year period were provided under a limited-use, restricted data agreement. The data include students' demographic characteristics, entrance and enrollment records, major choice, and certificate and degree completion from each of the state's higher education institutions (universities, branch campuses, and community colleges). These are linked to elements from

self-reported survey data, prior research has found UI data to provide comparable estimates of program impacts (Kornfeld & Bloom, 1999).

state unemployment insurance (UI) data over a ten-year period, including quarterly earnings and unemployment claims to enable us to examine students' labor market outcomes. The data do not include any measure of students' academic ability upon admission (such as SAT/ACT scores, high school grade point average or test scores, or college entrance or placement exam scores), nor do they include financial aid application data or family income information. The data do include information on financial aid receipt for some years; however, for this project we choose to prioritize elements that are available for all analytic cohorts.

B. Methods and metrics

Our basic methodology includes the following six steps, which we discuss in more detail below:

1) Construct outcomes of interest at the individual level.
2) Define key analysis groups: graduates by degree level, degree institution, program and year; entrants by institution, major, and year.
3) Compute mean outcomes by group (for now, we focus on institution-level rather than program-level comparisons).
4) Compute regression-adjusted "institutional fixed effects" to account for compositional differences across institutions.
5) Standardize group-level means/fixed effects in order to be able to compare metrics that have different natural scales.
6) Assess resulting metrics using correlation matrices and graphical analysis.

Outcomes. We construct four labor market accountability metrics based on cohorts of BA/BS graduates for four-year institutions and cohorts of certificate/degree completers for two-year institutions. We examine outcomes in the fourth full calendar year post-graduation (so, for a Spring 2002 graduate, this would be calendar year 2006). We test sensitivity to examining these outcomes earlier or later, from 6 months to 7 years post-graduation. To avoid contaminating our estimates with out-of-state mobility (those who move out of state are indistinguishable from those in state but not working), we limit all labor market measures to individuals who have at least some in-state earnings during the focal year. Currently, we are not restricting our samples to those who are not subsequently enrolled, an issue we will return to in our interpretation of findings. Additional details on each outcome and its rationale are below:

1) Full-time, full-year employment (proxy). This measure is intended to capture the stable employment margin: what percent of graduates are substantially and consistently engaged in the labor market? We do not have any measure of full-time status or hours worked, so we approximate this as employment in all four quarters of the year, with real earnings in each quarter above an amount roughly corresponding to 35 hours per week at minimum wage.[4]

2) Annual earnings conditional on full-time, full-year employment. This is intended to capture the intensive earnings margin. This is the sum of real quarterly earnings, adjusted to constant 2013 dollars. In practice since we cannot observe hours of work, this measure captures both variation in wages as well as variation in hours.

[4] The minimum wage for [State] in 2013 was 7.85 dollars according to the US Department of Labor. Therefore, the average quarterly minimum wage for full-time employees in 2013 was approximately 4,396 dollars.

3) Employment in "social service" sectors. The rationale for this measure is to give credit for potential positive social externalities of public/social sector employment; and to acknowledge that some sectors offer benefits and job protections that are not captured by wages alone. Since we only have industry codes in the employment data, this is only a rough proxy and is driven largely by employment in educational services.

4) Percent ever claiming unemployment since graduating. This is intended to capture particularly negative employment outcomes that might carry additional weight in policymakers' social welfare function and might not be captured by average earnings. As opposed to the other outcomes, this is a cumulative metric.

5) Degree completion (or transfer) within 150% of time (3 years for two-year entrants, 6 years for 4-year entrants). For two-year entrants, we include completion of any credential, including short-term certificates (less than one year), long-term certificates (more than one year) and associate's degrees, as well as students who transferred to a four-year institution within three years of entry. We count students as completers regardless of whether they completed at their entry institution. Note, however, that the data only track students in public in-state institutions, so students who transfer to a private institution or out of state will not be counted here.

Key analysis groups. For the labor market metrics, we use 6 cohorts of baccalaureate and sub-baccalaureate graduates/transfers who earned their first degree or certificate (or transferred, for two-year students) between 2000 and 2005. We examine baccalaureate and sub-baccalaureate institutions separately in all analyses. For now, we aggregate across those who graduated in different years but plan eventually to test sensitivity of these measures across years. We also aggregate across fields of study within a given institution; however, in our adjusted models we do control for differences in field mix across institutions.

Computing mean outcomes. The first and simplest thing to do once outcomes are constructed is to compute mean outcomes by campus. It is also straightforward to compute them by program or program-campus; for simplicity we focus on campus. An obvious concern, however, is that differences in outcomes across campus will reflect many factors other than institutional performance: they could reflect differences in students' fields of study, background characteristics (age, race, gender), or differences in local labor markets. This suggests the need to adjust these observed means for compositional differences, a process we describe below.

Computing regression-adjusted institutional fixed effects. The institutional "fixed effect" is simply the estimated contribution of the institution to students' outcomes after accounting for other factors via regression analysis. If no other factors are included in the regression, the fixed effect is equivalent to the unadjusted institutional mean. Our most complete regression model (run separately for two-year and four-year institutions) is the following, run on the individual-level data (we run this without a constant, in order to estimate a full set of institution fixed effects):

$$(1)\ y_i = instFE + majorFE + \delta X_i + entZIPFE + \varepsilon_i$$

where *i* indexes individuals, y_i is a labor market or academic outcome, *instFE* is a vector of institutional fixed effects (entered as a set of dummy variables indicating the institution initially attended), *majorFE* is a vector of discipline areas using the two-digit CIP major category[5], X_i is a vector of individual background characteristics including gender, race/ethnicity, age, and dummy variables for missing values in student characteristics, and *entZIPFE* is a vector of student's residence or ZIP codes at entry fixed effects. We add these covariates in groups to help understand which appear most important.

Controlling for ZIP code at entry is a way to account both for regional differences in family wealth/SES, which we have no other way to capture, as well as to account for differences in local labor markets. Note these ZIP codes are at initial enrollment, not the time of actual employment. This is preferable because controlling for location at employment (which we do not have in any case) could potentially absorb some of the real impacts of a successful education, if graduates migrate to stronger labor markets in-state. For first-time college students enrolled in a two-year institution, we also added fixed effects for different categories of students' declared intent at entry (e.g. upgrade skills, train for a new career, transfer before completing, obtain a AA/AS degree).

Standardizing institutional means/fixed effects. Once the institutional fixed effects are estimated, an entirely separate challenge is what to do with them. It can be particularly difficult to detect patterns across metrics when the metrics are all in different natural scales. While the simplest solution might be to simply rank the institutions on each metric and compare the ranks, this is also limiting because the ranks eliminate valuable information on how far apart institutions are from each other—a small difference in ranks could represent a huge difference in institutional outcomes for some measures but not others, or could represent large difference in the tails of the distribution but not in the middle.

We thus take the middle path of standardizing the institution-level fixed effects by subtracting the overall mean and dividing by the standard deviation. The result is a standardized rating metric that expresses how far above or below the mean the institution is, in standard deviation units for that outcome. This allows us to more easily compare across our different metrics, but note that it produces inherently *relative* ratings. If policymakers were to use this standardization process in practice, it may make sense to standardize using the mean and standard deviation for an earlier cohort, so that institutions could show improvement over time. Note that this standardization is performed separately for four-year and two-year institutions.

Assessing results. We examine correlations across metrics to see which analytic choices are particularly consequential for the resulting ratings, and which are not. In addition, we use graphs to illustrate the range of ratings institutions receive across measures.

In these graphs, each vertically-aligned set of points represents an institution's rating on one of our five measures (standardized to mean zero and s.d. of one, to enable comparisons across metrics). If a point lies above zero, that indicates the institution rates above average on that metric. A point at -2, on the other hand, would indicate an institution fell two standard deviations below the institutional mean for that metric.

[5] We use the 2010 Classification of Instructional Programs (CIP) list to create discipline areas.

To the extent all points for a given institution are very tightly clustered, that indicates consistency in the institution's rating across metrics. If the points are very far apart vertically (i.e. for a given institution), it means that an institution's rating could be dramatically different depending upon the measure used. Finally, to help reveal patterns in the data, most graphs are sorted by the degree completion metric (including transfers for two-years), with the lowest ranking institution on this metric on the left and the highest ranking on the right. This makes it easy to identify how top institutions on this metric fare on the labor market metrics, and vice versa.

IV. Key preliminary findings

While newly accessible state UI databases present great opportunities for enhancing states' ongoing efforts to measure college student outcomes, it is no straightforward task to figure out how to use these data most effectively. We draw the following tentative conclusions from our analyses:

1. *Earnings-based metrics alone are unlikely to capture all of the relevant information that can be gleaned from state UI databases.* Our four labor market metrics, while all positively correlated with BA/BA completion rates in the four-year sector and generally positively correlated with each other, do appear to capture different aspects of post-college labor market success, and institutions could receive markedly different ratings depending upon which measure or group of measures is used.

2. *Institutional metrics based upon degree completion/transfer versus labor market outcomes are much less correlated in the two-year sector than in the four-year sector.* Indeed, metrics based upon degree completion/transfer rates are negatively correlated with 3 of our 4 labor market outcome metrics. This suggests either that degree completion/transfer are relatively poor proxies for students' longer term outcomes; alternatively, these labor market measures may be particularly contaminated or deceptive for two-year graduates.

3. *Statistical adjustments for differences in student composition matter greatly for some measures (earnings and social sector employment) but less so for others (full-time, full-year employment rates).* To the extent adjusting for student composition matters a lot, it suggests caution in attempting to interpret unadjusted measures, but it does not necessarily imply that the adjusted measures represent truth. It is possible that even our fully adjusted model omits important factors that if incorporated, could change institutions' ratings further. Moreover, it is clear that incorporating statistical adjustments improves the consistency of institutional ratings across metrics.

4. *For earnings-based metrics in the four-year sector, statistical adjustments for differences in student composition appear more important when outcomes are measured early.* This suggests states may be able to choose between using an adjusted measure soon after graduation, or an unadjusted measure after a longer period of time, depending upon which is more feasible. This tradeoff is not evident, however, for the two-year sector.

5. *Statistical adjustments appear to affect institutional ratings based on labor outcomes more in the two-year sector than in the four-year sector.* In both sectors, field of study and zipcode appear to be more influential than student demographics (age, race, gender). In contrast to the findings for the four-years, these statistical adjustments do not appear to become any less important over time for two-year colleges (with the possible exception of for our UI metric).

6. *When we examine the correlation of our metrics over different lengths of follow up, we find that our* ***adjusted*** *conditional earnings metric is relatively stable over time in both the two- and four-year sectors.* In the four-year sector the correlation of 7 year earnings with earnings measured earlier ranges from 0.88 to 0.91 while in the two-year sector the equivalent correlations range from 0.79 to 0.97. The correlation of other adjusted metrics over time depends on the metric and the sector.

Limitations. These analyses are preliminary and we may yet perform additional tests that change these conclusions. Currently we use several cohorts of entrants/graduates to estimate each institution's fixed effect. We have not yet examined what would happen if these effects were estimated with only one or two cohorts at a time. We have not incorporated any controls for student ability or family income, which have been used in other studies of accountability metrics. For the two-year sector, it may be more appropriate to exclude any students with continued enrollment after degree/transfer from the labor market analyses. We want to rule out ongoing enrollment as an explanation for the negative correlations we find. However, given that these negative correlations persist up to 7 years post-graduation, it is possible that excluding ongoing enrollment will not dramatically alter the patterns found here.

Conclusion. Overall, our preliminary conclusion is that labor market data, even when imperfect, can provide valuable information distinct from students' academic outcomes. Institutional ratings based on labor market outcomes, however, are quite sensitive to the specific metric constructed. The simplest labor market metric at policymakers' disposal– unadjusted average earnings within a year after graduation – proves to be relatively unreliable, substantially influenced by incoming student characteristics, and fails to capture other aspects of economic wellbeing that may be valued by both policymakers and students themselves. Our findings suggest a cautious approach: while a mix of feasible labor market metrics may be better than none, reliance on any one metric—particularly an unadjusted metric measured early—may unintentionally undermine policymakers' ongoing efforts to accurately quantify institutional performance.

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