

# FORECASTING COMMUNITY COLLEGE ENROLLMENT

October 2016



In the following report, Hanover Research examines best practices for developing enrollment forecasting models for community colleges. The report assesses model variables and forecasting tools and profiles models used by institutions across the United States.

# TABLE OF CONTENTS

<b>Executive Summary .....</b>	<b>3</b>
INTRODUCTION .....	3
KEY FINDINGS.....	3
<b>Section I: Enrollment Forecasting Strategies.....</b>	<b>5</b>
OVERVIEW OF FORECASTING STRATEGIES .....	5
FORECASTING MODELS.....	6
Case Study: Predicting Student Hours .....	9
ENROLLMENT FORECASTING TOOLS.....	10
Enrollment Forecasting Software .....	11
Enrollment Forecasting Consultants.....	11
<b>Section II: Enrollment Prediction Variables .....</b>	<b>13</b>
ECONOMIC INDICATORS.....	13
COMBINING MULTIPLE VARIABLES .....	14
Case Study: Multiple Characteristics Used by Yavapai College .....	14
ENROLLMENT FORECASTING STRATEGIES AND CHARACTERISTICS FOR STOPOUT STUDENTS .....	16
<b>Section III: Enrollment Forecasting Model Profiles .....</b>	<b>19</b>
CALIFORNIA COMMUNITY COLLEGES .....	19
METROPOLITAN COMMUNITY COLLEGE .....	20
TEXAS HIGHER EDUCATION COORDINATING BOARD .....	22

# EXECUTIVE SUMMARY

## INTRODUCTION

As community colleges face decreased funding from state sources, it is increasingly important for colleges to be able to project enrollment numbers for the coming years. Accurately estimating enrollment can help institutions to more effectively determine funding streams, capital outlay projects, and potential space and campus needs. To track future enrollment effectively, individual institutions must implement accurate enrollment forecasting models that take into account the unique context and needs of the college.<sup>1</sup>

In the following report, Hanover Research (Hanover) examines enrollment forecasting strategies and models used by community colleges across the United States. The report is intended to provide a broad understanding of forecasting model options and their benefits and challenges. The report includes the following three sections:

- **Section I** reviews a variety of enrollment forecasting models and strategies, as well as analytical tools for forecasting.
- **Section II** examines the characteristics and variables that institutions may consider when projecting enrollment. This section also discusses specialized variables that may be used to model enrollment for student subgroups.
- **Section III** provides in-depth profiles of enrollment forecasting models used at one community college and two community college systems.

## KEY FINDINGS

- **Common enrollment forecasting models include linear regression and time series analyses, but institutions often use a combination of different approaches.** It is essential for institutions to tailor an enrollment forecasting model to their needs and goals. Consequently, institutions typically use components from multiple models to account for the particular geographic, financial, enrollment, or demographic trends of the institution.
- **A panel time series regression model can reduce the chances of forecasting errors.** This approach, used by Hanover Research in its enrollment forecasting for community colleges and other higher education institutions, increases the sample size of observations by incorporating historical data from other, similar institutions. A standard time series regression model, for instance, might use 20 years of data for one institution (i.e., just 20 observations); a panel time series regression model, by

---

<sup>1</sup> See, for example: [1] Mitchell, M., and M. Leachman. "Years of Cuts Threaten to Put College Out of Reach for More Students." Center on Budget and Policy Priorities, 2015. <http://www.cbpp.org/research/state-budget-and-tax/years-of-cuts-threaten-to-put-college-out-of-reach-for-more-students>

[2] Kurz, K. and J. Scannell. "Enrollment Management Grows Up." *University Business*, May 2006. <https://www.universitybusiness.com/article/enrollment-management-grows>

incorporating historical enrollments for 50 or more comparable institutions, can increase the number of observations to more than 1,000.

- **Institutions generally evaluate the accuracy of an enrollment forecasting model by assessing historical projections data.** The accuracy of six-month or one-year projections can be determined relatively quickly, while the accuracy of longer-term projections may take a number of years to assess. Moreover, longer-term projections often cannot take into account qualitative trends, such as the overall economic health of an area or institutional program changes.
- **Projections for specific subgroups of students, such as stopouts, can often be determined through a segment analysis and an examination of student satisfaction variables.** Many institutions use an enrollment projections model to examine student subgroups, such as stopouts. Once an institution identifies key variables that define its stopout students, a forecasting model can be limited to these variables to determine stopout projections. A 2013 study of community college retention also suggests that examining student satisfaction variables can be valuable in determining re-enrollment projections.
- **Most enrollment forecasting models examine variables related to enrollment and credit hours, demographics, budgets and expenditures, population, and state and local high school graduation.** A combination of variables allows institutions to develop a comprehensive picture of potential future enrollments. Variables are typically from available historical data from the institution or public sources. Some institutions also include qualitative factors in their analyses to account for regional or institutional trends that may affect enrollment in the future.
- **Many institutions develop custom enrollment forecasting models, but some use analytical software tools designed for forecasting or partner with consulting firms.** For example, Kennesaw State University uses the SAS Business Intelligence Platform to develop both long-term and short-term enrollment models, while Howard Community College partners with ASR Analytics to build an enrollment forecasting model that integrates historical enrollment, unemployment, and high school graduate data.

## SECTION I: ENROLLMENT FORECASTING STRATEGIES

In this section, Hanover reviews multiple enrollment forecasting models and strategies used by a sample of community colleges.

### OVERVIEW OF FORECASTING STRATEGIES

Enrollment management and forecasting is a constantly evolving facet of higher education. Enrollment forecasting models and strategies have grown increasingly complex in response to greater and more far-reaching needs and applications of data. Forecasting models are highly contextual and commonly based on an institution's mission and goals. Institutions should adjust their forecasting approaches over time as their institutional challenges and goals or student demographic changes.<sup>2</sup>

Community colleges may face more complicated challenges than four-year public or private institutions when developing enrollment projections, as they typically enroll more non-traditional students. Non-traditional students often present greater demographic variance (such as age, work competencies, and educational backgrounds) that must be accounted for in any projection analysis. The diversity of characteristics among non-traditional students may present community colleges with greater analytical challenges than less diverse traditional college students.<sup>3</sup> In addition, community college students often do not follow a "regular enrollment pattern" and instead require more sophisticated forecasting models.<sup>4</sup>

*Community colleges typically attract non-traditional students with irregular enrollment patterns, and it can be challenging to develop accurate enrollment forecasting models for these institutions.*

Despite these complexities, predictive analytics can provide numerous benefits for community colleges, including improved understandings of student recruitment, enrollment management, capital outlay needs, and budget predictions. Enrollment forecasting works as an integral part of many broader efforts toward strategic long-term decision making at a community college. Figure 1.1 details how enrollment forecasting can affect or contribute to four key areas of interest in higher education management.

<sup>2</sup> Kurz and Scannell, Op. cit.

<sup>3</sup> Guo, S. "Three Enrollment Forecasting Models: Issues in Enrollment Projection for Community Colleges." Research and Planning, Chancellor's Office, California Community Colleges. Presented at the 40<sup>th</sup> RP Conference, May 2002. pg. 4.

[http://ibrarian.net/navon/paper/Three\\_Enrollment\\_Forecasting\\_Models\\_Issues\\_in\\_En.pdf?paperid=306140](http://ibrarian.net/navon/paper/Three_Enrollment_Forecasting_Models_Issues_in_En.pdf?paperid=306140)

<sup>4</sup> Miller, K. "Predicting Student Retention at Community Colleges." Ruffalo Noel Levitz, 2015. [https://www.ruffalonl.com/documents/gated/Papers\\_and\\_Research/2015/CommunityCollegeStudentSatisfaction.pdf?code=401211830201628](https://www.ruffalonl.com/documents/gated/Papers_and_Research/2015/CommunityCollegeStudentSatisfaction.pdf?code=401211830201628)

**Figure 1.1: Applications for Enrollment Forecasting Across an Institution**

<p><b>Student Recruitment</b><sup>5</sup></p>	<ul style="list-style-type: none"> <li>Enrollment projections can statistically identify likely students (by demographics, location, program of study, GPA, etc.), as well as identify and target high schools with high populations of likely students.</li> </ul>
<p><b>Enrollment Management</b><sup>6</sup></p>	<ul style="list-style-type: none"> <li>As a key aspect of enrollment management, projections use demographic, labor market, and student demand data to predict the state of the economy (which often correlates with increases and decreases in community college enrollment).</li> </ul>
<p><b>Budget Predictions</b><sup>7</sup></p>	<ul style="list-style-type: none"> <li>Enrollment projections should be a key consideration during strategic long-term budgetary planning. It is important to use a quantitative model, document assumptions, examine existing plans, account for uncertainty, and regularly evaluate and adjust the forecast.</li> </ul>
<p><b>Capital Outlay Needs</b><sup>8</sup></p>	<ul style="list-style-type: none"> <li>While operating budgets typically require two years of enrollment projections, 10-year enrollment projections are essential to make necessary long-term decisions about new campuses, centers, and other physical spaces.</li> </ul>

## FORECASTING MODELS

Community colleges across the United States use a variety of forecasting models to determine long-term projections for enrollment. Some institutions recommend a combination of models, while other institutions explore different models over time. According to the Association of Institutional Research (AIR), there are nine categories of enrollment forecasting models. A college’s choice of which model to use depends on “the availability of data, user skills, appropriateness of method, cost, and usability of the software packages.”<sup>9</sup> Figure 1.2 on the following page summarizes these nine models and their salient characteristics.

<sup>5</sup> “Possibilities for Improving Student Success Using Predictive Analytics.” The RP Group, September 2014. p. 5-6. [http://rpgroup.org/system/files/Predictive%20Analytics%20Environmental%20Scan\\_FINAL.pdf](http://rpgroup.org/system/files/Predictive%20Analytics%20Environmental%20Scan_FINAL.pdf)

<sup>6</sup> Ibid.

<sup>7</sup> “Best Practices in Community College Budgeting.” Government Finance Officers Association. p. 3. <http://www.gfoa.org/sites/default/files/u36/1B-2014.07.01.pdf>

<sup>8</sup> “California Community Colleges Long-Range Master Plan.” California Community College Chancellor’s Office, 2016. p. 18. [http://californiacommunitycolleges.cccco.edu/Portals/0/Reports/MasterPlan\\_2016\\_ADA\\_Final.pdf](http://californiacommunitycolleges.cccco.edu/Portals/0/Reports/MasterPlan_2016_ADA_Final.pdf)

<sup>9</sup> “An Integrated Enrollment Forecast Model.” *IR Applications*, American Institutes of Research, (15), January 18, 2008. p. 3. <http://files.eric.ed.gov/fulltext/ED504328.pdf>

**Figure 1.2: Nine Categories of Enrollment Forecasting Models**

MODELS	DESCRIPTIONS
<b>Subjective Judgment</b>	When objective measures are not available, qualitative research of current trends and estimates of influential factors and future events can help predict general enrollment trends.
<b>Ratio Method</b>	This method predicts future first-year enrollments by examining historical and projected high school graduation data.
<b>Cohort Survival Study</b>	This model predicts retention rates by examining the ratio of returning students in a single cohort. It can be extended to predict future enrollment.
<b>Markov Transition Model</b>	By tracking enrollments from one year to the next, this model “predicts the probabilities of future occurrence based on currently known probabilities.”
<b>Neural Network Model</b>	Running this analysis for one variable can “train” the model to predict enrollment across many other variables and can process information “in parallel and non-linear capabilities.”
<b>Simulation Method</b>	This is a complex model that can modify inputs to assess “what-if” scenarios by considering multiple, interrelated variables.
<b>Time Series Analysis (ARIMA)</b>	This model predicts enrollment by collecting data points sequentially through equally spaced time periods. Correlations from one time period to another reveals reliable forecasts.
<b>Fuzzy Time Series Analysis</b>	This technique primarily relies on data mining approach to forecast enrollment rather than explain enrollment changes.
<b>Regression Analysis</b>	This model can predict enrollment “as soon as the key indicators and their lead times are determined” by examining the relationship between different indicators.

Source: American Institutes of Research<sup>10</sup>

According to a manual scan of enrollment forecasting models, **the most common models appear to be time series analysis and regression analysis.** For example, the Maryland Higher Education Commission uses a linear regression analysis to determine credit enrollment at community colleges, public four-year institutions, and “noncredit continuing education enrollments” at community colleges.<sup>11</sup> The Office of Institutional Research at Monroe County Community College (MCCC) in Michigan created an Autoregressive Integrated Moving Average (ARIMA) time series analysis to “determine whether unemployment rate and tuition predict total credit hour enrollment...over a span of 32

<sup>10</sup> Ibid., pp. 4-5.

<sup>11</sup> “Enrollment Projections, 2010-2019, Maryland Public Colleges and Universities.” Maryland Higher Education Commission. p. 9.  
<http://msa.maryland.gov/megafile/msa/speccol/sc5300/sc5339/000113/013000/013002/unrestricted/20100879e.pdf>

years.” The study found that this type of predictive model was “an excellent fit” for these data variables and recommended that MCCC use the model going forward.<sup>12</sup>

When adopting an enrollment forecasting model, it is important that a model be tailored directly to the needs and resources of a specific institution and type of institution. For example, Metropolitan Community College (MCC) in Missouri based its forecasting model off of a model originally used by St. Charles Community College. However, after a full assessment of the model, MCC concluded it would “require a more complicated model because of its size and the number of counties in the service district.” MCC was able to use an existing model but adjust it to best fit the institution’s direct context.<sup>13</sup>

Likewise, four-year Eastern Tennessee State University (ETSU) uses a Markov Chain Model because it fits the particular goals of the institution. This model “looks at past practice to predict future outcomes,” and the institution uses the model to track students by status from year to year, calculate recruitment and drop-out rates, and use consistent formulas to predict future enrollments. ETSU chose this model for three reasons:<sup>14</sup>

- The model is used by similar institutions both in-state and out-of-state.
- The model uses only institutional data.
- Studies show the model is accurate for one-year projections.

ETSU did not choose a population-based model because this approach relies on external projections, nor did it choose ARIMA or other SAS projections due to these models’ “complexity without increased accuracy.”<sup>15</sup> In 2014, ETSU found success with the Markov Chain Model, with 98.8 percent accuracy in predicting 2014 enrollments one year out, and 99.9 percent accuracy in predicting 2015 enrollments.<sup>16</sup> ETSU provides a clear example of how an institution should examine its own needs when choosing a forecasting model.

Institutions should also ensure that an enrollment forecasting model will be sustainable for an institution over time. Overly complex or involved projections may not be easily replicated by different staff in a manner that will regularly address key institutional issues. For example, to assess the effectiveness of enrollment forecasting models, researchers at the California Community Colleges system analyzed the accuracy of three different enrollment projection models (regression, autoregression, and the three-component model) across six

---

<sup>12</sup> DeLeeuw, J. “Unemployment Rate and Tuition as Enrollment Predictors.” Monroe County Community College, September 2012.  
<https://www.monroeccc.edu/institutionalresearch/analyses/Unemployment%20Rate%20and%20Tuition%20as%20Enrollment%20Predictors%20Final.pdf>

<sup>13</sup> “Enrollment Forecasting Model.” Metropolitan Community College, October 2013.  
[http://blogs.mcckc.edu/HLC\\_Evidence\\_Files/fileid\\_88930.pdf](http://blogs.mcckc.edu/HLC_Evidence_Files/fileid_88930.pdf)

<sup>14</sup> Hoff, M. “Fall 2014 Enrollment.” Institutional Research and Effectiveness, Eastern Tennessee State University, September 25, 2014. p. 5. <http://www.etsu.edu/academicaffairs/ir/projects/projections.aspx>

<sup>15</sup> Ibid.

<sup>16</sup> [1] Ibid., p. 9. [2] Hoff, M. “ETSU Fall 2014 Enrollment Projections.” Institutional Research, October 31, 2013. p. 9.  
<http://www.etsu.edu/academicaffairs/ir/projects/projections.aspx>



community colleges. The study found that all three models were at least fairly successful at predicting future enrollments for these institutions. In the end, the study did not recommend one particular model as being the most effective but instead noted that **when accuracy is the same, institutions should choose the least complex model to simplify an already potentially complicated process.**<sup>17</sup>

### CASE STUDY: PREDICTING STUDENT HOURS

As a part of a larger strategy to accurately predict enrollment for community colleges across the state, the California Community College Chancellor’s Office (CCCCO) develops annual forecasts of Weekly Student Contact Hours (WSCH). The WSCH data assist the CCCCCO in determining “future facilities needs” of the member colleges. Prior to 2011, the CCCCCO used an **econometric regression model** to determine the WSCH forecast.<sup>18</sup> The model used the variables and assessment methodology described below in Figure 1.3.

**Figure 1.3: Variables and Methodology for Former California Community College Enrollment Projections Analysis**

VARIABLES	
<ul style="list-style-type: none"> <li>▪ Past actual fall student <b>enrollment</b> for each community college district</li> <li>▪ The California Department of Finance’s county <b>adult population</b> forecasts</li> </ul>	<ul style="list-style-type: none"> <li>▪ Estimated district <b>budgets</b></li> <li>▪ Estimated student <b>cost of attendance</b> and mandated student enrollment fees</li> </ul>
PROJECTIONS METHODOLOGY	
<p>“The latest projected enrollment is derived from a fall enrollment of districts. This estimated fall enrollment becomes the base year for the projected annual changes from the regression. The last year of actual enrollment and actual WSCH data is used to compute the enrollment to WSCH ratio. This enrollment/WSCH ratio is assumed to be constant for future years and is applied to the projected headcount enrollments to calculate the future WSCH forecasts.”</p>	

Source: RP Group<sup>19</sup>

In 2011, the Research and Planning Group (RP Group) of CCCCCO was tasked with developing a more accurate WSCH forecasting model. To determine which model would be most effective for California community colleges, the RP Group explored a variety of methodologies, including ARIMA, Ordinary Least Squares (OLS) regression, moving average, Prais-Winsten regression, OLS regression with differenced WSCH, and Cochrane-Orcutt regression. The group also examined a series of predictor variables across five pilot districts in the state.<sup>20</sup>

<sup>17</sup> Ibid., p. 9.

<sup>18</sup> Gibbons, B. Et al. “Weekly Student Contact Hours Forecast Report.” Research and Planning Group of California Community College, June 2011. p. 2. <http://rpgroup.org/sites/default/files/EnrlForecast07012011.pdf>

<sup>19</sup> Ibid.

<sup>20</sup> Ibid., p. 6.

After the initial assessment, the RP Group focused their efforts on 17 “promising indicators or predictor variables” that were organized in three main categories:<sup>21</sup>

- District level population counts segmented by age groups
- District level population counts segmented by ethnicity
- Small set of economic/financial indicators

Ultimately, the RP Group employed three main analyses—Population Participation Rates (PPR), OLS regressions, and ARIMA—and determined that the best model for the CCCCCO was an average of the results of the OLS regression and a PPR method. Both methods “have desirable characteristics that balance each other’s weak points.”<sup>22</sup> The RP Group identified this combination of methods as the recommended model for the CCCCCO because it has “more technically desirable properties.” However, this model also requires a larger amount of resources. Consequently, the group presented an additional model option that would be a “reasonable alternative if resources are limited.”<sup>23</sup> The alternative model would use a maximum population participation rate that converts to WSCH.<sup>24</sup>

## ENROLLMENT FORECASTING TOOLS

A manual scan of enrollment forecasting models suggests that many institutions build their own forecasting models with software. The models are typically developed and run by an office of institutional research, which can concentrate on evaluating and adjusting the model for accuracy and keep track of results from year to year. For community colleges in some states (such as California and Texas), forecasting models are primarily developed by a state-wide higher education organization to which individual institutions must submit data. Other institutions, however, use their own forecasting tools to assist in developing or running prediction models. **Two common tools appear to be outside consultants with relevant analytical capabilities and dedicated forecasting software.**

---

<sup>21</sup> Ibid.

<sup>22</sup> Ibid., p. 13.

<sup>23</sup> Ibid., p. 14.

<sup>24</sup> Ibid., p. 15.

## ENROLLMENT FORECASTING SOFTWARE

One analytical software package used to track enrollment forecasts is SAS Analytics Software (SAS).<sup>25</sup> SAS offers a suite of tools that provide analytics for a variety of forecasting needs. For example, Kennesaw State University uses the SAS Business Intelligence Platform to develop two different forecasting models to understand enrollment projections at its institution. One model uses the SAS Enterprise Guide to create a ratio-based, short-term, semester-by-semester model, while the other uses SAS Forecast Studio to create a time series-based, long-range, five-year model.<sup>26</sup> The SAS tool for the short-term model uses traditional programming techniques, while the tool for the long-term model “allows robust models to be constructed and modified using a graphical user interface.”<sup>27</sup>

Other tools provide additional data information. Student Tracker, a research source from National Student Clearinghouse, “provides continuing collegiate enrollment and degree information on [an institution’s] current and former students as well as...former admission applications.”<sup>28</sup> Institutions that subscribe to Student Tracker can “query [its] participating institutions’ student data to perform all types of education research and analyses.”<sup>29</sup> A variety of four-year and two-year higher education institutions subscribe to Student Tracker and use the data to track transfer students, understand student retention, and identify college choice factors that may impact marketing.<sup>30</sup> Tools such as Student Tracker can help enhance an institution’s enrollment forecasts.

## ENROLLMENT FORECASTING CONSULTANTS

Institutions in need of more comprehensive assistance in developing enrollment projections may look to partner with consulting firms. For example, ASR Analytics assists its clients to “make better decisions through the integration, validation, and analysis of their operational data.” ASR Analytics builds predictive analytics applications that help institutions understand and apply their data more effectively. Howard Community College hired ASR Analytics to create a student enrollment forecasting model that integrates historical institutional enrollment data, Bureau of Labor Statistics unemployment data, and projected high school graduation data from the state of Maryland. The model provides long-term enrollment forecasts for seven years.<sup>31</sup>

---

<sup>25</sup> SAS. [http://www.sas.com/en\\_us/home.html](http://www.sas.com/en_us/home.html); Note: Hanover uses Stata or R, but any statistical software that allows for time series modeling can be used.

<sup>26</sup> Bowe, E. and S. Merritt. “Forecasting Enrollment in Higher Education using SAS Forecast Studio.” North Carolina State University, 2013. p. 1. <http://analytics.ncsu.edu/sesug/2013/SD-05.pdf>

<sup>27</sup> Ibid., p. 5.

<sup>28</sup> “FAQs.” National Student Clearinghouse. <http://www.studentclearinghouse.org/colleges/studenttracker/faqs.php>




<sup>29</sup> “Student Tracker.” National Student Clearinghouse. <http://www.studentclearinghouse.org/colleges/studenttracker/>

<sup>30</sup> “Case Studies.” National Student Clearinghouse. [http://www.studentclearinghouse.org/colleges/studenttracker/case\\_studies.php](http://www.studentclearinghouse.org/colleges/studenttracker/case_studies.php)

<sup>31</sup> “ASR Demonstrates Student Enrollment Forecasting with Howard Community College.” ASR Analytics. <http://www.asranalytics.com/news/asr-demonstrates-student-enrollment-forecasting-howard-commu>

In its own work for clients, Hanover Research uses similar variables to develop enrollment projections for community colleges and other institutions. Depending on client needs and other factors, Hanover has used various forecasting methodologies, such as a panel vector autoregressive model, to accommodate different types of institutions. However, the most typical approach used by Hanover is the **panel time series regression model**. In addition to its incorporation of multiple variables, including historical enrollments, local economic conditions, and demographic trends, the main advantage of this model is its expansion of the available sample size: instead of using a time series for a single institution, the model incorporates data from multiple, similar institutions to increase the number of observations in the data set (Figure 1.4).

**Figure 1.4: Panel Time Series Regression Model**

	<i>STANDARD TIME SERIES</i>	<i>PANEL TIME SERIES</i>
<b>INSTITUTIONS</b> 	1	>50
<b>TIME SERIES (YEARS)</b> 	20	20
<b>OBSERVATIONS</b> 	20	>1,000

## SECTION II: ENROLLMENT PREDICTION VARIABLES

In this section, Hanover examines notable characteristics used to predict enrollment for community colleges. The section analyzes the value of economic indicators and the use of multiple variables. The section also assesses the models and characteristics used to evaluate and project enrollment for particular student subgroups, including stopout students.

### ECONOMIC INDICATORS

Data from the American Association of Community Colleges indicates that “enrollment trends at community colleges can typically be predicted based on how the economy is doing.” Between 2000 and 2006, community college enrollment increased by an average of 2.2 percent per year. During the economic recession, the average annual increase jumped to 5.6 percent per year. It then stabilized in 2011 and has decreased by an average of 3.5 percent each year.<sup>32</sup> Consequently, **many institutions point to overall economic indicators as useful variables when examining long-term enrollment projections, but these variables may not be consistent for all locations.**

At Northwest College in Wyoming, for example, enrollment during the 2015-2016 academic year increased for the first time since the 2009-2010 academic year. College administrators, local leaders, and economists all noted that the increase in enrollment in 2009 was primarily due to “plummeting oil and natural gas prices and a weak state and local economy.” As oil and gas workers were laid off, many chose to return to school. However, as the economy improved, college enrollment decreased. Northwest College president Stefani Hicswa noted that as oil prices dropped again in 2015, the pattern seemed to repeat and enrollment increased slightly.<sup>33</sup>

However, the relationship between community college enrollment and regional unemployment may not always directly correlate. According to an analysis from the state government of Minnesota, unemployment rates can effect college enrollment in two ways: “actual unemployed people returning to school,” and “the motivation of the general population to get ahead of the storm.” When unemployment is high, people may be more likely to pursue additional training to remain competitive in the market. The analysis compared longitudinal enrollment numbers to seasonally adjusted unemployment rates. Enrollment and unemployment tended to rise and fall together between 2003 and 2010. The study also examined whether unemployment could predict new enrollments but found that the relationship was minimal in Minnesota. Unemployment may be one factor in

---

<sup>32</sup> “Watching the economy for enrollment trends.” Data Points: American Association of Community Colleges, October 2015. [http://www.aacc.nche.edu/Publications/datapoints/Documents/DP\\_WatchTrends.pdf](http://www.aacc.nche.edu/Publications/datapoints/Documents/DP_WatchTrends.pdf)

<sup>33</sup> Olson, I. “Northwest College enrollment stabilizes.” *Powell Tribune*, August 6, 2015. <http://www.powelltribune.com/news/item/13910-northwest-college-enrollment-stabilizes>

encouraging new enrollments, but other factors such as region and institution type were also strong predictors.<sup>34</sup>

## COMBINING MULTIPLE VARIABLES

Institutions typically use a combination of variables when creating a model to project future enrollment. Many institutions examine variables related to enrollment and credit hours, demographics, budget and expenditures, population, and local and state high school graduation rates. Most of these variables derive from historical data and are available from institutional or public sources, allowing institutions to build a comprehensive picture of potential enrollment. Some institutions also include qualitative factors into their analyses to account for social, regional, or institutional changes or trends that may affect enrollment.

For instance, when developing a master plan for its four campuses, Tulsa Community College (TCC) conducted a multi-phase enrollment projection to determine the potential physical space needed for each campus. The projection project took into account a wide variety of characteristics in different phases. The first phase of the projection analyzed “education participation rates by zip code, population and demographic projections, and estimated workforce needs of the Tulsa area.” This information provided TCC with a general idea of the population and demographic factors contributing (or not contributing) to enrollment. The second phase focused on internal data related to “planning assumptions and future initiatives.” The variables included “changes in the number of program offerings, development of outreach centers, marketing and recruitment strategies, and tuition policies.”<sup>35</sup> Analyzing such characteristics can inform an institution of its capacity and identify opportunities for growth. A combination of demographic and internal factors can be assessed simultaneously to reveal more robust enrollment projection trends.

## CASE STUDY: MULTIPLE CHARACTERISTICS USED BY YAVAPAI COLLEGE

Yavapai College (Yavapai), located in Arizona, submits annual full-time student equivalency (FTSE) projections to the Economic Estimates Commission of Arizona. Yavapai uses FTSE projections in the “budgeting, planning, and strategic enrollment management processes at the college” and to predict FTSE both by course subject and division. It uses an autoregressive time series model to determine FTSE and considers elements of a subjective judgment model as well. Selected faculty, staff, and administrators submit their own “perceptions of enrollment factors and growth issues,” which are then “integrated into the

---

<sup>34</sup> Gehring, A. “Using Unemployment Rates to Predict Post Secondary Enrollment.” Minnesota Employment and Economic Development, February 2013. <https://mn.gov/deed/newscenter/publications/review/february-2013/unemployment-college-enrollment.jsp>

<sup>35</sup> “Tulsa Community College: The role of enrollment forecasting in master planning.” Paulien and Associates. <http://www.paulien.com/services/enrollment-forecasting/tulsa-community-college-the-role-of-enrollment-forecasting-in-master-planning/>

model and the final projections.”<sup>36</sup> Yavapai began using its projection model in the 2004-2005 academic year.<sup>37</sup>

Yavapai incorporated 12 characteristics into its 2012-2013 forecasting. These assumptions come from internal and external sources and incorporate both quantitative data and qualitative observations.

**Figure 2.1: Characteristics Used by Yavapai College**

CHARACTERISTIC	DESCRIPTION AND ASSUMPTION
<b>Population</b>	<ul style="list-style-type: none"> <li>Used Economic Modeling Specialists Incorporated Yavapai County population estimates (small increase to 223,659)</li> </ul>
<b>Tuition/Fee Structure</b>	<ul style="list-style-type: none"> <li>Yavapai moved from a flat tuition structure to a differentiated tuition model, which eliminated course fees. Though it may cause confusion for current students, it should not have a significant effect on long-term enrollment.</li> </ul>
<b>High School Graduates and Local School Information</b>	<ul style="list-style-type: none"> <li>Population projections forecast that the number of high school students in the county will flatten. Yavapai consistently enrolls 30% of high school graduates, and expects enrollment to increase due to rising tuition prices at large state schools.</li> </ul>
<b>Dual Enrollment and Joint Technical Education District</b>	<ul style="list-style-type: none"> <li>Expected to grow minimally.</li> </ul>
<b>Adult Basic Education</b>	<ul style="list-style-type: none"> <li>These courses are no longer credit bearing, but clock hour courses still generate FTSE.</li> </ul>
<b>Summer School</b>	<ul style="list-style-type: none"> <li>Overall summer FTSE is expected to be lower due to construction and closure of the Verde campus for summer 2012.</li> </ul>
<b>Public Services</b>	<ul style="list-style-type: none"> <li>While public safety is expensive for municipalities, current cuts for police and fire are not likely and consequently Yavapai can expect flat to modest growth in this area.</li> </ul>
<b>Occupational Outlook</b>	<ul style="list-style-type: none"> <li>Yavapai offers many programs related to high-growth occupations in the county and state, particularly in allied health programs.</li> </ul>
<b>Nursing</b>	<ul style="list-style-type: none"> <li>Nursing enrollment should stay the same, with a cap at 256 students.</li> </ul>
<b>Allied Health</b>	<ul style="list-style-type: none"> <li>This area should expect modest to high enrollment growth, which will be enhanced by the addition of a new full-time faculty member.</li> </ul>
<b>Career and Technical Education Center (CTEC)</b>	<ul style="list-style-type: none"> <li>Occupational programs should increase almost 8 percent through 2012-13, particularly in aviation and gunsmithing.</li> </ul>
<b>Economic Outlook</b>	<ul style="list-style-type: none"> <li>Overall economic outlook for Arizona is positive, and Yavapai should expect increasing enrollment of traditional age students who will look to community college for a more affordable option.</li> </ul>

Source: Yavapai College<sup>38</sup>

<sup>36</sup> “Enrollment Forecast for 2012-2013.” The Office of Administrative Services, Yavapai College, Spring 2012. pp. 2, 7. [https://yc.edu/v5content/strategic-planning/docs/FTSE\\_Projections\\_2012.pdf](https://yc.edu/v5content/strategic-planning/docs/FTSE_Projections_2012.pdf)

<sup>37</sup> Ibid., p. 10.

<sup>38</sup> Ibid., pp. 3-6.

Yavapai tracked the accuracy of its enrollment forecasts since its first projection of the 2005-2006 academic year. Figure 2.2 displays the accuracy of enrollment projections for the first six years of forecasts.

**Figure 2.2: Accuracy of Yavapai Enrollment Projections**

YEAR	FORECASTED FTSE	ACTUAL FTSE	ERROR
2005-06	3,342	3,351	0.003
2006-07	3,540	3,617	0.020
2007-08	3,799	3,691	-0.029
2008-09	3,838	3,921	0.022
2009-10	3,984	3,920	-0.016
2010-11	4,086	4,205	0.029

Source: Yavapai Community College<sup>39</sup>

## ENROLLMENT FORECASTING STRATEGIES AND CHARACTERISTICS FOR STOPOUT STUDENTS

For many institutions, predicting stopout student rates is considered to be a retention issue and may not always be addressed through an enrollment forecasting model. However, some institutions use general forecasting models to predict stopout and determine the motivations and characteristics of stopout students. Predicting stopouts is often part of a larger analysis of enrollment forecasting or retention.

A 2013 study from the University of California system examined stopout rates at California colleges by using data already gathered through the 2011-2012 California Young Adult Study. To create predictions of stopout students, the study compared high school age students by specific variables (financial aid receipt and income level) and used a logistic regression analysis to “determine the likelihood that they would stop out of higher education at some point in the future.” The model also controlled for high school GPA and enrollment in advanced courses to compare academically similar students by financial outlooks.<sup>40</sup> In this case, institutions could use the same system-wide data sets for an analysis of stopout students for enrollment forecasting purposes.

<sup>39</sup> Ibid., p. 10.

<sup>40</sup> Terriquez, V., O. Gurantz, and A. Gomez. “California’s College Stopouts: The Significance of Financial Barriers to Continuous School Enrollment.” *Policy Report*, University of California All Campus Consortium on Research for Diversity, (7), July 2013. p. 3. [https://pathways.gseis.ucla.edu/publications/201307\\_StopoutsPR.pdf](https://pathways.gseis.ucla.edu/publications/201307_StopoutsPR.pdf)

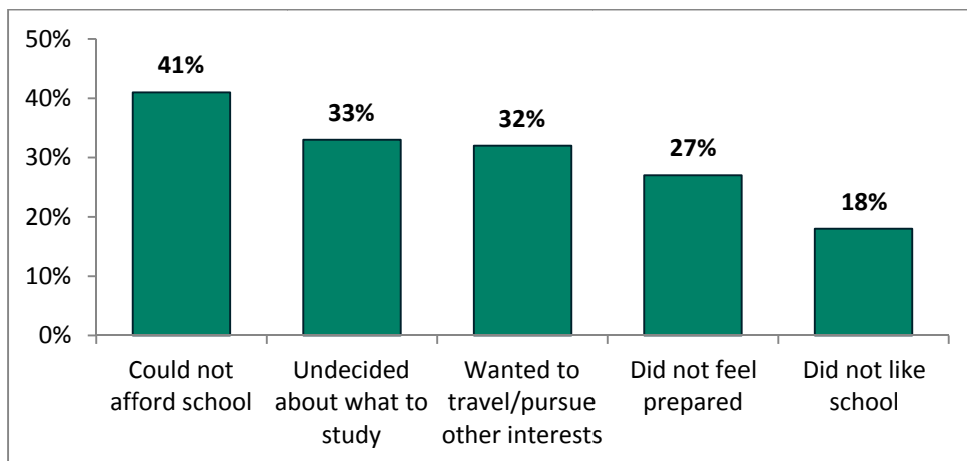


Other institutions use segmentation analysis within an enrollment model to determine information about stopouts and other student subgroups. Seattle Pacific University, for example, notes that segmenting an analysis by student type, gender, ethnicity, intended major, or merit/non-merit can inform leaders of certain academic characteristics of these subgroups, including:<sup>41</sup>

- Different rates for moving through the application/admissions process
- Different completion rates
- Different yield rates
- Different intervention points

An essential part of building a forecasting model to predict stopout students is to identify the relevant data variables to use in the model, based on the unique geographical or economic context of the institution. This can be done by examining historical profiles of stopout students at an institution. For example, if most stopout students did not receive financial aid or were from low income areas, then these would be important variables to include in a projection. The 2013 University of California study found that the most common reason students in both community colleges and four-year institutions across the state stopped out was because students could not afford to continue their program.<sup>42</sup> Figure 2.3 shows other common reasons for stopping out at California higher education institutions.

**Figure 2.3: Most Common Reasons for Stopping Out of College (California)**



Source: University of California All Campus Consortium on Research for Diversity<sup>43</sup>

<sup>41</sup> Ward, J. "Forecasting Enrollment Using Historical Trends." Seattle Pacific University, presented at AACRAO Conference, April 23, 2010. p. 17. [http://handouts.aacrao.org/am10/finished/F0100p\\_J\\_Ward.pdf](http://handouts.aacrao.org/am10/finished/F0100p_J_Ward.pdf)

<sup>42</sup> Terriquez, V., O. Gurantz, and A. Gomez. Op. cit., p. 2.

<sup>43</sup> Ibid.

Other variables to predict student persistence at community colleges can also be leveraged to prevent stopouts and integrated into enrollment projections. A 2015 study from consulting firm Ruffalo Noel Levitz identified a number of satisfaction variables that had either a positive impact on spring-to-spring retention or could help predict retention at community colleges (see Figure 2.4).<sup>44</sup>

**Figure 2.4: Satisfaction Variables for Community College Students**

SATISFACTION VARIABLES THAT PREDICT RETENTION	
<ul style="list-style-type: none"> <li>▪ Satisfaction with the relationships between students and campus staff.</li> <li>▪ Satisfaction with the college culture.</li> </ul>	<ul style="list-style-type: none"> <li>▪ NOT Predictive: Satisfaction with academic variables.</li> </ul>
VARIABLES WITH AN IMPACT ON ENROLLMENT/RETENTION	
POSITIVE	NEGATIVE
<ul style="list-style-type: none"> <li>▪ Attending a larger institution</li> <li>▪ Students with a higher GPA</li> <li>▪ Attending an institution with a large number of students receiving financial aid</li> <li>▪ Attending an institution that has a larger full-time population</li> <li>▪ High overall satisfaction</li> <li>▪ No regret about enrolling originally</li> <li>▪ Helpful and approachable library staff</li> <li>▪ Student carrying a full-time class load</li> <li>▪ Helpful financial aid counselors</li> </ul>	<ul style="list-style-type: none"> <li>▪ Institution located in a suburban environment</li> <li>▪ Institution located in an urban environment</li> <li>▪ Student having an educational goal of certificate</li> <li>▪ Student having a higher class level or year in college</li> <li>▪ Student indicating an enrollment status of weekend</li> <li>▪ Child care facilities available on campus</li> <li>▪ Business office open convenient hours</li> <li>▪ Clear policies and procedures</li> <li>▪ Student having an employment status of full-time, off campus</li> </ul>

Source: Ruffalo Noel Levitz<sup>45</sup>

<sup>44</sup> Miller, K. Op. cit., p. 4.

<sup>45</sup> Ibid.

## SECTION III: ENROLLMENT FORECASTING MODEL PROFILES

In this section, Hanover profiles enrollment forecasting models of three community college or community college systems. These examples provide a more in-depth look at the motivations and concerns around enrollment forecasting at a specific institution, variables used for different models, and the accuracy rates of particular enrollment forecasting models.

### CALIFORNIA COMMUNITY COLLEGES

Prior to the 1990s, the California community colleges system calculated “long-term enrollment projections for capital outlay planning” through a model developed by the California State Department of Finance. The model applied “expected ‘participation rates’ (enrollment divided by population) to projections of future population groups, categorized according to age and gender.” Expected participation rates were determined using past trends, local district data, and qualitative assessments by department staff.<sup>46</sup>

In 1991, the Chancellor’s Office took over the task of developing long-term enrollment projections and began using a linear regression model “based on 30-plus years of data that weighed all the data equally.” The model, however, “overemphasized negative trends” from a number of the underlying assumptions, including declining budgets, fee increases, and decreases in adult county population. Consequently, the long-term enrollment projections presented an “atypical picture of student enrollment.”<sup>47</sup>

In response to the limitations of the traditional linear regression model, the Chancellor’s Office worked to develop a new model in partnership with the Association of Chief Business Officers and the RP Group. The new model forecasts enrollments using a Population Participation Rate (PPR) based on a combination of variables, including:

- Student participation rates
- “In district” and “out of district” enrollment
- Weekly student contact hours to enrollment ratios
- Adult population projections based on Geographic Information Systems zip code data

As a result of integrating these variables, the PPR model “demonstrates less volatility and will be a more accurate planning tool for community college facilities.”<sup>48</sup> With the PPR model, the CCCCO has calculated fall enrollment and fall WSCH numbers from 2000 to 2023.<sup>49</sup>

---

<sup>46</sup> “California Community Colleges Long-Range Master Plan.” Op. cit., p. 20.

<sup>47</sup> Ibid.

<sup>48</sup> Ibid.

<sup>49</sup> Ibid., p. 22.

## METROPOLITAN COMMUNITY COLLEGE

Metropolitan Community College (MCC), located in Kansas City, Missouri, uses a linear regression model with SPSS software to predict enrollment across its five campuses. The model was developed in 2013 by the Office of Institutional Research and Assessment and based off an enrollment forecasting model used at St. Charles Community College. MCC needed a more complex model than that of St. Charles Community College to account for its size and the number of counties in its district. MCC also decided to examine enrollment across the whole district, rather than analyze the data by campus, because in recent years the input process for enrollment has changed at various campuses. To account for these complexities, the Office of Institutional Research and Assessment reached out to faculty and administrators for additional assistance.<sup>50</sup>

MCC's linear regression forecasting model incorporates historical data, including:<sup>51</sup>

- **Fall enrollment by district** (1969-2012)
- **Spring enrollment by district** (1993-2013)
- **Summer enrollment by district** (1993-2012)
- **Overall Census population** by county service district (1993-2012)
- **Unemployment data** (1993-2012)
- **Consumer price index** – annual average (1993-2012)
- **Per capita income** – median by county then averaged for all counties (1993-2011)
- **MCC retention data** (1990/91-2011/12)
- **Missouri high school graduate numbers** and analysis of future enrollment (2002-2012)
- **MCC in-district credit hour rate** (1983/84-2016/17)
- **Age distribution** of current MCC students (2008-2013)

Overall, MCC found the model to be effective, but there are limitations of linear regression models. Figure 2.5 on the following page displays the methodology and the limitations of the model for MCC.

---

<sup>50</sup> "Enrollment Forecasting Model." Op. cit., p. 1.

<sup>51</sup> Ibid., p. 1.

**Figure 2.5: Methodologies and Limitations for MCC Enrollment Forecasting Model**

	METHODOLOGY	LIMITATIONS
1	Normalized tuition using per capita income and MCC in-district credit hour rate by dividing the credit hour for that year by the average per capita income and multiplying the credit hour rate for 2011.	<ul style="list-style-type: none"> <li>▪ The model can only use <b>independent variables</b> that are available for future and historical values.</li> </ul>
2	Normalized tuition using the consumer price index and MCC in-district credit hour rate by dividing the credit hour rate for that year by the annual average consumer price index and multiplying the credit hour rate for 2012.	<ul style="list-style-type: none"> <li>▪ The model will need to be <b>reconstructed and reevaluated as years progress</b> because of the uncertainty that surrounds enrollment forecasting (Chen, 2008). As time progresses, the model may become less accurate due to unforeseeable changes in the economy, social conditions, and practices of the college.</li> </ul>
3	Compared MCC’s age distribution percentage for each category to census population projections to determine an available pool of students. This was accomplished by multiplying census population by age range by the percentage of MCC students in that age range. Then the totals were added for a total pool.	<ul style="list-style-type: none"> <li>▪ The following <b>variables should remain constant</b> when dealing with enrollment forecasting: National and State Economy, Federal and State financial aid programs, State Funding for Higher Education, Admission Standards, Graduation rates, and so forth (Chen, 2008).</li> </ul>
4	Retention is considered a leading indicator in that the previous term or year retention would impact enrollment for the following term.	<ul style="list-style-type: none"> <li>▪ The <b>variables in this model are not independent</b> and this could be an assumption violation. This also occurs in St. Charles’s model.</li> </ul>
5	The following variables were input into SPSS: Year, fall enrollment, spring enrollment, AdjCPI, AdjPCI, unemployment, retention and population.	<ul style="list-style-type: none"> <li>▪ As with any prediction model, there is a <b>huge amount of instability</b> because of the variables included.</li> </ul>

Source: Metropolitan Community College<sup>52</sup>

<sup>52</sup> Ibid., pp. 2, 7-8.

## TEXAS HIGHER EDUCATION COORDINATING BOARD

The Texas Higher Education Coordinating Board (THECB) publishes the Texas Public College and University Forecasts, which include long-term enrollment projections for all higher education institutions in Texas. The projections are developed through “multiple regression techniques,” which, “in a few instances, were modified using documented adjustment factors submitted by individual institutions.”<sup>53</sup>

*“Past enrollment forecasts have been reasonably accurate...but have failed to adequately anticipate the rapid growth and shifts at some individual universities...”*

The board applies the same models to predict enrollment at four-year public universities and public community colleges. However, in 2001 in the 2000-2015 projections, the THECB noted that “past enrollment forecasts have been reasonably accurate for public universities overall, but have failed to adequately anticipate the rapid enrollment growth and shifts at some individual universities and at the community college.” To account for these changes and trends, the forecast underwent “several procedural modifications.”<sup>54</sup> Though THECB adjusted the model to account for these changes and trends, it uses the same general enrollment forecasting model across institution types.

As enrollment projections are determined by a central governing body for all institutions in the state, the forecasting process also includes a step that allows each institution to make adjustments based on its specific trends, characteristics, or needs. THECB sends the draft forecast to the institution for review. The accuracy of the individualized forecasts is compared to past predictions.”<sup>55</sup>

The enrollment forecasting model for public colleges and universities in Texas (including community colleges) uses “five years of past enrollment from Texas counties differentiated by age and race/ethnicity and applies these enrollment rates to population projections.” Enrollment projections for private institutions in Texas are determined through a simple linear regression also using the past five years of data. Neither model “consider[s] possible future changes that could affect enrollments, such as improvements in high school graduation rates, increases in the higher education enrollment rate by racial/ethnic groups, or changes in local policies.” Because the model only uses historical data, forecasts will consistently be conservative and based on current trends future enrollments.<sup>56</sup>

<sup>53</sup> “Enrollment Forecast 2013-2020.” Texas Institutions of Higher Education, January 2013. p. 23.

<http://www.txhighereddata.org/index.cfm?objectid=741AD72B-B7CE-2FED-FC1B8CD9C493453D>

<sup>54</sup> “Enrollment Forecasts 2000-2015.” Texas Institutions of Higher Education, January 2001. p. i.

<http://www.thecb.state.tx.us/reports/pdf/0380.pdf>

<sup>55</sup> “Enrollment Forecast 2013-2020.” Op. cit., p. 23-24.

<sup>56</sup> Ibid., p. 1.

## PROJECT EVALUATION FORM

Hanover Research is committed to providing a work product that meets or exceeds client expectations. In keeping with that goal, we would like to hear your opinions regarding our reports. Feedback is critically important and serves as the strongest mechanism by which we tailor our research to your organization. When you have had a chance to evaluate this report, please take a moment to fill out the following questionnaire.

<http://www.hanoverresearch.com/evaluation/index.php>

## CAVEAT

The publisher and authors have used their best efforts in preparing this brief. The publisher and authors make no representations or warranties with respect to the accuracy or completeness of the contents of this brief and specifically disclaim any implied warranties of fitness for a particular purpose. There are no warranties that extend beyond the descriptions contained in this paragraph. No warranty may be created or extended by representatives of Hanover Research or its marketing materials. The accuracy and completeness of the information provided herein and the opinions stated herein are not guaranteed or warranted to produce any particular results, and the advice and strategies contained herein may not be suitable for every client. Neither the publisher nor the authors shall be liable for any loss of profit or any other commercial damages, including but not limited to special, incidental, consequential, or other damages. Moreover, Hanover Research is not engaged in rendering legal, accounting, or other professional services. Clients requiring such services are advised to consult an appropriate professional.



4401 Wilson Boulevard, Suite 400

Arlington, VA 22203

P 202.559.0500 F 866.808.6585

[www.hanoverresearch.com](http://www.hanoverresearch.com)