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Identifying Strategies for Strengthening the Health Care Workforce in the Commonwealth of Virginia

Annex
About This Annex

This annex contains appendixes to the main report, Identifying Strategies for Strengthening the Health Care Workforce in the Commonwealth of Virginia, available at www.rand.org/t/RRA2903-1. These appendixes provide details on the methods and analysis used for the research summarized in the main report. The citations in this annex point to references listed in the main report.

This research was funded by the Virginia Health Workforce Development Authority (VHWDA) and carried out within the Access and Delivery Program in RAND Health Care. The Virginia General Assembly established VHWDA in 2010 to identify and address health workforce issues in the Commonwealth. As a public entity, VHWDA exercises public and essential governmental functions to secure the health, welfare, convenience, knowledge, benefit, and prosperity of Virginians. VHWDA’s mission is to “facilitate the development of a statewide health professions pipeline that identifies, educates, recruits, and retains a diverse, appropriately geographically distributed, and culturally competent quality workforce” (VHWDA, undated). VHWDA accomplishes this through core functions outlined in the Code of Virginia (Virginia’s Legislative Information System, undated).

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Appendix A

Resources on Virginia’s Health Care Workforce

In addition to other sources of information, this research relied on various data collection and aggregation efforts to glean insight into the national, state, and regional health care workforces. We used some of the data resources listed here to inform our model of nursing and physician workforce supply and demand (see Appendix E for more on that model). We used other data resources listed here to provide context and background for understanding Virginia’s health care workforce challenges and interventions designed to overcome those challenges.

Data Related to Health Care Education

We reviewed data from the State Council of Higher Education for Virginia (SCHEV) and the National Student Clearinghouse to better understand the pipeline of graduates in health care fields. The SCHEV data can be accessed in the Virginia Longitudinal Data System (Virginia Longitudinal Data System, undated), and we thank the Mason Center for Health Workforce for helping us to access and process these files.

Mason also collects education data directly from schools or programs, including data related to the career and technical education pipeline from high schools and college preparatory schools, by defined types of academic programs (Mason Center for Health Workforce, undated). We did not review these data, but we mention them to raise awareness that data exist to facilitate a more detailed and robust study of the health care education pipeline.

Data Related to Workforce Personnel

Various publicly available datasets attempt to measure the past and present supply and demand for nursing, primary care, behavioral health, and other health care workforces. We have relied primarily on the U.S. Bureau of Labor Statistics’ (BLS’s) Current Employment Statistics State and Local Areas to quantify the number of personnel and average wages for each job category in each Virginia locality (U.S. Bureau of Labor Statistics, undated).

Additionally, a pre-pandemic study conducted by the U.S. Department of Health and Human Services projected demand for registered nurses (RNs) in the United States (U.S. Department of Health and Human Services et al., 2017), which we used as a starting point for projecting demand for nursing labor by observing the ratio of nationwide bed occupancy to national demand, then using the same ratio for Virginia-specific bed occupancy to scale down to the state level. Although this
technique only roughly approximates demand for nurses in Virginia, the main purpose of our model was to forecast the relative change in demand and supply (from any given starting point), so the starting point need not be precise. Furthermore, quantifying demand is by nature a highly imprecise endeavor, because there is a numeric difference between minimum number of personnel to operate a hospital, desired number of personnel, optimal number of personnel from a financial perspective, and optimal number of personnel from the perspective of maximizing health outcomes.

The Virginia Employment Commission (VEC) also has data on health care workforce supply and demand, which the Virginia Hospital and Healthcare Association supplied to us through 2019, and we supplemented these data with additional VEC data through 2021 (Virginia Employment Commission, undated).

**Recruitment and Retention**

Preexisting survey data helped us to better understand workers’ motivations for joining or leaving the Virginia health care workforce. As mentioned in more detail in Appendix E, we relied on analyses conducted by McKinsey & Company on longitudinal national surveys on nurses carried out since the onset of the pandemic (Berlin, Lapointe, and Murphy, 2022) to enumerate and weight factors that affect the retention of workers. Additionally, to provide context on recruitment, retention, and the composition of the Virginia health care workforce, we reviewed survey data collected by the Virginia Department of Health Professions’ Healthcare Workforce Data Center, which conducts voluntary surveys on the department’s licensees through the department’s online application and renewal processes (Virginia Department of Health Professions, undated). We reviewed the Virginia Hospital and Healthcare Association’s Survey on Graduating Nurses for additional insights into the pipeline of nursing recruits (Virginia Hospital and Healthcare Association, undated). Lastly, we analyzed Virginia State Loan Repayment Program data from the Virginia Department of Health, Office of Health Equity, for insight into the effects, costs, and efficacy of state loan repayment programs (Virginia Department of Health, Office of Health Equity, undated).
Appendix B

Environmental Scan Methods

The environmental scan entailed a review of the peer-reviewed and grey literature related to interventions for health care workforce retention and recruitment published from 2013 to 2023. The scan includes interventions both within and beyond Virginia and the United States.

Methods

We conducted our environmental scan following methods defined by the Institute of Medicine (Eden et al., 2011). Based on those methods, we engaged in six steps to conduct the environmental scan: (1) defining the research team for the environmental scan, (2) collecting user and stakeholder input, (3) identifying the topic and research questions in the scan, (4) developing and implementing a review protocol (including the study screening and selection process), (5) screening and selecting studies, and (6) appraising and synthesizing selected studies, including quality of evidence.

Defining the Environmental Scan Research Team

The environmental scan research team is a subset of the overall study team and included a social scientist with expertise in quantitative research in education, labor markets, and workforce development and a policy researcher with expertise in qualitative and mixed methods, health care and health policy, and environmental scans. The team has extensive experience in environmental scans as well as the methodological and substantive expertise to evaluate relevant research and other literature. The larger research team discussed and informed the environmental scan, including the selection process and preliminary findings.

Collecting User and Stakeholder Input

To elicit user and stakeholder input, the environmental scan research team first identified key health care domains based on the original study proposal: primary and behavioral health care. The team then developed preliminary definitions for these domains based on National Academy of Medicine methods and identified different occupations and sites of care for each health care domain. Based on email feedback from the larger research team and key stakeholders over a two-week period, the environmental scan research team finalized the health care domain definitions, focal occupations, and sites of care in the environmental scan. Key stakeholder feedback was especially critical for flagging occupations and sites of care of particular relevance in the Commonwealth of Virginia.
Identifying Topics and Research Questions

Parameters of the scan, including focal health care domains, occupations in those domains, and sites of care for focal health care domains were iteratively defined by the environmental scan team with review and discussion by the larger research team and Virginia stakeholders, including the Virginia Health Authority, a study advisory board comprised of various Virginia stakeholders, and the larger Virginia health care practitioner and policy community at the multi-stakeholder conference. From this process, five basic topics emerged, outlined in Table B.1. Stakeholders also helped identify search engines and websites used in this environmental scan. A professional librarian identified the initial set of articles based on predefined search terms and processes.

Table B.1. Environmental Scan Topics and Research Questions

<table>
<thead>
<tr>
<th>Topic</th>
<th>Research Questions</th>
</tr>
</thead>
</table>
| Virginia health care workforce | • What are basic demographic characteristics of the health care workforce in Virginia?  
• How does it compare to other Mid-Atlantic states and the United States as a whole?          |
| Education and training       | • For a given health care occupation, what are the basic education and training requirements?  
• What are areas of concern in relevant education and training programs?  
• How does education and training compare to other Mid-Atlantic states and the United States as a whole? |
| Legislation and regulation   | • For a given health care occupation, what are the main governing and regulatory bodies in Virginia?  
• What are the main regulations for each health care occupation in Virginia?  
• What are recent proposed and instated changes in a given occupation’s regulation in Virginia?  
• How does legislation and regulation compare to other Mid-Atlantic states and the United States as a whole? |
| Recruitment and retention    | • What factors facilitate or impede recruitment into health care occupations in Virginia overall?  
• What factors facilitate or impede recruitment into health care occupations in Virginia for key subpopulations?  
• What factors facilitate or impede retention in health care occupations in Virginia overall?  
• What factors facilitate or impede retention in health care occupations in Virginia for key subpopulations?  
• How does recruitment and retention compare to other Mid-Atlantic states and the United States as a whole? |
| Promising programs and practices | • What are the best or promising programs and practices for supporting the health care workforce in Virginia?  
• How do best or promising programs and practices compare to other Mid-Atlantic states, the United States as a whole, and globally?  
• What is the quality of evidence vis-à-vis the effectiveness of these programs and practices?  
• How do best or promising programs and practices compare to other Mid-Atlantic states, the United States, and globally? |

For each topic, the environmental scan team identified specific research questions, also shown in Table B.1. Overall, the environmental scan was intended to provide a detailed description of the
Virginia health care workforce over time, the current education and training landscape, recent and pending legislation and regulations related to the Virginia health care workforce, and promising workforce development programs, policies, and practices to support the health care workforce in Virginia and elsewhere—particularly those dealing with recruitment and retention.

**Developing and Implementing a Review Protocol**

The professional librarian formulated detailed search strategies for PubMed (U.S. National Institutes of Health’s National Library of Medicine), Cumulative Index to Nursing & Allied Health (CINAHL) (EBSCOhost), and American Psychological Association PsycINFO (EBSCOhost). We applied the following limits for each database: articles in peer-reviewed literature, published in English, published in the past ten years (2013–2023), and U.S. studies only. We conducted searches for state legislation in Nexis Uni and BillTrack50. Additionally, we conducted searches for policy documents and other grey literature (2013–2023) in Google. All search strategies were based on the defined focal health care domains, occupations in those domains, and care settings for focal health care domains. The following health care domains, occupations, and settings further bounded the search:

- **health care domains**
  - primary care, including
    - internal medicine
    - family medicine
    - pediatrics
    - obstetrics and gynecology
  - behavioral health, including
    - psychotherapy
    - psychiatry
    - social work
    - drug and alcohol rehabilitation

- **occupations**
  - primary care, including
    - physicians
    - physician assistants
    - licensed midwives
    - nursing
  - behavioral health, including
    - psychiatrists
    - licensed alcohol and drug counselors
    - board-certified behavior analysts
    - licensed mental health counselors
    - licensed professional counselors
- licensed clinical social workers
- certified substance abuse counselors
- psychiatric nurse mental health clinical specialists
- licensed independent clinical social workers
- licensed marriage and family therapists

- care settings
  - hospitals
  - health systems
  - nursing homes/long-term residential care
  - clinics and medical offices (outpatient, ambulatory)
  - community health centers (federally qualified health centers)
  - mental health treatment centers, addiction treatment centers.

Table B.2. summarizes key topics and associated search terms.

For each identified topic of interest, the array of search terms was based on (1) basic research questions associated with each identified topic (e.g., “What are basic demographic characteristics of the health care workforce in Virginia?”), (2) a preliminary search of related research articles and grey literature on a given topic by the environmental scan team, and (3) search terms based on the environmental scan and larger research team discussions for a given topic.

After each initial search, the librarian and environmental scan team met to briefly review the search process and ensure the executed process and search terms followed the review protocol.

The librarian conducted the initial search over a three-week period, addressing one topic before moving to the next. The librarian limited a given search to a single health care workforce, including primary care and behavioral health care for physicians, nursing, counselors and social workers. The librarian provided a detailed Excel database of search results for each topic, including the article title, authors, journal or other place of publication, abstract, and URL. Searches were conducted in May and June 2023.
Table B.2. Key Concepts and Related Search Terms

<table>
<thead>
<tr>
<th>Topic</th>
<th>Key Concepts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Virginia health care workforce</td>
<td>• Health care workforce statistics including:</td>
</tr>
<tr>
<td></td>
<td>– Demographics</td>
</tr>
<tr>
<td></td>
<td>– Workforce trends + projections</td>
</tr>
<tr>
<td></td>
<td>– Staffing retention rates</td>
</tr>
<tr>
<td></td>
<td>– Retirement rates</td>
</tr>
<tr>
<td>Legislation and regulation</td>
<td>• State regulations/federal regulations/current legislation/policy affecting</td>
</tr>
<tr>
<td></td>
<td>health care workers, including:</td>
</tr>
<tr>
<td></td>
<td>– Virginia code + regulation + health care workforce</td>
</tr>
<tr>
<td></td>
<td>– Virginia Department of Health Professions + regulation/licensing</td>
</tr>
<tr>
<td></td>
<td>– Virginia + regulatory review + health care workforce</td>
</tr>
<tr>
<td></td>
<td>– Virginia + legislation + health care workforce</td>
</tr>
<tr>
<td></td>
<td>– Virginia + alternative licensing + health care workforce</td>
</tr>
<tr>
<td></td>
<td>– Current funding environment + health care workforce development</td>
</tr>
<tr>
<td></td>
<td>– State/ federal financial aid and loan forgiveness programs</td>
</tr>
<tr>
<td>Education and training</td>
<td>• Education/training/licensing/registration/accreditation/curriculum</td>
</tr>
<tr>
<td></td>
<td>• Continuing education/professional development/license renewal</td>
</tr>
<tr>
<td></td>
<td>• Education/training/licensing/registration/accreditation/curriculum +</td>
</tr>
<tr>
<td></td>
<td>postsecondary</td>
</tr>
<tr>
<td></td>
<td>• Education/training/licensing/registration/accreditation/curriculum +</td>
</tr>
<tr>
<td></td>
<td>K–12</td>
</tr>
<tr>
<td></td>
<td>• Education/training/licensing/registration/accreditation/curriculum + Area</td>
</tr>
<tr>
<td></td>
<td>Health Education Center</td>
</tr>
<tr>
<td>Recruitment and retention</td>
<td>• Continuing education/professional development/license renewal</td>
</tr>
<tr>
<td></td>
<td>• Continuing education/professional development/license renewal + Area</td>
</tr>
<tr>
<td></td>
<td>Health Education Centers</td>
</tr>
<tr>
<td></td>
<td>• Higher education student financial assistance + health care workforce</td>
</tr>
<tr>
<td></td>
<td>• Education/training + faculty</td>
</tr>
<tr>
<td></td>
<td>• Education/training + clinical placement</td>
</tr>
<tr>
<td></td>
<td>• Support/ continuing education/training for providers</td>
</tr>
<tr>
<td></td>
<td>• Promoting/impeding factors + health care professions for immigrants,</td>
</tr>
<tr>
<td></td>
<td>veterans, military spouses—disparities/inequities/underrepresented,</td>
</tr>
<tr>
<td></td>
<td>underserved</td>
</tr>
<tr>
<td></td>
<td>• Promoting/impeding factors + health care professions + immigrants,</td>
</tr>
<tr>
<td></td>
<td>veterans, military spouses</td>
</tr>
<tr>
<td></td>
<td>• Barriers/facilitators + health care professions + immigrants, veterans,</td>
</tr>
<tr>
<td></td>
<td>military spouses</td>
</tr>
<tr>
<td></td>
<td>• Incentives/incentivizing + health care education + training + professions</td>
</tr>
<tr>
<td>Promising programs and practices</td>
<td>• Best practices/promising programs/successful programs + health care</td>
</tr>
<tr>
<td></td>
<td>workforce/jobs/occupation/front line health workers</td>
</tr>
</tbody>
</table>

NOTE: K–12 = kindergarten through 12th grade.

Screening and Selecting Studies

Members of the environmental scan team independently screened and selected articles across two iterations. In the first iteration, a team member reviewed the full array of articles identified in an initial search, using specified databases and search terms (see “Developing and Implementing a Review Protocol” and Table B.2). Across all health care occupations and searches, a total of 1,405 articles were included in the full, initial array. In the second iteration of screening and selection, a team member reviewed articles for topical relevance based on the title and abstract. If the article topically
matched specified research questions, it was retained—regardless of research methods used or the geographic focus of the research. Team members reviewed each other’s work and discussed and resolved any discrepancies in retained articles. This topically relevant but methodologically and geographically broad array of articles ($N = 357$) served as the core set of articles for the environmental scan.

**Appraising and Synthesizing Selected Studies**

To analyze and synthesize selected studies in our environmental scan, the environmental scan team engaged in four steps: (1) an initial overview of articles to understand broad patterns, (2) coding and otherwise assessing articles according to research questions and identified patterns or themes in Step 1, and (3) drafting and discussing text regarding main findings within the environmental scan team and the larger research teams. In Step 4, the team presented preliminary findings to Virginia stakeholders for comment and discussion.
Appendix C

Interview and Focus Group Guide

1. From your perspective, what are the main causes of shortages among Virginia’s primary care workforce?
   - Behavioral health?
   - Nursing?

2. What strategies and/or policies have you observed in Virginia to retain its primary care workforce? Which ones are effective (or ineffective) in your view? Please elaborate.
   - Behavioral health?
   - Nursing?

3. What strategies would you like to see your community or state government use to boost retention of its existing primary care workforce?
   - Behavioral health?
   - Nursing?
   [Probe on role of strategies such as: increased compensation/monetary incentives, supporting work-life balance, and transportation, etc.]

4. What strategies might Virginia use to help recruit new practitioners to expand its existing health care workforce in:
   - Primary care?
   - Behavioral health?
   - Nursing?

5. A few states have created alternative pathways to licensure for international doctors, veterans, military spouses, and other populations seeking work in in health care. Should Virginia pursue similar strategies to boost workforce in the following fields? Describe the risks and/or benefits of doing so.
   - Primary care?
   - Behavioral health?
   - Nursing?

6. How much of a barrier do the costs associated with education and/or licensure (and re-licensure) present for people seeking practice in health care, nursing, and behavioral health?
   - How about requirements for long periods of supervised practice?
How about stresses related to work in these fields (e.g., workload, paperwork/charting burden, stressful work environment)?

7. Should Virginia aim to incentivize more high school and/or college students to enter the following fields? If yes, how would you do it?
   - Primary care?
   - Behavioral health?
   - Nursing?

8. What steps need to be taken in order for state, federal, and private funding to be allocated to workforce development programs?

9. What strategies do you recommend be used to boost the number of training positions for health professionals in
   - Primary care?
   - Behavioral health?
   - Nursing?

10. We’ve heard that there are not enough nursing faculty, clinical preceptors, and training sites. What ideas do you have to address this challenge?

11. Should Virginia change its processes for awarding and managing educational scholarships and/or loan forgiveness to incentivize individuals to pursue careers in primary care, behavioral health, and nursing? What ideas do you have to accomplish this?

12. Based on your expertise, name an actionable step or strategy you believe Virginia should and can take in the next 6 months to address workforce shortages in primary care, nursing, and behavioral health?
   - In one year?
   - Next two years?

13. What strategies can be used to ensure that efforts around health care workforce development are sustained over time?
Appendix D

Hospital Survey Questions

1. Which of the following strategies has your hospital/health system used to retain nurses? Mark all that apply.

[ ] Increased salary
[ ] Bonuses
[ ] Educational loan repayment
[ ] More flexibility in work hours
[ ] Transportation vouchers
[ ] Convenient and/or free parking
[ ] On-site childcare
[ ] Subsidizing cost of housing
[ ] Meal coverage
[ ] Mental health services for staff
[ ] Job training to improve and/or expand skillsets
[ ] Diversity, equity, and inclusion strategies
[ ] Strategies that promote teamwork
[ ] Covering cost of maintaining licensure
[ ] Changed patient flow or staffing models
[ ] Offering educational advancement opportunities as part of employment
[ ] Supervisory training and/or ombudsman program to address employee concerns
[ ] How have you changed practices and/or technology to support flexible staffing models?
Appendix E

The Mathematical Formulation of Our System Dynamics Simulation Model

Introduction

In early 2022, we developed a simulation model focusing on the short- and medium-term impact of the COVID-19 pandemic on the nurse labor market. Our model incorporated a wide variety of factors, including epidemiological trends, behavioral dynamics, hospitalization patterns, relief programs, and wage considerations. In this appendix, we present a revised model that, building on this precursor model, simulates and tracks the dynamics of key variables related to the health care workforce in Virginia over time. While our revised model does incorporate the effects of the COVID-19 pandemic, our primary objective here is to simulate the medium- to long-term supply and employment trends within Virginia’s health care workforce. We explore scenarios under both baseline (status quo) conditions and various policy interventions. The central aim is to offer a comprehensive set of projections for Virginia’s health care workforce, moving beyond the sole assessment of the pandemic’s impact over time.

Although our model encompasses workforce dynamics among nurses, physicians, and behavioral health specialists within Virginia, our focus in this appendix will predominantly revolve around nurses. The foundational framework remains consistent for physicians and behavioral health specialists, albeit with variations in initial state variables and input parameters. Our model provides insights into the health care workforce in Virginia, encompassing both state-level and regional perspectives, spanning the eight Area Health Education Centers (AHEC) regions of Virginia. It calculates medium- to long-term dynamics, yielding output projections for the next 15 years.

Our model employs a system dynamics approach. This approach ensures a deterministic representation of aggregate population dynamics. The system dynamics method proves advantageous when studying labor markets during prolonged non-equilibrium periods, such as those induced by pandemics. It offers a macroscopic perspective for analyzing research questions and facilitates scenario exploration and sensitivity testing.

The choice of the system dynamics approach is driven by its ability to specify causal mechanisms driving system dynamics and its suitability for examining labor markets affected by extraordinary events, such as pandemics, which often operate outside equilibrium for extended durations. Furthermore, the system dynamics approach is computationally efficient, quicker to develop, easier to understand, and faster to execute compared with individual-level microsimulation or agent-based models, particularly when dealing with a substantial number of parameters.

The system dynamics approach involves formulating the model using coupled ordinary differential equations (ODEs) and numerically integrating them using specialized solvers. The numerical
integration poses a stiff problem, where the step size of the numerical solution is limited more by the
stability of the numerical technique than by its accuracy (Hindmarsh and Petzold, 1995). For our
implementation, we used the R programming language with the deSolve package (Soetaert, Petzoldt,
and Setzer, 2010). DeSolve employs Fortran solvers of the Livermore family to solve initial value
problems for stiff ODEs, and it offers various types of solvers for this purpose. We used the default
integration method, LSODA, that switches automatically between using methods for stiff and
nonstiff systems.

Our model operates with a weekly timestep for generating outputs, although the solver typically
uses much smaller time steps during numerical integration. Because many input model parameters and
rate values are provided on a yearly basis, we convert these values into weekly rates to maintain
consistency with the model’s weekly timestep.

The System Dynamic Model and Its Differential Equations

The state variables include the supply of nurses, \( q_s(t) \); the qualified pool of potential nurses,
\( n_s(t) \); the yearly wage for nurses, \( w(t) \); and the perceived barriers affecting their willingness to work
as nurses relative to a baseline, \( z(t) \). We also consider nurse demand, \( q_d(t) \), which represents the
need for nurses and is externally specified as an input to the model.

The nurse supply variable, \( q_s(t) \), represents the proportion of available nurses actively choosing
and desiring to work as nurses, including those currently employed or actively seeking nursing
positions. On the other hand, the qualified pool variable, \( n_s(t) \), includes individuals who possess the
necessary qualifications to work as nurses but may have temporarily chosen not to do so. This
category encompasses retired nurses who could potentially return to the workforce, individuals in less
demanding professions with lower pay, and nurses experiencing hidden unemployment. However,
nurses who have pursued completely different career paths outside nursing, such as becoming doctors
or researchers, are not considered. The actual number of available nurses is determined as the
minimum between demand and supply, given by \( q(t) = \min[q_d(t), q_s(t)] \).

Our model assumes that the supply of nurses, \( q_s(t) \), depends on the qualified pool of potential
nurses, \( n_s(t) \); the yearly wage for nurses, \( w(t) \); and the perceived barriers affecting their willingness
to work in the nursing field relative to a baseline, summarized by one variable, \( z(t) \), whose size is
proportional to the strength of said barriers.

To derive an explicit expression for \( q_s(t) \) as a function of these quantities, we assume that the
decision to work made by the nurses in the qualified pool follows a simple utility maximization
principle. We assume that nurses receive a utility, \( \ln(w) \), from working for wage \( w \), and a utility,
\( \ln(w_0) \), if they do not work, where \( w_0 \) has the interpretation of a reservation wage, because nurses
only work if \( w > w_0 \). We assume that there is variation in the reservation wage in the nurses’
population, and therefore we model \( w_0 \) as a random variable with a log normal distribution.
Therefore, the total number of nurses working is:

\[
q_s = n_s P(\ln(w) > \ln(w_0)) = \frac{1}{2} n_s [1 + \text{erf}(s_s (\ln(w) - \ln(w_0)))],
\]
where \( s_x \) is a parameter that is inversely proportional to the variance of the reservation wages \( w_0 \).

Qualitatively, the supply of nurses is an increasing function of wages, which is 0 when wages are 0, is exactly one half when wages are equal to the reservation wage (because nurses are then indifferent to the two options) and becomes equal to the entire pool \( n_s \) when wages tend to infinity.

What is missing from this formulation is the reluctance to work, \( z \). We assume that the reluctance to work influences the reservation wage \( w_0 \) and that higher levels of reluctance to work raise the reservation wage. We model the relationship between reluctance to work and reservation wage with an S-shaped function:

\[
    w_0(z) = K \left[ 1 + \frac{1}{2} \left[ 1 + \text{erf}(s_x (\ln(z) - \ln(m_z))) \right] \right].
\]

When the reluctance to work is 0, the reservation wage is \( K \) and the supply of nurses is maximum. As the reluctance to work grows to infinity, the reservation wage reaches its maximum value (2 \( K \)), and the supply reaches its minimum value. We assume that \( K = \rho_w w_0(1) \). This is because we choose to set to the reluctance value \( z \) equal to 1 to represent our baseline setting.

In our model, \( q_s(t) \) adheres to a specific functional form represented by a sigmoidal S-surface specified by the equations for \( q_s \) and \( w_0(z) \) given above. It is important to note that this specific function for \( q_s(t) \) is just one of many possible choices or models to describe how supply reacts to changes in wages and perceived barriers to work. Essentially, it is just one way we model supply changes. In a more general context, \( q_s(t) \) can be characterized using alternative functional forms, potentially dependent on a different set of parameters. For clarity, we denote this specific model as \( q_s(t) = S_\theta(n_s, w, z) \), where \( S_\theta(n_s, w, z) \) represents the particular functional form we’ve chosen to represent supply. Here, \( \theta \) is a parameter set that defines the specific shape of the sigmoidal function we’ve selected. The parameter set \( \theta \) includes of \( \rho_w, w_0(1), m_z, s_s, \) and \( s_x \). In the subsequent text, we will use \( q_s(t) \) as a general reference to the nurse supply and use \( S_\theta(n_s, w, z) \) to denote the specific functional form we use to model supply. Our sigmoidal S-surface for supply is visually presented in Figure E.1. The contour plot beneath the S-surface demonstrates that as health care work reluctance increases, real wages must increase to sustain the nurse supply. This aligns with the concept of compensating-wage differentials in economic theory.
The time evolution of supply of nurses is determined by the interplay of various variables that change over time. To capture these dynamics, we consider a differential equation describing the rate of change of the supply function \( q_s(t) \) with respect to time \( t \). The differential equation is given by:

\[
\frac{dq_s}{dt} = \frac{\partial q_s}{\partial t} + \frac{\partial q_s}{\partial n_s} \frac{dn_s}{dt} + \frac{\partial q_s}{\partial w} \frac{dw}{dt} + \frac{\partial q_s}{\partial z} \frac{dz}{dt}.
\]

In this equation, the total derivative of supply with respect to time is expressed as a sum of terms containing partial derivatives of the supply with respect to its controlling variables. The first term, \( \frac{\partial q_s}{\partial t} \), represents the long-term supply trend independent of changes in real wages, pandemic-related outcomes, and the qualified pool of registered nurses. We have assumed that variations in supply are solely attributed to changes in the qualified pool \( n_s \), wages \( w \), and reluctance \( z \), and, as a result, we have omitted this term from consideration. The second term captures the long-term supply dynamics of the qualified pool of registered nurses, considering changes due to recruitment and expansion policies, as well as contractions such as permanent retirements. The medium- to short-term dynamics are mainly described by the last two terms, quantifying how the supply changes with wages and work reluctance. These terms depend on the derivatives \( \frac{\partial q_s}{\partial w} \) and \( \frac{\partial q_s}{\partial z} \), as well as the rates of change of real wages and work reluctance \( \frac{dw}{dt} \) and \( \frac{dz}{dt} \). By applying these equations, we derive the expressions for \( \frac{\partial q_s}{\partial n_s}, \frac{\partial q_s}{\partial w}, \) and \( \frac{\partial q_s}{\partial z} \).
The differential equation for supply is a general equation that applies to our overall expression of supply, denoted as $q_s(t)$. Now, we move forward by calculating the partial differentials that contribute to the equation for the total derivative of supply. In this context, we will be dealing with our specific representation of supply, $S_\theta(n_s, w, z)$. The derivatives of $S_\theta$ correspond to scaled log-normal probability density functions (PDFs), because $S_\theta(n_s, w, z)$ represents a scaled log-normal cumulative distribution function. The expressions are as follows:

$$
\frac{\partial S_\theta}{\partial n_s} = \frac{s_s \exp{-s_s^2 [\ln w - \ln m_s(z)]^2}}{w\sqrt{\pi}} = S_\theta(1, w, z),
$$

$$
\frac{\partial S_\theta}{\partial w} = \frac{n_s s_s \exp{-s_s^2 [\ln w - \ln m_s(z)]^2}}{w\sqrt{\pi}}.
$$

The expression for $\frac{\partial S_\theta}{\partial z}$ is obtained by taking the product of $\frac{\partial S_\theta}{\partial n_s}$ and $\frac{\partial m_s(z)}{\partial z}$, given by:

$$
\frac{\partial m_s}{\partial z} = \frac{m_s(z) s_z \exp{-s_z^2 [\ln m_z - \ln z]^2}}{z\sqrt{\pi}}.
$$

With the expressions for $\frac{\partial S_\theta}{\partial n_s}$, $\frac{\partial S_\theta}{\partial w}$, and $\frac{\partial S_\theta}{\partial z}$ derived, we proceed to specify the models describing the rates of change of $n_s$, $w$, and $z$ over time in the next sections.

**Modeling the Rate of Change of the Qualified Pool**

Here we present our model for $\frac{dn_s}{dt}$, which describes the changes in the overall qualified pool of workers over time. The model takes into account factors that increase the workforce, such as enrollment and graduation rates from nursing schools, which contribute to the growth of the nurse supply. It also encompasses factors that decrease the workforce, including rates of permanent retirement or nurses transitioning to other career paths. The basic form of the model subtracts the outflows from the inflows to describe how $n_s$ changes over time. We assume that the inflow of qualified nurses is proportional to the current supply, represented by the constant $\nu$ scaled by the normalized scaling factor $S_\theta(1, w, z) = \frac{S_\theta(n_s, w, z)}{n_s}$. On the other hand, the outflow is determined by a fixed yearly probability $\omega$ of permanently leaving the qualified pool because of retirement or irreversible decisions. Thus, the simplest model for $\frac{dn_s}{dt}$ is

$$
\frac{dn_s}{dt} = \nu S_\theta(1, w, z) - \omega n_s.
$$

The stationary solution is obtained by setting $\frac{dn_s}{dt} = 0$, resulting in $\omega = \frac{\nu S_\theta(1, w, z)}{n_s}$. It is worth noting that the depletion of the qualified pool may vary between nurses in the supply and those in the
qualified pool but not in the supply. We assume that the per-person depletion rate for nurses in the qualified pool but not in the supply \((\omega_1)\) is greater than the rate for nurses in the supply \((\omega_2)\) by a constant factor \(\kappa_\omega\). Therefore, \(\omega_1 = \kappa_\omega \omega_2\). Combining these considerations, we have:

\[
\omega n_s = \omega_1 n_s [1 - S_\theta (1, w, z)] + \omega_2 n_s S_\theta (1, w, z),
\]

which leads to:

\[
\omega = \omega_1 [1 + S_\theta (1, w, z)(\kappa_\omega - 1)].
\]

It is important to note that the outflow, representing the permanent retirement of nurses from the qualified pool, implicitly depends on wages and health care work reluctance through the term \(S_\theta (n_s, w, z)\) that multiplies \(\omega_1\) and \(\omega_2\). As wages decrease or work reluctance increases, the supply increases. Because \(\omega_1 > \omega_2\), nurses retire at a higher rate or switch to alternative occupations or careers. Similarly, the inflow depends on wages and work reluctance through \(S_\theta (1, w, z)\). As real wages increase or work reluctance decreases, the normalized supply increases, signaling to prospective students that nursing is an abundant and desirable occupation to pursue.

Returning to the steady-state solution \(\frac{dn_s}{dt} = 0\), we find

\[
\omega_1 = \frac{\nu S_\theta (1, w, z)}{n_s [1 + S_\theta (1, w, z)(\kappa_\omega - 1)]}.
\]

**Wage Dynamics**

In our model, nurse wages are influenced by the imbalance between demand and supply, and they are assumed to have limited flexibility, resulting in asymmetric adjustments. When wages are below the market-clearing rate, hospitals need to increase real wages to fill vacancies. On the other hand, when wages exceed the market-clearing rate, hospitals may desire to reduce them, but contractual arrangements prevent such adjustments. The real rate of change of nurse wages, denoted as \(\frac{dw}{dt}\), is described by the equation

\[
\frac{dw}{dt} = [(\alpha_d - \alpha_s) H(q_d - q_s) + \alpha_s] \cdot (q_d - q_s) w.
\]

Here, \(H(x)\) represents the Heaviside step function, which we approximate using an inverse logistic function for integration in our model implementation. The parameters \(\alpha_d\) and \(\alpha_s\) determine how the wage gap between demand and supply affects wage changes. We assume that real wages increase more rapidly when there is excess demand for nurses than when there is excess supply. Hence, the rate \(\alpha_d\) is numerically greater than \(\alpha_s\) to reflect this assumed faster growth rate of wages.

**Health Care Work Reluctance**

A key component of our model is the health care work reluctance measure \(z(t)\) and its evolution over time. Working during a pandemic is undeniably more challenging than under normal
circumstances, and \( z \) increases based on various pandemic-related factors, including fatigue from COVID-19 hospitalization surges, increased risk of contracting the virus at work, unclear quarantining guidelines, increased proximity to preventable deaths, shortages of personal protective equipment, and higher patient-to-nurse ratios during surges.

Health care work reluctance \( z(t) \) is assumed to change according to an exponential weighted moving average (EWMA) process over \( \Delta(t) \), which captures nurses’ weekly evaluations affecting their reluctance to work. The variable \( \Delta(t) \) quantifies nurses’ weekly assessments regarding their willingness to work. One way of expressing the dynamics of the EWMA by a differential equation is as follows:

\[
\frac{dz}{dt} = (1 - s)[\Delta(t) - z(t)].
\]

Here, \( s \) is a weekly discount parameter and plays a crucial role in determining the relative significance of past nurses’ weekly assessments compared with the current ones in forming a nurse’s overall reluctance in health care work. The discount parameter can be calculated by specifying a half-life duration \( \tau \) using the formula \( \ln(2)/(1 - s) \). The half-life represents the duration for past evaluations to contribute half as much to the work reluctance measure.

A broader range of perceived barriers affect \( \Delta(t) \). We assume that these barriers can be grouped into three main categories, namely distress, disengagement, and fatigue. From a mathematical perspective, we express these factors as components influencing the assessment of \( \Delta(t) \). Our assumption is as follows:

\[
\Delta(t) = \beta_D \phi_D(t) + \beta_E \phi_E(t) + \beta_F \phi_F(t),
\]

where \( \beta_X \phi_X(t) \), with \( X \in D, E, F \), representing the contributions from three different components: distress, disengagement, and fatigue, respectively. The coefficients \( \beta \) represent weights that sum up to one. Each of the components \( \phi \) represents evaluations. Specifically, \( \phi_F \) measures nurses’ fatigue, while \( \phi_D \) quantifies their distress.

Fatigue (\( \phi_F(t) \)) is assumed to be fully determined by the demand level, which can be measured using the patient-to-nurse ratio (\( \eta_t \)) and its changes over time (\( t \)). We assume that a fixed proportion \((1 - \xi_f)\) of distress depends on the demand level. Therefore, \( \phi_D = \eta_0[(1 - \xi_f)\eta_t/\eta_0 + \xi_f\psi_D] \), where \( \psi_D \) is considered a fixed effect that does not depend on demand and can be influenced by policy interventions unrelated to demand. The default value for \( \psi_D \) is one, representing the baseline fixed effects.

Disengagement (\( \phi_E \)) is assumed not to change with demand and is considered as a fixed effect that can be influenced by policy interventions unrelated to demand. Combining all the above points, we have the following expression:

\[
\Delta(t) = \beta_F \eta_t/\eta_0 + \beta_D[(1 - \xi_f)\eta_t/\eta_0 + \xi_f\psi_D] + \beta_E \psi_E.
\]

For the initial condition at \( t = 0 \), the patient-to-nurse ratio \( \eta_t \) is set to its baseline value \( \eta_0 \). Therefore, by design the baseline default value for \( \Delta(t) \) is set equal to one. As a result, the baseline value for health care work reluctance is represented by \( z = 1 \). This is because from the differential
equation, under the stationary condition (i.e., \( \frac{dz}{dt} = 0 \)), health care work reluctance does not change and remains at its baseline value, \( z(t) = \Delta(t) \).

**Informing the Model Inputs**

Our model draws from a variety of inputs, including parameter values and their ranges, initial conditions for state variables, and historical time-series data for such variables as occupied hospital beds, nurse employment numbers, and real wages. These inputs guide the model’s behavior and serve as targets for calibration. In this section, we offer a concise overview of the model inputs and the data sources that informed our parameter estimation.

**The State Variables’ Initial Conditions**

To start, we describe how we computed our state variables’ initial conditions. Our model encompasses several key state variables, namely: demand, supply, and the qualified number of nurses within the system. All these variables are quantified in units of nurses. Additionally, our state variables encompass the average annual wage of nurses (measured in dollars), the health care work reluctance metric, and the proportion of hospitalizations attributed to COVID-19 patients.

The model relies on input values to establish the initial conditions for these six state variables. We work with two distinct sets of initial conditions. The first set is employed for calibration purposes, defining the initial states just prior to the onset of the pandemic. This calibration enables our model to operate throughout the pandemic years, facilitating a comparison between projected trajectories of select state variables and the observed data from our time series. Notably, we focus on trajectories related to annual wages and the number of employed nurses. By contrasting these trajectories with empirical data, we refine the input parameter values via our model calibration process.

The second set of initial conditions delineates the starting states during the current post-acute pandemic phase. These are used for forecasting policy interventions and their relative impacts. It enables us to predict potential outcomes and make comparisons among different policy strategies. When new initial conditions for this phase are absent, we adopt the final conditions derived from our model calibration runs as the basis for the forecast phase.

Here, we delve into the specifics of the first set of initial conditions. Our baseline for analysis is derived from our time series data for Virginia, specifically focusing on the employment figures for nurses in hospitals as of April 5, 2020. On this date, the number of nurses employed in hospitals across the state of Virginia totaled 66,450, with an average annual wage of $74,380. We assume that demand exceeded supply on this date, enabling us to estimate supply as the existing number of nurses employed in Virginia’s hospitals. Given the nascent stage of the pandemic in the United States at that time, we consider the proportion of COVID-19 hospitalizations to be negligibly small, approximating it to zero. Additionally, we initialize the healthcare work reluctance metric at its baseline value of one. Using these foundational estimates, we proceed to determine the range of values for nurse demand in Virginia on this pivotal date.

Nationally, the demand for nurses has been assessed at 3,154,000 (Haines, 2022). To localize this demand to the Commonwealth of Virginia, we employ a scaling methodology. This approach
capitalizes on data pertaining to the count of staffed beds and the average bed occupancy rate in Virginia, facilitating the alignment of national demand with the state’s contextual factors.

Specifically, within Virginia, the inventory of inpatient beds aggregates to 15,177, with an average occupancy rate of 70 percent. To contextualize the national demand within Virginia’s framework, we necessitate insights into the total count of staffed beds at the national level and the corresponding average bed occupancy rate. As per recent data, the cumulative tally of staffed beds across U.S. hospitals reaches 919,649, accompanied by a bed occupancy rate of 64 percent (American Hospital Association, 2023; Michas, 2022).

Calculating the ratio between the product of bed occupancy and staffed beds in Virginia and their national equivalents enables us to ascertain the scaling factor. The multiplication of this scaling factor by the national demand yields an approximation of the initial demand tailored to Virginia’s circumstances. This methodology customizes the demand projection by integrating the state’s health care infrastructure and bed utilization dynamics.

An alternative estimation for demand in Virginia involves assuming that its demand-to-supply ratio mirrors the national level. Consequently, we simply need to multiply this ratio by our supply estimation for Virginia. Nationally, demand surpasses supply, with supply closely aligned to the estimated number of employed nurses at 3,072,000 (Haines, 2022), marginally lower than the 3,154,000 demand estimate. This results in a demand-to-supply ratio of approximately 1.027. Assuming that initial demand surpasses supply in Virginia, we employ this ratio to upscale the estimated count of employed nurses in the state. This furnishes an estimation for Virginia’s demand.

By employing both of these methodologies, we arrive at distinct estimations for the pre-pandemic initial demand scenario in Virginia. The estimated demand ranges from 59,800 to 76,600, with a central value of 68,224 that we consider the most plausible. The lower bound approximates the estimate from our first methodology, and the central value is derived from the second methodology. To establish the upper bound, we apply the same difference between the central and lower values to the difference between the upper bound and the central value. Within this range of uncertainty lies a diversity of values, collectively assuming a critical role within our model calibration procedure.

**Informing the Behavioral Model for Health Care Work Reluctance**

Here, we outline the parameters that shape our behavioral model for health care work reluctance. We begin by estimating the $\beta$ weights, which quantify the significance of each behavioral component in influencing evaluations. The most reliable source for estimating these $\beta$ weights is through surveys that assess work-related attitudes and the desire to continue working, specifically targeting nurses. For this purpose, we utilized the analyses conducted by McKinsey on longitudinal national surveys on nurses carried out since the onset of the pandemic (Berlin, Lapointe, and Murphy, 2022).

In exploring the drivers of nurses’ intentions to leave their positions, we focused on respondents who expressed a likelihood of leaving within a year. These respondents were required to provide scores for 15 specific factors and 24 barriers, such as insufficient staffing levels, emotional toll, approaching retirement age, fear of COVID-19, lack of career prospects, uncertainty, unmanageable workload, and no work-life balance. We categorized each factor and barrier under fatigue, distress, or disengagement, depending on their nature. While some factors, such as no development opportunities, clearly fell under
disengagement, others, such as *move to desirable location*, did not fit neatly into these categories and were excluded from analysis.

Our examination of the McKinsey survey data revealed that fatigue was the most influential factor, accounting for approximately 50 percent of the importance. Distress followed closely, constituting around 30 percent of the total importance. Based on the data and respondent numbers, we estimated an accuracy range of approximately ±15 percent of their values (i.e., ±7.5 percentage points for the case of fatigue) for these importance weights.

Given the constraint that the weights must sum to 100 percent, we derived the importance weight for disengagement by considering the sampled values of importance weights associated with fatigue and distress. This allowed us to establish a comprehensive understanding of the impact of these behavioral components on health care work reluctance.

Alongside the $\beta$ weights, our behavioral model introduces two additional parameters: $\xi_f$, which represents the portion of distress that does not depend on the demand level, and the discount parameter $s$. Regrettably, despite extensive searches through the McKinsey surveys and existing literature, we were unable to discover any data or sources to aid in estimating $\xi_f$ — the parameter describing the fixed proportion of distress independent of perceived fatigue. In response, we made an assumption that $\xi_f$ falls within the range of 50 percent ±7.5 percent.

However, in stark contrast, the outcomes derived from the McKinsey surveys provide invaluable insights into the temporal evolution of nurses’ intentions to leave their positions. These insights can be effectively leveraged to estimate the discount parameter $s$. The percentage of nurses contemplating leaving their jobs surged from 22 percent in February 2021 to 32 percent by November 2021. This heightened level endured until September 2022, signifying a substantial increase by a multiplicative factor of 1.45, likely attributed to the pandemic-induced circumstances.

Given our analysis that points to fatigue as the predominant influencer of health care work willingness and considering our access to national weekly data on both COVID-19 and non-COVID-19 hospitalizations, we opted to merge the McKinsey survey findings with hospitalization data. This fusion allowed us to estimate the value of the discount parameter $s$, or equivalently, the half-life duration of work reluctance evaluations. The underlying concept is that heightened hospitalizations and an increased proportion of COVID-19 patients among hospitalizations affect fatigue, which manifests with a lag in time following peaks in hospitalizations and COVID-19 proportion. This enables us to evaluate the perceived increased fatigue after a certain lag period. By interlinking these datasets, we aimed to unravel the dynamic interplay between work reluctance and hospitalization trends.

However, it is important to consider the limitations of our assumption. Initially, the pandemic saw a decrease in overall hospitalizations even as the proportion of COVID-19 hospitalizations increased. During this period, nurses experienced significant fatigue because of increased workloads. The decline in non-COVID-19 hospitalizations contributed to COVID-19 hospitalizations forming a larger proportion of total hospitalizations.

To ensure that our analysis yields meaningful results and our simulation model is realistic, we must quantify the additional effort COVID-19 patients demand from nurses in comparison to non-COVID-19 patients. Our approach involves considering factors such as evolving nurse demand, increased intensive care unit (ICU) patient ratios during the pandemic, and varying levels of effort
needed for COVID-19 patients versus non-COVID-19 patients. Our goal is to calculate and use an effective patient-to-nurse ratio $\eta_t$ that captures the added efforts that resulted from serving COVID-19 patients, serving as a proxy for effort that scales linearly with fatigue.

We start by assessing the pre-pandemic and baseline efforts. Nationally, the nurse-to-patient ratio during this period ranged from 1:4 to 1:5 for medical-surgical units, and 1:2 for ICUs (Wolters Kluwer, 2016). For our calculations, we consider a baseline nurse-to-patient ratio of 1:4. The national proportion of patients admitted to the ICU pre-pandemic had a median of 12 percent with an interquartile range of 9 percent to 17 percent (Seymour et al., 2012). This information aligns with our data from Virginia on hospitalizations. With these values, our baseline patient-to-nurse ratio $\eta_0$ is 3.76.

To estimate the added effort for COVID-19 patients, we consider multiple factors. These include comparing the average length of stay between COVID-19 and non-COVID-19 patients, the proportion of COVID-19 patients requiring ICU care, and the increased daily effort required for COVID-19 patients both inside and outside ICU settings.

In 2018, the average length of stay for a hospitalization in the United States was 5.5 days based on 36.4 million inpatient stays (Tipton et al., 2021). In contrast, the estimated length of stay for COVID-19 hospitalizations was 15.35 days, with a 95 percent confidence interval of 13.47 to 17.23 days (Alimohamadi et al., 2022). This suggests that the effort required for a COVID-19 patient is roughly three times that of a non-COVID-19 patient based on length of stay.

During the pandemic, the national rate of ICU admission for COVID-19 patients was initially reported as 32 percent (Abate et al., 2020). However, our analysis of COVID-19 data for Virginia suggests this proportion to be closer to 20 percent.

By integrating these factors, we reevaluated the time-series data on total and COVID-19 hospitalizations, correlating them with the McKinsey survey results when the percentage of nurses considering leaving their jobs peaked. This analysis allowed us to estimate the half-life duration of work reluctance evaluations, indicating a range of three to 12 months. The substantial uncertainty stems from relying on only two time points from the McKinsey surveys. While the accuracy is limited, we chose to work with the available data and exercise our judgment in interpreting plausible outcomes from the analysis.

### Informing How Supply Responds to Changes in Health Care Work Reluctance

Having elucidated our behavioral model for work reluctance and its parameter estimation process, our focus now shifts to estimating how changes in health care work reluctance impact nurse supply. This entails the estimation of the supply parameters $\theta$, which govern the relationship $\frac{\partial S_\theta}{\partial z}$. Specifically, we delve into $m_z$ and $s_z$, which define the supply's response to increasing work reluctance. These parameters, being intrinsic to our model’s intricacies, require an indirect estimation method based on the model calibration process, which is detailed in a subsequent section of this appendix.

However, in a bid to enhance the model’s input intuitiveness, we’ve opted to derive and compute the values of $m_z$ and $s_z$ from more readily understandable input parameters. While these parameters still pose challenges for estimation, they boast more intuitive definitions, which could aid experts in
behavioral health economics to provide better assessments of their values and the associated ranges of uncertainty.

These intuitive input parameters include the initial proportion of nurses within the supply relative to the total pool of qualified nurses. This proportion acts as our supply’s baseline when health care work reluctance assumes its baseline value of one. Nationally, approximately 84.1 percent of licensed RNs are employed in the nursing sector (American Association of Colleges of Nursing, 2022). We consider an uncertainty range for this proportion around our central estimate of 84.1 percent spanning 80 percent to 88 percent. This estimate serves as our baseline proportion of nurses in the supply.

Furthermore, we need a second estimation of the proportion of nurses within the supply concerning the total qualified nurse pool. This estimation comes into play when health care work reluctance surpasses its baseline value while keeping other factors, including the annual wage, constant. Our methodology involves setting this second supply proportion to 50 percent of the baseline supply value. Subsequently, we attempt estimating the range of health care work reluctance values denoted as $z_2$, which would trigger this particular level of supply reduction.

Our estimation for $z_2$ spans a wide range from 1.1 to 3, with the most plausible and central value hovering around 1.5. This extensive range reflects the significant uncertainty associated with this parameter. Nevertheless, this range does encompass a specific estimate derived from the analysis of the McKinsey surveys.

The surveys highlighted a variety of factors influencing nurses’ decisions to leave during the pandemic, varying from 22 percent to 32 percent. This variability suggests that the supply of nurses during the same period might have varied between 68 percent and 78 percent of the qualified nurse pool $n_s$. A simple analysis or estimation reveals that when the leave factor increases by 45 percent (i.e., a factor of 32/22), the supply diminishes by approximately 13 percent (i.e., $1 - 68/78$). It is important to note that this provides a lower bound of the response, because the quoted 22 percent factor was not a baseline estimate but was also estimated within the pandemic period.

The final input parameter essential for estimating how changes in health care work reluctance affect nurse supply pertains to the percentage of the current wage required to sustain the existing workforce if all factors causing work reluctance were eradicated (i.e., $z = 0$). This concept proves challenging to source directly, given its hypothetical nature. The scenario delves into the hypothetical realm of nurses potentially trading a portion of their wages in return for the complete removal of perceived barriers in their work environment. The crux of the matter lies in identifying the minimum portion of their current wage that nurses would be amenable to accept before it significantly influences their likelihood of opting to leave their nursing profession.

Our estimation for the wage that nurses might accept in exchange for the complete elimination of perceived barriers in their workplace spans a broad spectrum from 70 percent to 99 percent of their current wage, with the most plausible and central value gravitating around 80 percent because of the highly skewed distribution of results. This parameter encompasses a diverse range, reflecting the substantial uncertainty inherent in this scenario. Nonetheless, the central estimate aligns with a plausible value that nurses might be willing to consider in a scenario devoid of the barriers influencing their work reluctance.

Sampling the values of these more intuitive parameters within their respective uncertainty ranges leads to the specification of the values for $m_x$ and $s_x$ used in the simulation model.
**Informing the Model Describing the Wage Dynamics**

Our model component that describes how real wages change over time is guided by two key parameters, $\alpha_d$ and $\alpha_s$. They control how much real wages increase each week. The larger rate, $\alpha_d$, applies when there is more demand for nurses than there is supply. The smaller rate, $\alpha_s$, applies when there is more supply than demand. We derive these weekly changes from the yearly rates. When there is a higher demand for nurses than there is supply, the real wages increase more rapidly each year. We expect this increase to be somewhere between 0 percent and 10 percent every year, but our best estimate is centered at 2 percent. When there is more supply than demand, the real wages still go up, but at a slower rate, and our estimate can be anywhere from 0 percent to 2.5 percent every year, and our best estimate is centered at 0.5 percent.

**Informing How Supply Responds to Changes in Wage**

After discussing our wage increase model and how we estimate its parameters, our attention now shifts towards determining the impact of wage changes on nurse supply. This involves the estimation of the supply parameters, denoted as $\theta$, that govern the relationship $\frac{\partial S_{\theta}}{\partial w}$. Specifically, we delve into two key parameters, $m_s(0)$, representing the wage when health care work reluctance is zero, and $s_s$, which defines the supply’s responsiveness to wage changes. Drawing a parallel with our previous parameter estimation for supply response to health care work reluctance, these parameters are intrinsic to our model’s complexities and are challenging to estimate directly. However, there is a greater potential for accurate estimation in this case compared with the parameters linked to health care work reluctance. This is because the relationship between wage changes and nurse supply has been extensively studied in economics over the years. Researchers have attempted to estimate the elasticity of nurse supply in response to wage rates, which measures the sensitivity of the quantity of nurses supplied to wage variations. In simpler terms, this elasticity quantifies how much an increase or decrease in real wages influences the influx or exodus of nurses from the workforce that are employed or are actively looking for employment as a nurse. A high elasticity implies that even minor wage adjustments can lead to substantial shifts in nurse availability, whereas a low elasticity suggests that wage changes have limited impact on nurse supply.

Nevertheless, it is important to note that, in line with our sigmoid supply surface, the elasticity of nurse supply in response to wage rates is itself contingent on the prevailing wages and supply levels. Therefore, the elasticity estimation is a localized measure provided under baseline conditions.

Let us begin by introducing the local elasticity of supply equation:

$$\epsilon_s = \frac{(q_s^{-1} \partial q_s)}{(w^{-1} \partial w)}$$

where $q_s$ represents the local supply of nurses. This equation can be rearranged as follows:

$$w \frac{\partial q_s}{\partial w} = \epsilon_s q_s.$$
\[
\frac{\partial S_\theta(n_s, w, 1)}{\partial w} = n_s s_s e^{-\bar{w}^2/\sqrt{\pi}}.
\]

In this context, \(\bar{w}\) is defined as \(\bar{w} = s_s[\ln(w) - \ln(m_s(1))]\). Moreover, based on the equation defining our sigmoid supply surface, \(\bar{w}\) can also be expressed as \(\text{erf}^{-1}[2S_\theta(1, w, 1) - 1]\), where \(\text{erf}^{-1}\) is the inverse error function, and \(S_\theta(1, w, 1)\) denotes the baseline proportion of the supply of nurses from the qualified pool of nurses. We determined this baseline proportion to be 84.1 percent based on a previous study (American Association of Colleges of Nursing, 2023). This allows us to compute the value of \(\bar{w}\) and subsequently use it to determine the values of \(s_s\) and \(m_s(0)\). The expressions for these parameters are provided by

\[
\bar{w} = \text{erf}^{-1}\left(\frac{2q_s}{n_s} - 1\right),
\]

\[
s_s = \frac{\epsilon_s q_s \sqrt{\pi} e^{\bar{w}^2}}{n_s},
\]

\[
m_s = we^{-\bar{w}/s_s}.
\]

Thus, we successfully derive the values of \(m_s(0)\) and \(s_s\), which are presumed to characterize the pre-pandemic supply curve.

**Informing the Model Describing the Dynamics of the Qualified Pool of Nurses**

The component of the model that describes how the number of nurses in our qualified pool changes due to recruitment and permanent retirement is influenced by three key factors: \(\nu\), \(\omega_1\), and \(\kappa_\omega\). These parameters determine the amount of new nurses entering and nurses leaving the qualified pool.

Looking at the national context, we observe that there are approximately 155,000 new RN graduates each year (Salsberg, 2018). This number accounts for around 5 percent of the total employed nurse population of 3.07 million. To estimate the suitable value of \(\nu\) for Virginia, we apply a similar growth rate that considers the portion of the supply within the qualified pool. This suggests that \(\nu\) for Virginia should fall between 3,500 and 7,000 new graduates annually.

To gauge the rate at which nurses leave the qualified pool, we assume that this pool changes slowly and remains relatively steady \(\left(\frac{dn_s}{dt} \approx 0\right)\). We also assume that the rate of nurses leaving the workforce supply, but not belonging to the qualified pool, ranges from being equal to the leave rate of employed nurses, up to twice that rate. Consequently, we estimate that \(\kappa_\omega\) varies within the range of \([1, 2]\).

By using our determined values for \(\nu\) and \(\kappa_\omega\), along with the assumption of steady changes, we can derive an estimated value for \(\omega_1\). Within our analysis, we vary \(\omega_1\) between 0.75 percent and 1.25 percent. This range encompasses the value that we found during our estimation process.
The Experimental Design for Model Calibration

Having established the model inputs, estimated their values, and detailed the data sources we relied on for both estimation and uncertainty assessment, we move on to describing the process of model calibration. This step involves leveraging the collected information to refine our model’s performance. Calibration is a crucial step in doing so. It entails a systematic exploration of various combinations of parameter values within the predefined uncertainty range. To achieve this, we conducted a total of 40,000 distinct parameter value combinations, with each serving as an independent simulation, referred to as a “case run.” This selection of parameter values and the quantity of case runs collectively define our experimental approach. Our calibration strategy involves aligning the trajectories of output state variables, particularly those related to nurse supply and wages, with our predefined calibration time-series targets. These calibration targets are summarized in Table E.1 for reference.

<table>
<thead>
<tr>
<th>Date</th>
<th>Average Wage ($)</th>
<th>Number Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Registered nurses</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-04-05</td>
<td>74,380</td>
<td>66,450</td>
</tr>
<tr>
<td>2021-04-04</td>
<td>76,680</td>
<td>66,980</td>
</tr>
<tr>
<td>2022-04-03</td>
<td>81,860</td>
<td>69,510</td>
</tr>
<tr>
<td>Primary care providers</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-04-05</td>
<td>159,021</td>
<td>15,080</td>
</tr>
<tr>
<td>2021-04-04</td>
<td>163,543</td>
<td>16,890</td>
</tr>
<tr>
<td>2022-04-03</td>
<td>155,095</td>
<td>16,880</td>
</tr>
<tr>
<td>Behavioral health specialists</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2020-04-05</td>
<td>58,618</td>
<td>18,350</td>
</tr>
<tr>
<td>2021-04-04</td>
<td>63,301</td>
<td>18,560</td>
</tr>
<tr>
<td>2022-04-03</td>
<td>64,099</td>
<td>20,450</td>
</tr>
</tbody>
</table>

This comparison enables the identification of a subset of case runs whose trajectories most closely align with our calibrated targets. Notably, many input parameter values were intentionally selected with substantial uncertainty ranges around their estimated central values. This deliberate choice provides the model with flexibility during the calibration process. While numerous input parameters possess significant uncertainty ranges, they may have distinct sampling schemes. These schemes can encompass either a uniform distribution spanning the uncertainty range or a PERT distribution. The latter, known as the beta PERT distribution, introduces a bias toward the provided central value or mode, reflecting desired probabilities. Consequently, even when parameters have broad uncertainty ranges, if they are sampled with a beta PERT distribution, most of the sampled values cluster around the central value.
Our input model parameters and their values, ranges, and sampling methods are summarized in Table E.2. It is important to note that while some parameters in the table are fixed and not altered, others undergo variation and are thus sampled. To efficiently create our experimental designs encompassing a wide array of parameter values, we employ Latin Hypercube Sampling (LHS) (Iman, Helton, and Campbell, 1981a; Iman, Helton, and Campbell, 1981b). LHS empowers the exploration of unique parameter input combinations, effectively capturing the inherent variability and uncertainty within the model. The LHS process involves dividing each parameter’s range into intervals and randomly selecting a value from each interval. This strategy results in the creation of unique combinations of parameter values. This approach ensures that each parameter is sampled across its entire range, preserving the overall distribution and inter-parameter correlation. By carefully constructing this sampling design, LHS facilitates a streamlined exploration of the parameter space, providing valuable insights into how the simulation model behaves and performs. This strategic approach enhances our ability to consider various parameter combinations that might influence the model’s outcomes and behavior.

Table E.2. Input Model Parameters, their Values, Ranges, and Sampling Methods

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mode</th>
<th>Lower</th>
<th>Upper</th>
<th>PDF</th>
</tr>
</thead>
<tbody>
<tr>
<td>initial.demand (RN)</td>
<td>Initial demand of nurses</td>
<td>68,200.000</td>
<td>59,800.000</td>
<td>76,600.000</td>
<td>PERT</td>
</tr>
<tr>
<td>initial.supply (RN)</td>
<td>Initial supply of nurses</td>
<td>66,400.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>initial.demand (PCP)</td>
<td>Initial demand of primary care providers</td>
<td>15,793.735</td>
<td>13,572.000</td>
<td>18,015.471</td>
<td>PERT</td>
</tr>
<tr>
<td>initial.supply (PCP)</td>
<td>Initial supply of primary care providers</td>
<td>1,5080.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>initial.demand (BH)</td>
<td>Initial demand of behavioral specialists</td>
<td>21,671.000</td>
<td>16,515.000</td>
<td>26,826.161</td>
<td>PERT</td>
</tr>
<tr>
<td>initial.supply (BH)</td>
<td>Initial supply of behavioral specialists</td>
<td>18,350.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>supply.prop</td>
<td>Initial proportion of providers belonging to the supply out of the whole qualified pool of providers</td>
<td>0.840</td>
<td>0.798</td>
<td>0.882</td>
<td>Uni</td>
</tr>
<tr>
<td>initial.work.reluctance</td>
<td>Initial work reluctance measure (defined in report); the initial pre-pandemic work reluctance is equal to 1 by definition</td>
<td>1.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>initial.yearly.wage (RN)</td>
<td>Initial yearly wage of nurses as defined by the BLS</td>
<td>74,400.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>initial.yearly.wage (PCP)</td>
<td>Initial yearly wage of primary care providers as defined by the BLS</td>
<td>159,021.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
<td>Mode</td>
<td>Lower</td>
<td>Upper</td>
<td>PDF</td>
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<tr>
<td>--------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
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<td>-------</td>
</tr>
<tr>
<td>initial.yearly.wage (BH)</td>
<td>Initial yearly wage of behavioral specialists as defined by the BLS</td>
<td>58,618.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>num.staffed.bed</td>
<td>Total staffed beds in all U.S. hospitals</td>
<td>15,200.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>bed.occup.rate</td>
<td>Bed occupancy rate as defined by the curative care hospital bed occupancy rate in the U.S. from 1960 to 2019</td>
<td>0.699</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>covid.prop</td>
<td>Proportion of all hospitalizations that are due to COVID-19</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>Derived</td>
</tr>
<tr>
<td>yearly.growth.demand</td>
<td>Yearly growth in demand as a proportion of the current demand</td>
<td>0.060</td>
<td>0.045</td>
<td>0.075</td>
<td>Uni</td>
</tr>
<tr>
<td>patient.to.nurse.nonICU</td>
<td>Initial patient-nurse ratio for non-ICU setting</td>
<td>4.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>patient.to.nurse.ICU</td>
<td>Initial patient-nurse ratio for ICU setting</td>
<td>2.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>ICU.rate</td>
<td>Proportion of all hospitalizations that require ICU care</td>
<td>0.121</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>yearly.covid.prop.growth</td>
<td>Yearly growth of COVID-19 cases as a proportion of total hospitalizations</td>
<td>0.350</td>
<td>0.250</td>
<td>0.400</td>
<td>Uni</td>
</tr>
<tr>
<td>ICU.covid.rate</td>
<td>Proportion of all COVID-19 hospitalizations that require ICU care</td>
<td>0.198</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>extra.effort.covid.nonICU</td>
<td>Multiplicative scaling factor of the effort required by a COVID-19 patient</td>
<td>1.500</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>extra.effort.covid.ICU</td>
<td>Multiplicative scaling factor of the effort required by a COVID-19 patient in the ICU</td>
<td>2.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>LOS</td>
<td>Average length of stay (LOS) of patients in a hospital</td>
<td>5.500</td>
<td>3.800</td>
<td>7.000</td>
<td>PERT</td>
</tr>
<tr>
<td>LOS.covid</td>
<td>Average length of stay of COVID-19 patients in a hospital</td>
<td>15.400</td>
<td>13.500</td>
<td>17.200</td>
<td>Uni</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
<td>Mode</td>
<td>Lower</td>
<td>Upper</td>
<td>PDF</td>
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<td>-----------------------------------------------------------------------------</td>
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<td>-------</td>
</tr>
<tr>
<td>( n_s ) (RN)</td>
<td>Yearly number of new graduating nurses that join the supply of nurses under baseline conditions</td>
<td>7,910.000</td>
<td>5930.000</td>
<td>9,890.000</td>
<td>Uni</td>
</tr>
<tr>
<td>( n_s ) (PCP)</td>
<td>Yearly number of new graduating primary care providers that join the supply of primary care providers under baseline conditions</td>
<td>165.000</td>
<td>110.000</td>
<td>247.500</td>
<td>Uni</td>
</tr>
<tr>
<td>( n_s ) (BH)</td>
<td>Yearly number of new graduating behavioral specialists that join the supply of behavioral specialists under baseline conditions</td>
<td>218.452</td>
<td>145.635</td>
<td>327.679</td>
<td>Uni</td>
</tr>
<tr>
<td>( \kappa_w )</td>
<td>Multiplicative scaling factor describing the increase rate in workforce depletion among nurses not belonging to the supply</td>
<td>1.500</td>
<td>1.000</td>
<td>2.000</td>
<td>Uni</td>
</tr>
<tr>
<td>( \omega_1 )</td>
<td>Yearly probability of exiting and no longer participating in the workforce among those belonging to the supply</td>
<td>0.010</td>
<td>0.007</td>
<td>0.013</td>
<td>Uni</td>
</tr>
<tr>
<td>yearly.growth.wage</td>
<td>Net yearly percentage increase in wages when the demand for providers is greater than the supply after discounting for inflation</td>
<td>0.020</td>
<td>0.000</td>
<td>0.100</td>
<td>PERT</td>
</tr>
<tr>
<td>reduced.yearly.growth.wage</td>
<td>Yearly percentage increase in wages when the supply for providers is greater than the demand</td>
<td>0.005</td>
<td>0.000</td>
<td>0.025</td>
<td>PERT</td>
</tr>
<tr>
<td>( \beta_F )</td>
<td>Proportion of the change in work reluctance that is attributable to increased fatigue</td>
<td>0.500</td>
<td>0.425</td>
<td>0.575</td>
<td>Uni</td>
</tr>
<tr>
<td>( \beta_D )</td>
<td>Proportion of the change in work reluctance that is attributable to increased distress</td>
<td>0.300</td>
<td>0.255</td>
<td>0.345</td>
<td>Uni</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
<td>Mode</td>
<td>Lower</td>
<td>Upper</td>
<td>PDF</td>
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<td>-------</td>
</tr>
<tr>
<td>$\beta_E$</td>
<td>Proportion of the change in work reluctance that is attributable to decreased engagement</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>Derived</td>
</tr>
<tr>
<td>$\chi_f$</td>
<td>Proportion of the distress that responds linearly to increased demand</td>
<td>0.500</td>
<td>0.375</td>
<td>0.625</td>
<td>Uni</td>
</tr>
<tr>
<td>$\psi_D$</td>
<td>Initial distress component attributable to the portion that does not depend on demand</td>
<td>1.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>$\psi_E$</td>
<td>Initial engagement component attributable to the portion that does not depend on demand</td>
<td>1.000</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
<tr>
<td>$\tau_S$</td>
<td>The half-life parameter represents the time-scale in years in an exponential weighted moving average model, used to discount past experiences in work reluctance, indicating the time it takes for the weighting of past observations to reduce to half of its original value</td>
<td>0.250</td>
<td>0.020</td>
<td>1.000</td>
<td>PERT</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>Elasticity of supply with wages</td>
<td>0.644</td>
<td>0.250</td>
<td>1.000</td>
<td>PERT</td>
</tr>
<tr>
<td>wage.prop</td>
<td>The percentage of the current wage needed to maintain the existing workforce if all factors causing work reluctance were eliminated</td>
<td>0.950</td>
<td>0.700</td>
<td>0.990</td>
<td>PERT</td>
</tr>
<tr>
<td>$z_2$</td>
<td>The level of the work reluctance metric required to reduce the nurse supply to the value specified by parameter &quot;supply.prop2&quot; while keeping wages unchanged</td>
<td>1.500</td>
<td>1.100</td>
<td>3.000</td>
<td>PERT</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
<td>Mode</td>
<td>Lower</td>
<td>Upper</td>
<td>PDF</td>
</tr>
<tr>
<td>------------------</td>
<td>------------------------------------------------------------------------------</td>
<td>------</td>
<td>-------</td>
<td>-------</td>
<td>--------</td>
</tr>
<tr>
<td>supply.prop_2</td>
<td>The value of the supply that will be achieved when the work reluctance metric reaches the level specified by the parameter ( z_2 ), assuming there are no changes in wages</td>
<td>0.500</td>
<td>NA</td>
<td>NA</td>
<td>Fixed</td>
</tr>
</tbody>
</table>

NOTE: NA = not applicable; PCP = primary care physician; PDF = probability density function.

Pairing the LHS scheme with Bayesian inference methods offers an efficient iterative calibration approach. In this context, Iterative Monte Carlo Approximate Bayesian Computation (IMABC) methods can be employed, progressively refining parameter estimates through a comparison of simulated and observed data, thereby enhancing model accuracy (Rutter et al., 2019). In contrast, a single LHS calibration lacks this iterative refinement, potentially leading to less precise parameter estimates and a limited ability to capture intricate parameter-data relationships. However, constrained by time and resources, we chose a single LHS method involving a large number of sampled case runs. Our approach calculates the error for each model run trajectory based on target output alignment and then selects the top one percentile of trajectories closest to the target values. This method efficiently identifies promising model runs, streamlining calibration within our time constraints—although, in the future, the consideration of IMABC methods remains a possibility.

**Sensitivity Analysis**

We systematically adjusted input values to discern the inputs wielding the most substantial influence on the outcomes of interest (labor force supply and demand). This exploration of various parameter values yielded insights into how different factors affect model outputs. The process also illuminated interactions among parameters, enhancing our comprehension of the model's behavior.

Additionally, we produced an Excel-based tool that allows policymakers to more easily view how adjusting scenario inputs affects outcomes. For example, the tool allows the user to toggle between wage increase scenarios including baseline (2 percent real annual wage growth), 3 percent, and 4 percent real annual wage growth. By toggling between various scenarios and immediately viewing the effects on outcomes of interest, the user gains better insight into how sensitive the model is to each input.

**Limitations and Extensions**

In the realm of simulation modeling, simplifying assumptions and reliance on challenging-to-estimate parameter values often become essential because of data limitations. Consequently, model inputs frequently harbor significant uncertainty, emphasizing the need for sensitivity and robustness analyses to gauge policy effectiveness across a variety of scenarios.

Despite its apparent mathematical intricacy, our model actually incorporates several simplifications and disregards various complexities intrinsic to the nurse supply, retention, and
recruitment challenge. Acknowledging these limitations, many of which arise from deliberate strategic simplifications to balance model accuracy and simplicity, we have engaged in sensitivity analyses and devised experiments to span a range of potential outcomes. However, it is crucial to acknowledge key constraints intrinsic to our model. Here we list a few examples of the limitations of our model:

1. Our current simulation model focuses on retention and recruitment at a broad level, without accounting for distinct health care worker population groups categorized by demographic indicators or pertinent characteristics, such as age strata. This omission overlooks the impact of aging nurses on wage trends and nurse supply dynamics, underscoring the need to stratify the nurse population by age to better capture these effects.

2. The model primarily addresses the influx of new health care workers into the state, but it does not consider the inflows and outflows from neighboring states. To enhance the model, it is essential to include such factors as perceived benefits and wages in Virginia compared with nearby states, offering insights into where graduating health care workers opt to begin their careers.

3. Because of temporal and data constraints, we calibrated the model at the state level and then extending predictions to regional levels using the calibrated parameters. For more accuracy, calibration should also be done at the regional level.

4. Our existing model simulates regions in isolation, disregarding interconnections between them. For a more accurate representation, regions should be simulated together, enabling the exploration of worker redistribution policies across different regions.

5. An expansion of the model could spotlight the potential gains from reallocating time spent on paperwork to patient care, leading to improved patient and worker satisfaction. Further exploration could delve into how efficiency changes and alterations in work types directly and indirectly impact health care worker supply. Additionally, the concept of “output” in health care should encompass improved health outcomes and care quality, transcending mere patient numbers. Structural changes should prioritize increased output without overwhelming health care providers, achieved by optimizing efficiency and work distribution.
Appendix F

System Dynamics Model Results for Registered Nurses

Model Experimental Design

This appendix focuses on the analysis of outputs from our dynamic model concerning nurses in Virginia. We complement our findings with informative plots derived from these outputs.

Our approach begins with conducting a sensitivity analysis and model calibration. For these tasks, we devised an experimental design by using our parameter value uncertainty range and generating 40,000 distinct case runs. Each case run encompasses a unique parameter combination derived from our sampling approach. For every case, we simulated trajectories for real wages, nurse supply, the qualified nurse pool, and health care work reluctance, serving as our calibration phase and spanning from the pre-pandemic initial conditions from April 5, 2020, to June 4, 2023. We then compared these wages and number of nurses employed against our calibration targets. The trajectories of output state variables, encompassing supply and wages, are aligned with our calibration time-series targets.

Calibration Phase Trajectories

In a single iteration, we calculate the trajectory error for each model run, aligning with the target outputs. We then narrow down our calibrated subset of case runs by selecting the top one percentile of trajectories that closely match the target values. This efficient method enables us to identify the most promising model runs, optimizing the calibration process within our time limitations.

Figure F.1 displays the outcomes of our calibration phase trajectories. There are four outputs showing the number employed, the qualified pool, the wage, and the health care work reluctance. We use a pink-to-purple scale to represent the distribution of model runs over time. The purple bands indicate distributions closer to the median, and the pink bands represent distributions further away from the median.
Within the plot, we can observe blue curves representing selected sample trajectories and red curves showcasing randomly chosen trajectories that align with our calibration targets. These trajectories are considered “calibrated” because they closely align with the wage and employed nurse calibration targets. These calibration targets are represented as black points on the plot, and the black lines above and below the points indicate the calibration window. The calibration window represents the tolerance we typically allow for a trajectory to pass through in terms of its distance to the calibration target point.

In Figure F.2, we present the same results, but this time we only consider the set of calibrated trajectories. The four outputs are again displayed, and the color scale now ranges from yellow to orange, showcasing the distribution of calibrated model runs over time. The orange bands represent distributions closer to the median, and the yellow bands represent distributions further away from the median.
Sensitivity Analysis

Before finalizing the subset of calibrated runs and proceeding to policy experiments, we conducted a sensitivity analysis to explore how different parameter values influence model outputs using our full set of 40,000 case runs. Here we summarize the main findings of our analysis.

During the calibration phase, demand remains an exogenous input, leading to no significant correlations with inputs aside from the initial demand value. The wage trajectory is mainly tied to yearly wage growth and initial demand. An intriguing finding is the weak yet meaningful negative correlation between wages and parameter \( z_2 \), indicating that as nurses become less responsive to increased work reluctance, the necessity for wage hikes diminishes. The qualified nurse pool is primarily influenced by initial demand and the influx of new nurses, holding more sensitivity to new nurse inflow relative to workforce depletion, as suggested by its correlations with \( \omega_1 \) and \( \omega_K \). Health care work reluctance aligns with our behavioral model parameters, including fatigue importance (\( \beta_F \)), fixed effect proportion (\( \xi_f \)), and the discount parameter (or half-life \( \tau_s \)). A notable observation is its strong negative correlation with LOS (average length of stay of patients in a hospital; see Table E.2), because shorter LOS diminishes fatigue impact.
Supply dynamics involve multiple factors, such as wages, new nurse inflow, and parameters influencing work reluctance. Notably, supply acts as a pivotal mediating output influenced by a diverse range of inputs, shaping the dynamics of other outputs in our model.

Policy Experiments

Starting from our selected calibrated set of case runs, we conduct several policy experiments. In the formulation of our policy intervention runs, the primary step entails procuring final state variables from our calibrated cases, which then serve as initial conditions for our model projections. Notably, we are not constrained to employ the initial conditions derived from the calibration process’s final states. Alternatively, we can opt for distinct calibrated case run parameters while initiating projections from the same initial condition. This approach circumvents the use of diverse initial conditions generated from final states of selected calibrated runs, which were determined based on historical data.

The policy experiments we conducted involve modifying specific input values that can be controlled through policy interventions. We examine the following policy scenarios separately:

1. **Reduced barriers**: This scenario involved a 50 percent reduction in the impact of certain barriers.
2. **Increased recruitment rate**: In this scenario, we amplified the value of the recruitment rate \( \nu \) by 25 percent, leading to a 1.25-fold annual increase in newly graduated nurses.
3. **Elevated wage growth rate**: Here, we boosted the wage growth rate \( \alpha_d \) by 50 percent. While the initial calibration assumed a 2 percent average annual real wage growth, this scenario accelerates the growth to an average of 3 percent per year.
4. **Multi-intervention**: We concurrently implemented all three of the above interventions.

In conjunction with the aforementioned policies, we execute the baseline scenario, entailing no policy interventions and adhering to status quo conditions. To assess the potential impacts of the specified policy adjustments on the qualified nurse pool and supply within the context of Virginia over the next 15 years, we utilize projected trajectories as depicted below. Projected trajectories serve as the basis to evaluate the ramifications of these policy adjustments on Virginia’s nurse’s supply over the next 15 years.

Consolidating our outcome distribution analysis across all policies, we showcase a unified visualization in Figure F.3 by selecting the most representative case run. This encompassing figure comprises four plots, each representing an outcome metric, displaying trajectories under different policies. This arrangement streamlines the assessment of policy impacts across output metrics, fostering an intuitive grasp of their combined effects.
Regional Analysis

Drawing from our calibrated case runs tailored to the state of Virginia, we adjusted the initial conditions of state variables in alignment with the wage and population characteristics of each of the
state’s eight unique AHEC regions. Figure F.4 is a map of Virginia that delineates these eight AHEC regions. This delineation was achieved through proportional adjustments to parameters associated with nurse counts, leveraging demographic data to create a model that effectively encapsulates the distinct attributes of these AHEC regions.

We employed distinct initial conditions for each of the eight regions and conducted independent policy model runs for each region. Focusing solely on the most representative case runs, we constructed analogous plots for each of the eight regions. These plots, akin to the one showcased in Figure F.5 for the entire state of Virginia, illustrate the ramifications of policy interventions across various outputs. These region-specific plots are showcased in Figure F.6. Importantly, each of these figures encompasses eight individual plots, each corresponding to a unique region under analysis. It is worth noting that these simulations for the eight regions were executed independently, with outcomes in one region holding no influence over the outcomes in the others. Because of this independence and because the primary differences between the regions are related to demographics and wages, the output plots for each region are essentially scaled versions of one another.

![Figure F.4. Map of Virginia and How It Is Divided into Eight Regions of Analysis](image)
Figure F.5. Results of Policy Interventions on Employment of Registered Nurses, by AHEC Region

Figure F.6. Results of Policy Interventions on the Gap Between Supply of and Demand for Registered Nurses, by AHEC Region
Appendix G

System Dynamics Model Results on Primary Care Providers

Model Experimental Design

This appendix contains our dynamic model’s results for Virginia’s primary care providers. It is structured similarly to Appendix F, which covered nurse-related outputs, but in a more streamlined manner. Like before, we complement our findings with enlightening plots derived from these outcomes. However, we have chosen to exclude certain plot types that appeared in Appendix F, prioritizing those that provide the most insightful information. Sensitivity analysis plots are omitted as well. Our primary focus is on policy analysis plots for the representative case runs, excluding plots displaying outcome bands and distributions across all case runs.

Following a similar methodology, our process starts with model calibration and experimental design. We use parameter uncertainty ranges to generate 40,000 distinct case runs, each representing a unique parameter combination. These cases simulate trajectories for real wages, physician supply, qualified physician pool, and work reluctance. Calibration spans from pre-pandemic conditions on April 5, 2020, to June 4, 2023. Output trajectories are compared with calibration targets, aligning wage and employed primary care provider numbers with predefined benchmarks. This ensures thorough alignment with calibration time-series targets.

Calibration Phase Trajectories

Figure G.1 illustrates the calibrated trajectories for the four outputs: number employed, qualified pool, wage, and health care work reluctance. These trajectories are labeled “calibrated” because they closely match the wage and employed primary care providers calibration targets. The calibration targets are depicted as black points on the plot, with black lines above and below indicating the calibration window. This window signifies the allowed tolerance for trajectories in relation to the calibration target point’s distance.

A color scale ranging from yellow to orange is used, showcasing the distribution of calibrated model runs over time. Orange bands represent distributions closer to the median, while yellow bands signify distributions further away from the median.
Upon examining Figure G.1, a notable observation arises—our model struggles to effectively track the four designated calibration points, two pertaining to primary care providers employed and two relating to their wages. This disparity stems from the fact that our calibration targets vividly illustrate a decline in physicians' real wages during the pandemic, occurring between 2021 and 2022, while the count of employed primary care providers remained relatively constant during the same period. However, our model does not account for the scenario in which real wages experience a gradual decrease over time.

Furthermore, based on our initial conditions and calibration targets, it becomes evident that the count of employed primary care providers exhibited a swift surge between 2020 and 2021, followed by a consistent level between 2021 and 2022. Regrettably, our model fails to replicate this rapid upswing in employed primary care providers between 2020 and 2021, instead fitting a more gradual growth curve. Despite these challenges, we are not overly concerned about the perceived noncalibration of our model because of this issue.

This perspective is founded on the understanding that the pandemic-induced conditions of negative wage growth and the dynamics of primary care provider employment are unlikely to be sustained or replicated in the medium to long term. Consequently, we proceed with confidence by selecting the showcased set of case runs in Figure G.1 for our policy projections.
Policy Experiments

Repeating our approach for nurses described in Appendix F, we build on our calibrated case runs selection and perform policy experiments for primary care providers.

Projected trajectories serve as the basis to evaluate the ramifications of these policy adjustments on Virginia’s primary care provider pool and supply over the next 15 years. Consolidating our outcome distribution analysis across all policies, we showcase a unified visualization in Figure G.2 by selecting the most representative case run. This encompassing figure comprises four plots, each representing an outcome metric, displaying trajectories under different policies. This arrangement streamlines the assessment of policy impacts across output metrics, fostering an intuitive grasp of their combined effects.
Commonwealth Analysis

Figure G.2. Comparative Trajectories of Policy Effects for Primary Care Providers
Regional Analysis

Applying the method outlined in Appendix F, Figures G.3 and G.4 display region-specific plots for primary care providers, each dedicated to one of the four outputs. Within each figure, there are eight distinct plots, each representing a specific region under analysis.

Figure G.3. Results of Policy Interventions on Employment of Primary Care Providers, by AHEC Region

![Graph showing the results of policy interventions on employment of primary care providers by AHEC Region.](image)
Figure G.4. Results of Policy Interventions on the Gap Between Supply of and Demand for Primary Care Providers, by AHEC Region
Appendix H

System Dynamics Model Results on Behavioral Health Specialists

Model Experimental Design

This appendix examines outcomes generated by our dynamic model for behavioral specialists in Virginia. It follows a streamlined structure similar to Appendix F, which detailed nurse-related outputs. As in Appendix F, we use insightful plots derived from these outcomes, focusing on informative plot types and excluding sensitivity analysis plots. Our focus is on presenting policy analysis plots for representative case runs, excluding plots showing bands and distributions across all case runs for each output.

We begin with model calibration and experimental design, using a parameter uncertainty range to create 40,000 distinct case runs. Each run captures a unique parameter combination. Within each case, we simulate trajectories for real wages, behavioral specialist supply, qualified pool, and health care work reluctance. The calibration phase spans from pre-pandemic conditions on April 5, 2020, to June 4, 2023.

During calibration, we compare output trajectories (e.g., supply and wages) against designated targets. We specifically assess wage outcomes and the number of employed behavioral specialists against predefined calibration benchmarks. This ensures alignment with our calibration time-series targets comprehensively.

Calibration Phase Trajectories

Figure H.1 illustrates the calibrated trajectories for the four outputs: number employed, qualified pool, wage, and health care work reluctance. These trajectories are labeled “calibrated” because they closely match the wage and employed behavioral health specialists calibration targets. The calibration targets are depicted as black points on the plot, with black lines above and below indicating the calibration window. This window signifies the allowed tolerance for trajectories in relation to the calibration target point’s distance.

A color scale ranging from yellow to orange is used, showcasing the distribution of calibrated model runs over time. Orange bands represent distributions closer to the median, while yellow bands signify distributions further away from the median.
Policy Experiments

Repeating our approach for nurses described in Appendix F, we build on our calibrated case runs selection and perform policy experiments for behavioral specialists.

Projected trajectories serve as the basis to evaluate the ramifications of these policy adjustments on Virginia’s behavioral specialist pool and supply over the next 15 years. Consolidating our outcome distribution analysis across all policies, we showcase a unified visualization in Figure H.2 by selecting the most representative case run. This encompassing figure comprises four plots, each representing an outcome metric, displaying trajectories under different policies. This arrangement streamlines the assessment of policy impacts across output metrics, fostering an intuitive grasp of their combined effects.
Commonwealth Analysis

Figure H.2. Comparative Trajectories of Policy Effects for Behavioral Health Specialists
Regional Analysis

Applying the method outlined in Appendix F, Figures H.3 and H.4 display region-specific plots for behavioral specialists, each dedicated to one of the four outputs. Within each figure, there are eight distinct plots, each representing a specific region under analysis.

Figure H.3. Results of Policy Interventions on Employment of Behavioral Health Specialists, by AHEC Region
Figure H.4. Results of Policy Interventions on the Gap Between Supply of and Demand for Behavioral Specialists, by AHEC Region
# Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AHEC</td>
<td>Area Health Education Centers</td>
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<tr>
<td>BLS</td>
<td>U.S. Bureau of Labor Statistics</td>
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<tr>
<td>COVID-19</td>
<td>coronavirus disease 2019</td>
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<tr>
<td>ICU</td>
<td>intensive care unit</td>
</tr>
<tr>
<td>LHS</td>
<td>Latin Hypercube Sampling</td>
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<td>PCP</td>
<td>primary care physician</td>
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<tr>
<td>PDF</td>
<td>probability density function</td>
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<tr>
<td>RN</td>
<td>registered nurse</td>
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