

Three Essays on Health Care Access

LAWRENCE BAKER

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Abstract

Government health programs must balance maximizing access with controlling costs while considering equity, geographic variation, and resource constraints. Health care reforms, whether in payment systems, quality measures, or new technologies, can significantly impact health care access. This dissertation examines how policy changes in three government health programs affect access to care across different settings.

Chapter 1 analyzes racial and ethnic disparities in COVID-19 vaccine distribution, providing the first national analysis of racial disparities in booster uptake. This study makes methodological contributions by calculating vaccination rates based on eligible populations and developing an equity metric comparing each group's share of vaccinations to their share of COVID-19 deaths. While Hispanic populations showed the highest uptake of the first dose, they had the lowest booster rates. Black populations showed consistently low uptake across all doses, which is particularly concerning given their elevated COVID-19 mortality rates. These patterns persisted across states.

Chapter 2 evaluates how Florida's 2012 transition from fee-for-service Medicaid to managed care affected children's access to dental services. Using emergency department visits for non-traumatic dental conditions as a proxy for access, this analysis employs an event study difference-in-difference design that leverages Florida's staggered managed care implementation across counties. Results show that managed care was associated with an 11% increase in emergency department visits for dental issues, suggesting the payment reform decreased access to dental care.

Chapter 3 uses a simulation model to examine whether expanding cognitive testing in primary care settings could increase access to novel Alzheimer's disease-modifying therapies. With an aging US population and a limited number of dementia specialists, this study assesses how implementing blood-based biomarker testing in primary care would affect wait times, health outcomes, and health care costs across U.S. states from 2025 to 2044. While blood-based testing could substantially reduce wait times for specialist care, it imposes significant costs on Medicare. Blood-based biomarker testing is not cost-effective at 2025 prices (\$26,500 annual drug cost and \$750 per blood biomarker test) but could become so with improved treatments.

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Introduction

Health policies must navigate difficult tradeoffs between access and cost. While most Americans believe health care should be universally available regardless of personal circumstances, there is also broad consensus on the need to contain spending. The US spends more than one-sixth of its GDP on health care (Hartman et al., 2024). All health care programs therefore operate under resource constraints – whether in budgets, health care provider availability, or stocks of supplies.

Private health care providers address scarcity through market forces, distributing services to those most willing and able to pay. Public health programs typically avoid market approaches since they often exist to address market failures. These failures include inequitable distribution of care, particularly for low-income and infirm individuals; insufficient provision of care with positive externalities, like vaccination; and missed opportunities to reduce lifetime costs through preventative care. Public programs must therefore determine how to utilize their constrained resources to maximize access.

Healthcare access means medical services are readily available, physically accessible, affordable, and culturally appropriate (Khanassov et al., 2016; Lazar & Davenport, 2018). However, people may be unwilling or unable to receive care due to various barriers. These include structural barriers like lack of transportation, long wait times, and limited operating hours; financial barriers such as expensive care, restricted provider networks, and high out-of-pocket costs; and cognitive barriers involving language differences or difficulty understanding medical needs (Carrillo et al., 2011). When health care programs aim to increase access, they typically focus on reducing one or more of these obstacles to care.

Because public health programs are often designed as social safety nets for those underserved by private markets, they must also consider equity in access. The health economics literature has long debated how to define a fair distribution of resources, variously arguing for equity in health care consumption, medical need, potential benefit, or health outcomes (Culyer & Wagstaff, 1993; Mooney, 1983). Programs must also determine across which demographic groups they measure outcomes, whether by race, ethnicity, age, geography, or gender. Geographic variation can be particularly difficult to address due to state-by-state variations in reimbursement, diagnostic practices, demographics, resource availability, and program design (Bronner et al., 2021; Donohue et al., 2012; Song et al., 2010).

Given the uneven distribution of wealth and health across the United States, some equity measures are mutually exclusive: programs cannot simultaneously achieve equity in both expenditures and outcomes (Culyer & Wagstaff, 1993). Similarly, there can be conflicts between efficiency and equity. For example, maximizing lives saved through COVID-19 vaccinations may involve focusing resources on the most densely populated areas with the highest case rates, conflicting with ensuring equal distribution between urban and rural areas.

Access to health care is a fundamental consideration in all health care programs, with most program design elements affecting accessibility even when not explicitly intended to do so. Payment reforms, for instance, may inadvertently restrict access by encouraging narrow provider networks or limited drug formularies (Baicker & Levy, 2015). Quality measurement systems can create incentives to avoid treating certain patient populations which could negatively impact quality scores (Mukamel et al., 2009). Additionally, insufficient planning for changes in workforce composition, patient demographics, and treatment options can result in shortages that restrict access (Buerhaus, 2008; Fox et al., 2014; Liu, Baker, Chen, & Wang, 2024).

Healthcare policies must be evaluated for their impact on access, whether they are new initiatives or changes to existing programs. Policies should be evaluated before and after implementation. This dissertation examines how policy changes affect health care access through three chapters, each analyzing a distinct health care policy.

Chapter 1 examines the racial and ethnic disparities in COVID-19 vaccine distribution during the pandemic. When vaccines first became available, limited supplies required the Centers for Disease Control and Prevention (CDC) to establish priority groups for vaccination (Bell et al., 2020). Priority was given to health care workers critical to the pandemic response and individuals at the highest risk of mortality, including the elderly and those with high-risk medical conditions (Jain et al., 2021). By the summer of 2021, as vaccine supply increased, attention shifted from managing scarcity to addressing low vaccination rates and inequitable distribution (Schmidt et al., 2021). In particular, there were concerns about racial and ethnic disparities in vaccine access (Gayle & Childress, 2021). In response, various organizations—including state and local governments, community groups, and philanthropic foundations—launched initiatives to improve vaccine access in under-vaccinated communities. These efforts included providing transportation assistance, translating vaccination information into multiple languages, and offering incentives (Faherty et al., 2022).

Chapter 1, originally published in 2022, evaluated COVID-19 vaccination equity across racial and ethnic groups, and provided the first national analysis of racial disparities in COVID-19 booster uptake (Baker et al., 2022). While primarily descriptive, this study makes two

methodological contributions. First, it calculates vaccination rates based on the eligible population rather than the total population—an important distinction since age-eligibility requirements can create misleading impressions of vaccine hesitancy in younger populations. Second, it constructs an equity metric that compares each racial and ethnic group's share of vaccinations to their share of COVID-19 deaths, adapting an approach previously used in HIV prevention research (Siegler et al., 2018).

Chapter 2 examines how payment policy changes in Florida's Medicaid program impacted children's access to dental services. Florida's Medicaid program has consistently struggled to provide adequate dental services to children—in 2021, less than one-third of eligible children received preventative dental care, despite guidelines calling for annual visits (Centers for Medicare and Medicaid Services, 2023a). There are several causes of low utilization: limited dentist participation due to low reimbursement rates, long wait times for appointments, and burdensome administrative requirements (Chalmers & Compton, 2017; Logan et al., 2015; Zolnikov et al., 2022).

Many states have transitioned components of their Medicaid programs, including dental services, to managed care models that use fully-capitated payments. Under managed care, private insurance plans receive fixed payments to provide services to Medicaid beneficiaries. States favor these arrangements partly because they transfer financial risk to the insurance plans—plans profit when costs are below expectations but lose money when costs greater than expected (Sparer, 2012). However, research on Medicaid managed care shows mixed results regarding both cost reduction and quality improvement (Duggan & Hayford, 2013; K. Sullivan, 2000). Evidence specific to dental services is particularly limited. The only prior study on dental managed care in Medicaid found decreased utilization, though this effect varied across states (Nasseh & Bowblis, 2022).

Chapter 2 evaluates how Florida's 2012 transition from fee-for-service Medicaid to managed care affected access to dental services. Under the managed care, Florida shifted from directly paying dentists to contracting with private dental plans that received capitated payments to establish provider networks. To measure changes in dental access, the study uses emergency department visits for non-traumatic dental conditions (NTDCs). NTDCs include dental issues like caries, abscesses, and inflammation, all of which should be treated in dental offices rather than in emergency departments. Patients are more likely to resort to the emergency department when they cannot access routine dental care, making visit rates a proxy for dental care access (Akinlotan & Ferdinand, 2020). The study employs an event study difference-in-difference design, utilizing Florida's managed care pilot programs and staggered implementation across counties to assess the policy's impact.

Chapter 3 explores whether expanding biomarker testing in primary care settings could increase access to disease-modifying therapies for Alzheimer's disease. In 2023, the first therapies capable of slowing Alzheimer's disease progression became widely available (Centers for Medicare and Medicaid Services, 2023b; Food and Drug Administration, 2023). These treatments could help reduce the substantial costs of Alzheimer's Disease, estimated at \$305 billion in 2020 (Nandi et al., 2024). However, the US health care system may have too few dementia specialists to diagnose for, prescribe, and monitor the use of Alzheimer's disease-modifying therapies. With approximately 21 million Americans experiencing cognitive impairment (Matthews et al., 2019; Rajan et al., 2021), several studies warn that this patient volume could overwhelm the limited number of dementia specialists, resulting in long wait times (Liu, Baker, Chen, Wang, et al., 2024; Mattke & Hanson, 2022).

Primary care triage using blood biomarker testing could help address specialist wait times for Alzheimer's disease. Blood tests for the proteins associated with Alzheimer's disease in primary care could reduce unnecessary specialist referrals among patients who do not have Alzheimer's disease pathology. This would effectively increase specialist capacity and decrease wait times. However, blood biomarker tests are costly, and their widespread adoption could significantly increase health care costs, particularly for Medicare, which covers most Alzheimer's disease patients.

Chapter 3 employs a simulation model to assess how implementing blood biomarker testing in primary care would affect wait times, health outcomes, and health care costs across the US. The model consists of three main components. First, a system dynamics group model simulates the clinical care pathway for Alzheimer's disease patients. Second, health and residence transition models track disease progression and predict nursing home entry. Third, a cost model calculates expenses and quality-adjusted life years (QALYs) based on clinical resource usage, health status, and residence type. The model simulates each US state from 2025 to 2044.

Racial and Ethnic Disparities in COVID-19 Booster Uptake

Lawrence Baker

Pardee RAND Graduate School and RAND

Brian Phillips

RAND

Laura J. Faherty

Pardee RAND Graduate School, RAND, and Maine Medical Center

Jeanne S. Ringel

Pardee RAND Graduate School and RAND

Ashley M. Kranz

RAND

Abstract

We investigate racial disparities in COVID-19 vaccine uptake from February 2021 – March 2022 using data from US Centers for Disease Control and Prevention. As of March 29, 2022, uptake of the first dose was higher among Hispanic and Asian people than among White and Black people. In contrast, uptake rates of the booster were higher among Asian and White people than among Black and Hispanic people.

Introduction

Black and Hispanic populations in the US have been disproportionately impacted by COVID-19, with higher rates of death than the population average documented during the first wave of the pandemic (Gold, 2020). Uptake of the first dose was slower and remains lower for Black individuals than for Asian, Hispanic, and White people (Reitsma et al., 2021). Numerous factors impact vaccination uptake. Individuals may choose not to get vaccinated or may be willing to get vaccinated but face barriers including transportation, language, and inability to take time off of work (Faherty et al., 2022). Improving vaccine uptake and achieving vaccine equity may be particularly challenging in the United States because it requires coordinating across federal and state public health infrastructures, rather than operating a single centralized vaccine delivery system, as in the United Kingdom (Nguyen et al., 2022).

In this study, we analyze COVID-19 vaccination rates for first doses and boosters across Asian, Black, Hispanic, and White populations over time, while accounting for age and vaccine-interval eligibility criteria. Reporting raw vaccination rates without accounting for eligibility can be misleading. For example, the White population has a higher proportion of adults over 65 compared to other racial groups, an age difference that granted greater vaccine eligibility during the initial vaccine rollout. By accounting for these eligibility criteria, our analysis provides a more accurate comparison of vaccine demand across racial groups. Vaccination rates can be used to evaluate the effectiveness of initiatives at the federal, state, and local levels to improve vaccine access (Boozang et al., 2021; Faherty et al., 2022; Schoch-Spana et al., 2021), and to identify communities that need additional support and resources.

Methods

We used national US time-series data from CDC on counts and rates of COVID-19 vaccinations by race and ethnicity (CDC, 2022d). We also used data on COVID-19 deaths by race and ethnicity (CDC, 2022a), state vaccine eligibility criteria (Raifman et al., 2020), population by race and ethnicity (Census Bureau, 2019), and state-level data on booster uptake by race

(Ndugga et al., 2022). Consistent with CDC’s approach, we defined the Hispanic population as all Hispanic individuals and each other group as non-Hispanics of that race (CDC, 2022d). Like other analyses (Reitsma et al., 2021), we omitted American Indian or Alaska Native and Native Hawaiian or Other Pacific Islander populations because their relatively small sizes make data less reliable. We did not separately report uptake rates for the initial full series because these were highly correlated with rates for first doses (Table 1.1).

To estimate vaccination rates among the eligible, we divided counts of total doses given to each group by the number of people in that group who meet requirements for age and the recommended interval between doses. To calculate relative vaccination rates by state, we normalized vaccination rates to the state population average.

The burden of the pandemic has not been borne equally across racial/ethnic groups. To account for the differential burden of COVID-19, we calculated an equity metric that captures one aspect of this burden by comparing the share of COVID-19 vaccinations to the share of deaths across each group. This metric draws on approaches used to examine disparities in HIV prevention (Siegler et al., 2018) and COVID-19 vaccination-to-infection risk in Massachusetts (Dryden-Peterson et al., 2021). Additional details on our approach are included in Appendix 1.

Results

After accounting for eligibility, uptake of the first dose among Hispanic and Asian individuals was, respectively, 26% and 19% higher than the population average (Table 1.1). By contrast, uptake of the first dose among White people was 6% lower than average and among Black people was 15% lower than average. Conditional on eligibility, uptake of the full series was similar across groups: relative rates for each race and ethnicity were within 5 percentage points. Uptake of the booster dose shows the starkest differences between groups. Relative to the population average, Asian people were 24% more likely to have received a booster, White people 7% more likely, Black people 15% less likely, and Hispanic people 21% less likely.

Table 1.1: Rates of vaccine eligibility and uptake by race, ethnicity, and dose as of March 29, 2022

Status by dose	Asian	Black	Hispanic	White	Overall
First dose					
Eligible	94.9%	93.5%	91.7%	95.1%	94.3%
Received	67.6%	47.7%	69.6%	53.5%	56.5%
Received of Eligible	71.2%	51.1%	75.9%	56.3%	60.1%
Full series					
Eligible	67.2%	47.3%	68.9%	53.4%	56.2%
Received	61.4%	41.8%	59.7%	48.7%	50.5%

Received of Eligible	91.3%	88.3%	86.6%	91.2%	90.0%
Booster					
Eligible	54.2%	35.8%	51.1%	44.6%	45.2%
Received	39.0%	17.7%	23.6%	27.6%	26.2%
Received of Eligible	71.9%	49.3%	46.1%	61.9%	58.0%

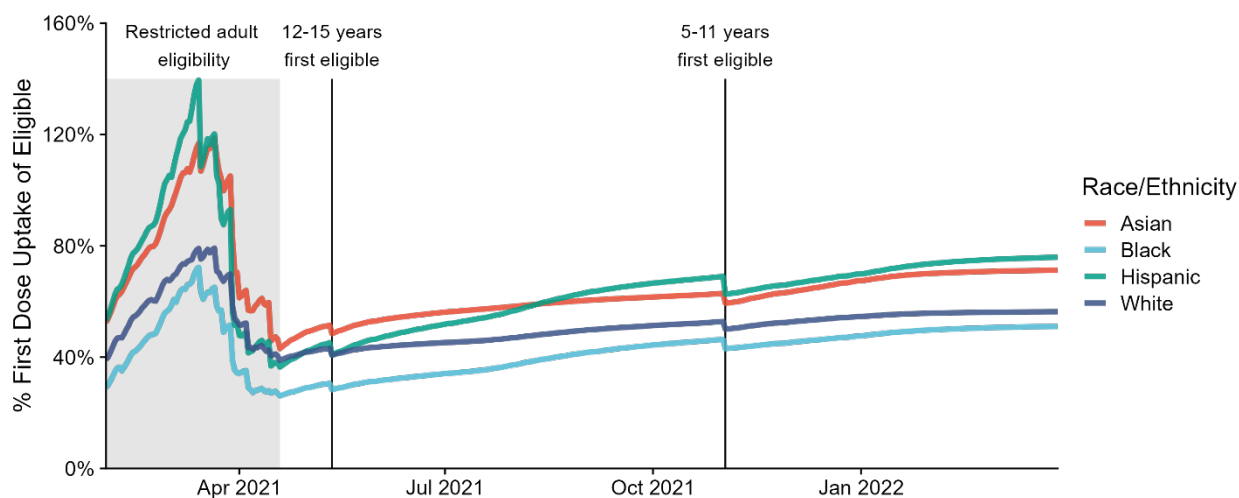
SOURCE: CDC vaccination data as of March 29, 2022 (data downloaded June 10, 2022) and 2019 national population estimates by race and ethnicity from the 2019 Intercensal estimates.

NOTES: The table shows population percentages for each racial/ethnic group and the population-weighted mean of the four groups.

Figures 1.1 and 1.2 show vaccination rates over time, conditional on eligibility.

Of those eligible, Asian and Hispanic people are the most likely to receive their first dose (Figure 1.1). Black people are the least likely. These patterns have been largely consistent over time. Eligible Hispanic people were always more likely than eligible White people to get their first dose.

Figure 1.1: First dose vaccination rates by race and ethnicity as a proportion of the eligible US population, February 1, 2021 – March 29, 2022



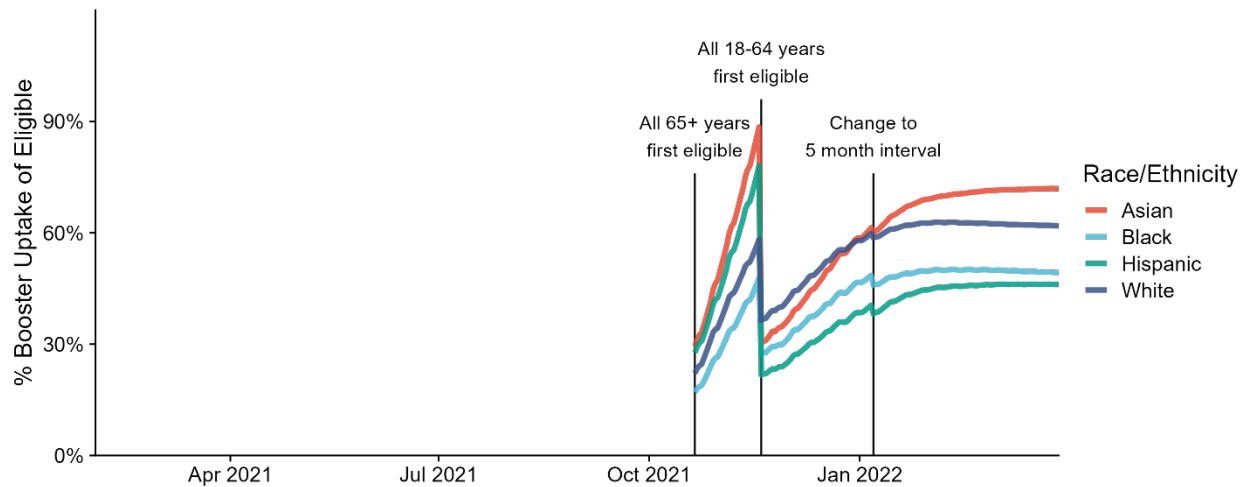
SOURCE: CDC vaccination data as of March 29, 2022 (data downloaded June 10, 2022) and 2019 national population estimates by race and ethnicity from the 2019 Intercensal estimates.

NOTES: Percentages are a proportion of the eligible population. Eligibility corrects for age. The period highlighted in grey has some percentages >100% because comorbidities and occupation were significant contributors to eligibility during this period and we were unable to include these in our analysis.

We see different patterns across racial/ethnic groups when examining boosters (Figure 1.2). Hispanic people are the least likely to receive a booster when eligible, despite being the most likely to receive a first dose when eligible. Rates for both a first dose and booster have plateaued

among all groups, which suggests that we are unlikely to see further changes in vaccination rates without the deployment of additional resources.

Figure 1.2: Booster vaccination rates by race and ethnicity as a percentage of the eligible US population, October 21, 2021 – March 29, 2022

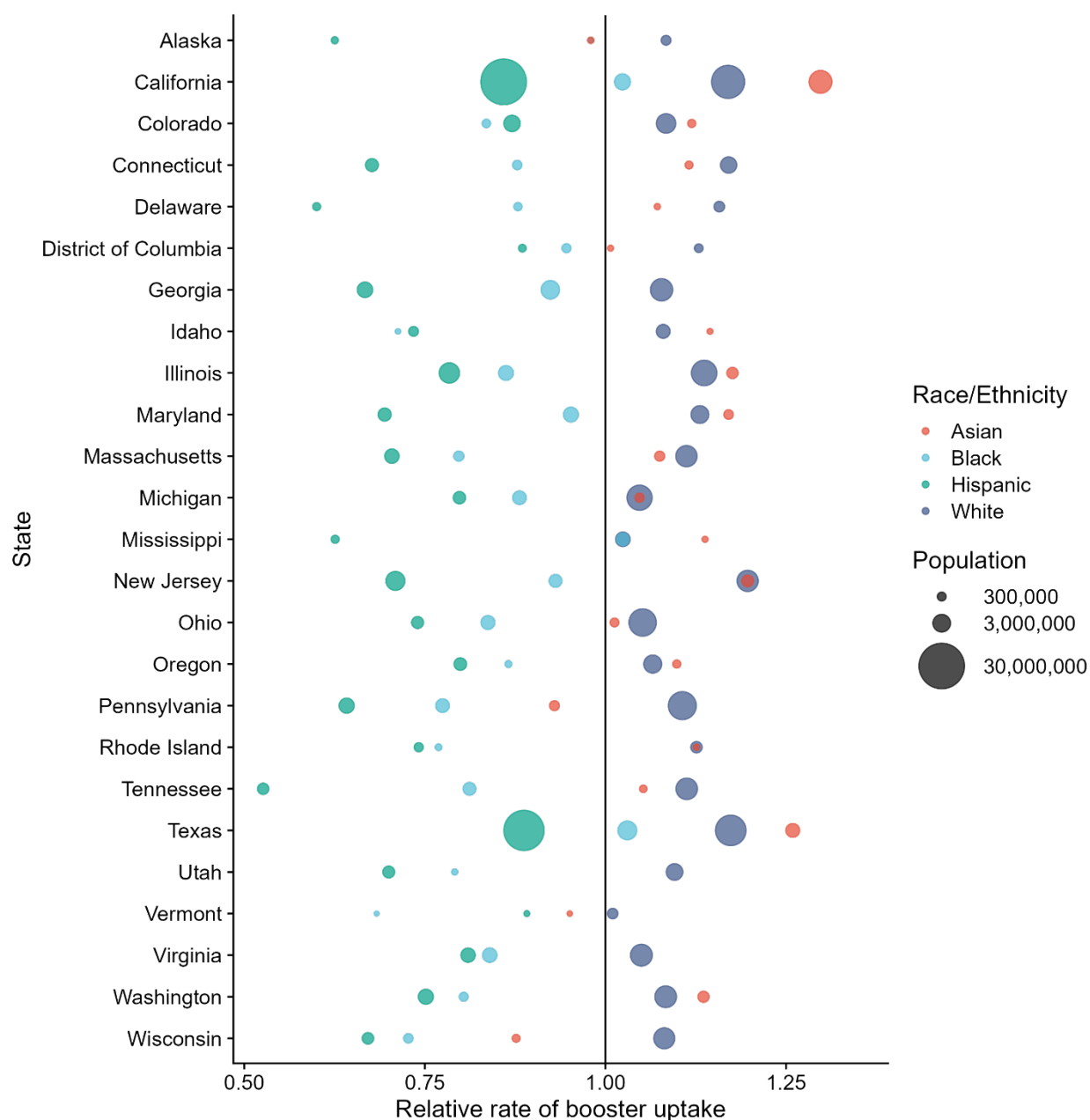


SOURCE: CDC vaccination data as of March 29, 2022 (data downloaded June 10, 2022) and 2019 national population estimates by race and ethnicity from the 2019 Intercensal estimates.

NOTES: Percentages are a proportion of the total population. Eligibility corrects for age and the interval since a full series dose.

National patterns of booster uptake are remarkably similar at the state level (Figure 1.3). As of April 1, 2022, in every state for which the KFF reported data (24 states and the District of Columbia), booster uptake is lower for Black and Hispanic people than White and Asian people (Ndugga et al., 2022).

Figure 1.3: Relative booster vaccination rates by state, race, and ethnicity as of April 1, 2022



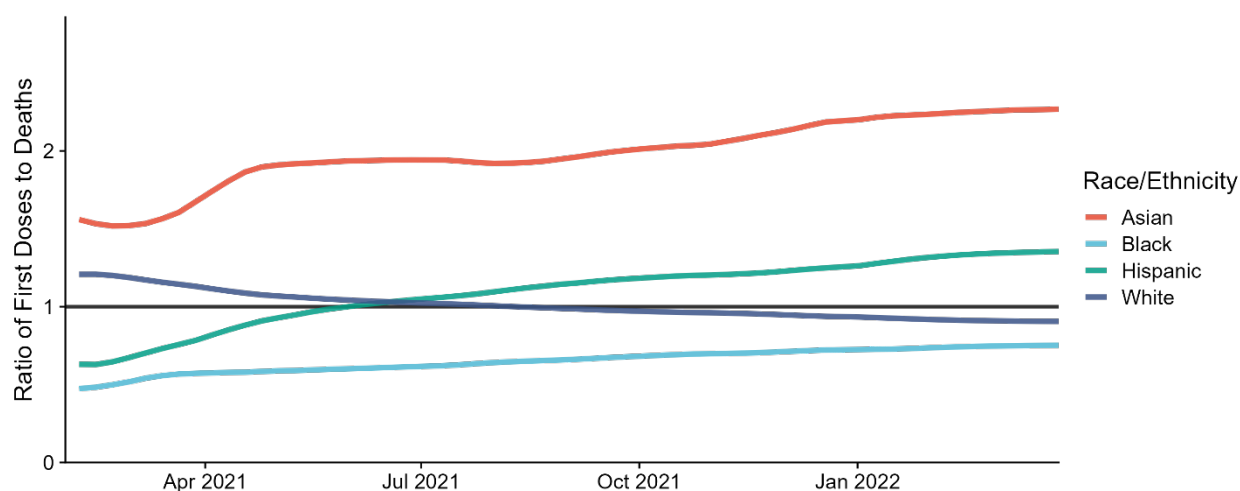
SOURCE: Data were downloaded on April 22, 2022 and were updated by the Kaiser Family Foundation on April 1, 2022.

NOTES: The size of each circle is proportional to the absolute population (more populous states have larger circles). Average rates among reported groups for each state are shown with a vertical black line. Relative booster vaccination rates were high for Asian individuals in Georgia (2.1), Utah (1.4), and Virginia (1.5). These rates were omitted to keep figure dimensions manageable.

The burden of the pandemic has not been borne equally across racial/ethnic groups. To account for the differential burden of COVID-19, we calculated an equity metric that captures one aspect of this burden by comparing the share of COVID-19 vaccinations to deaths across each group.

Our equity metric shown in Figures 1.4 and 1.5 compares the share of COVID-19 vaccinations to deaths across each group over time. Figure 1.4 shows that Asian people have always comprised a larger share of first doses than of deaths. Black people have always comprised a larger share of deaths than of first doses. Over time, White and Hispanic populations have traded places, and now White people have a relatively higher share of deaths than first doses. Similar relationships are observed for boosters (Figure 1.5). Again, the Black population constitutes a much larger share of deaths than booster doses. White and Hispanic ratios are both close to an equal share of deaths and vaccinations, although they are moving in different directions.

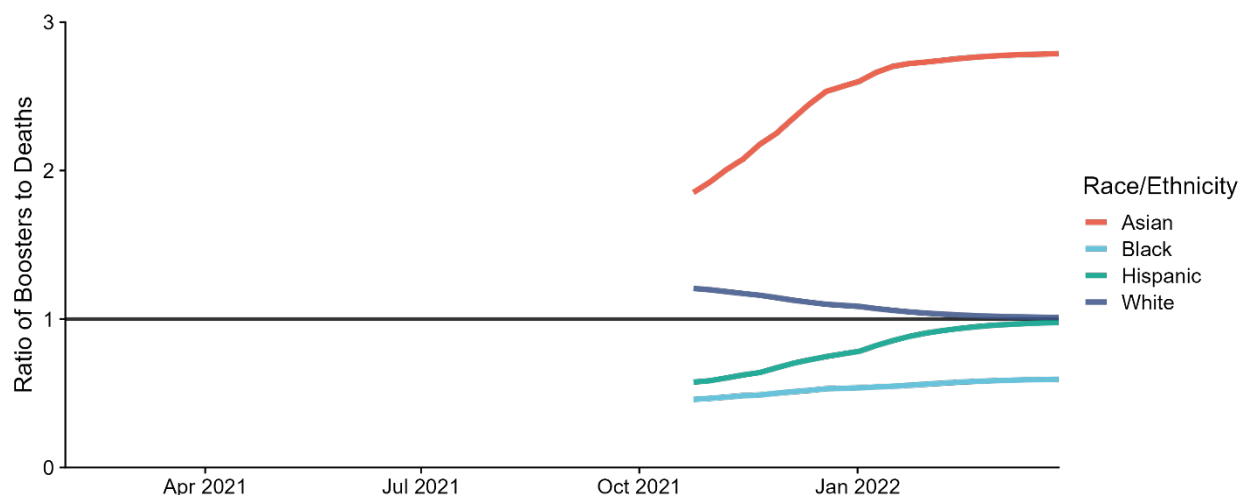
Figure 1.4: Relative ratio of COVID-19 vaccine first doses to deaths by race and ethnicity, February 6, 2021 – March 26, 2022



SOURCE: CDC vaccination data as of March 29, 2022 (data downloaded June 10, 2022) and CDC COVID-19 death data as of March 29, 2022 (data downloaded June 10, 2022).

NOTES: A value of 1 implies that the share of vaccinations matched the share of COVID-19 deaths. Values above 1 imply a higher share of vaccinations than of deaths. Values below 1 imply a lower share of vaccinations than of deaths.

Figure 1.5: Relative ratio of COVID-19 booster doses to deaths by race and ethnicity, October 23, 2021 – March 26, 2022



SOURCE: CDC vaccination data as of March 29, 2022 (data downloaded June 10, 2022) and CDC COVID-19 death data as of March 29, 2022 (data downloaded June 10, 2022).

NOTES: A value of 1 implies that the share of vaccinations matched the share of COVID-19 deaths. Values above 1 imply a higher share of vaccinations than of deaths. Values below 1 imply a lower share of vaccinations than of deaths.

Discussion

Across doses, we find large racial disparities in COVID-19 vaccination uptake. Vaccinations drive outcomes: relative to those who have received boosters, mortality rates are 78 times higher for those who are unvaccinated (Johnson, 2022). Low vaccine uptake among the Black population is consistent across doses, remains after controlling for eligibility, and is even starker when accounting for the mortality burden of COVID-19. It is worrying that rates are plateauing among all groups, and some are declining when accounting for eligibility. Despite high uptake for first doses, relatively few Hispanic individuals are receiving booster shots, a pattern unique to this group. Lower rates of booster uptake for Black and Hispanic populations are consistent across states (Ndugga et al., 2022).

This analysis may inform where resources must be directed to improve vaccination equity and reduce the ongoing burden of the pandemic. More resources to improve vaccination uptake are needed for all groups, but particularly to improve rates among Black people and, to a lesser extent, White people. Vaccination campaigns focused on Hispanic people may want to promote booster doses to address low rates of uptake among a population that has demonstrated both the willingness to receive, and ability to access, first doses.

There are several limitations to our analysis. First, vaccination data may be inconsistent: states may vary in how they report vaccination data to CDC and State data may not match Federal data.

Second, the way race and ethnicity were collected and categorized may have varied between states, and the full complexity of these social constructs may not be captured by categories in data. Third, we do not account for unknown race or ethnicity in vaccination uptake data. This results in undercounting vaccinations for every group: race-specific vaccination rates from CDC are approximately 20 percentage points lower than total population rates. If the unknown race or ethnicity is missing at random, then our conclusions about relative rates are unaffected. Fourth, we are unable to include eligibility criteria for comorbidities, residency in long-term care facilities, or occupation, because data on vaccination status by these criteria by race are not available. Omitting these requirements means we underestimate the eligible population for all groups, which biases the uptake among the eligible upwards. Finally, we assumed that all vaccination regimens consisted of a two-dose series with a single booster. Vaccines produced by Pfizer BioNTech and Moderna, which meet these criteria, constitute 92% of all full-series doses given (CDC, 2020).

Vaccination disparities are likely the product of interactions between many socioeconomic and demographic factors, including race, ethnicity, income, immigration status, rurality, and education. Data on the intersection of these factors are needed to enable further analyses that move beyond the examination of race and ethnicity alone. Exploring heterogeneity within populations is critical to informing more targeted and effective vaccination outreach. Decision-makers should also leverage the emerging evidence regarding effective local strategies to improve vaccine uptake and decrease disparities (Boozang et al., 2021; Faherty et al., 2022; Schoch-Spana et al., 2021).

References

- Boozang, P., Punukollu, N., & Michelle Savuto. (2021). *Strategies for States to Drive Equitable Vaccine Distribution and Administration*. Manatt Health.
- CDC. (2020, March 28). *COVID Data Tracker*. Centers for Disease Control and Prevention. <https://covid.cdc.gov/covid-data-tracker>
- CDC. (2021a, September 27). *CDC Statement on ACIP Booster Recommendations*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2021/p0924-booster-recommendations-.html>
- CDC. (2021b, October 27). *CDC Expands Eligibility for COVID-19 Booster Shots*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2021/p1021-covid-booster.html>
- CDC. (2021c, November 19). *CDC Expands Eligibility for COVID-19 Booster Shots to All Adults*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2021/s1119-booster-shots.html>
- CDC. (2021d, December 9). *CDC Expands COVID-19 Booster Recommendations to 16-and-17-year-olds*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2021/s1208-16-17-booster.html>
- CDC. (2022a). *Provisional COVID-19 Deaths by HHS Region, Race, and Age*. Centers for Disease Control and Prevention. <https://data.cdc.gov/NCHS/Provisional-COVID-19-Deaths-by-HHS-Region-Race-and/tpcp-uiv5>
- CDC. (2022b, January 5). *CDC Expands Booster Shot Eligibility and Strengthens Recommendations for 12-17 Year Olds*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2022/s0105-Booster-Shot.html>
- CDC. (2022c, January 10). *CDC Recommends Moderna Booster at 5 Months*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2022/s0107-moderna-booster.html>
- CDC. (2022d, January 31). *COVID-19 Vaccination Demographics in the United States, National*. Centers for Disease Control and Prevention. <https://data.cdc.gov/Vaccinations/COVID-19-Vaccination-Demographics-in-the-United-St/km4m-vcsb>

- CDC. (2022e, March 29). *CDC Recommends Additional Boosters for Certain Individuals*. Centers for Disease Control and Prevention. <https://www.cdc.gov/media/releases/2022/s0328-covid-19-boosters.html>
- Census Bureau. (2019). *Annual Estimates of the Resident Population by Sex, Age, Race, and Hispanic Origin: April 1, 2010 to July 1, 2019*. <https://www2.census.gov/programs-surveys/popest/tables/2010-2019/national/asrh/nc-est2019-asr6h.xlsx>
- Dryden-Peterson, S., Velásquez, G. E., Stopka, T. J., Davey, S., Gandhi, R. T., Lockman, S., & Ojikutu, B. O. (2021). Disparities in SARS-CoV-2 Vaccination-to-Infection Risk During the COVID-19 Pandemic in Massachusetts. *JAMA Health Forum*, 2(9), e212666. <https://doi.org/10.1001/jamahealthforum.2021.2666>
- Faherty, L. J., Schulson, L., Gandhi, P., Howell, K., Wolfe, R., & Ringel, J. S. (2022). Promising Practices for Ensuring Equity in COVID-19 Vaccination: The Devil's in the Details. *Public Health Reports*, 00333549221086579. <https://doi.org/10.1177/00333549221086579>
- Gold, J. A. W. (2020). Race, Ethnicity, and Age Trends in Persons Who Died from COVID-19—United States, May–August 2020. *MMWR. Morbidity and Mortality Weekly Report*, 69. <https://doi.org/10.15585/mmwr.mm6942e1>
- Johnson, A. G. (2022). COVID-19 Incidence and Death Rates Among Unvaccinated and Fully Vaccinated Adults with and Without Booster Doses During Periods of Delta and Omicron Variant Emergence. *MMWR. Morbidity and Mortality Weekly Report*, 71. <https://doi.org/10.15585/mmwr.mm7104e2>
- Ndugga, N., Hill, L., Artiga, S., & Haldar, S. (2022, January 12). *Latest Data on COVID-19 Vaccinations by Race/Ethnicity*. Kasier Family Foundation. <https://www.kff.org/coronavirus-covid-19/issue-brief/latest-data-on-covid-19-vaccinations-by-race-ethnicity/>
- Nguyen, L. H., Joshi, A. D., Drew, D. A., Merino, J., Ma, W., Lo, C.-H., Kwon, S., Wang, K., Graham, M. S., Polidori, L., Menni, C., Sudre, C. H., Anyane-Yeboah, A., Astley, C. M., Warner, E. T., Hu, C. Y., Selvachandran, S., Davies, R., Nash, D., ... Chan, A. T. (2022). Self-reported COVID-19 vaccine hesitancy and uptake among participants from different racial and ethnic groups in the United States and United Kingdom. *Nature Communications*, 13(1), Article 1. <https://doi.org/10.1038/s41467-022-28200-3>

Raifman, J., Nocka, K., Jones, D., Bor, J., Lipson, S., Jay, J., & Chan, P. (2020). *COVID-19 US state policy database*. Boston University.

Reitsma, M. B., Goldhaber-Fiebert, J. D., & Salomon, J. A. (2021). Quantifying and Benchmarking Disparities in COVID-19 Vaccination Rates by Race and Ethnicity. *JAMA Network Open*, 4(10), e2130343. <https://doi.org/10.1001/jamanetworkopen.2021.30343>

Schoch-Spana, M., Brunson, E., Hosangadi, D., Long, R., Taylor, M., Trotochaud, M., & Veenema, T. (2021). *A Waypoint on the Path to Health Equity: COVID-19 Vaccination at Month 11*. The Johns Hopkins Center for Health Security.

Siegler, A. J., Mouhanna, F., Giler, R. M., Weiss, K., Pembleton, E., Guest, J., Jones, J., Castel, A., Yeung, H., Kramer, M., McCallister, S., & Sullivan, P. S. (2018). The prevalence of pre-exposure prophylaxis use and the pre-exposure prophylaxis-to-need ratio in the fourth quarter of 2017, United States. *Annals of Epidemiology*, 28(12), 841–849. <https://doi.org/10.1016/j.annepidem.2018.06.005>

Appendix 1

Data date range

We report data through March 29, 2022, because this is when CDC first recommended second booster doses for select groups (CDC, 2022e). Since CDC data does not distinguish between first and second booster doses, data after March 29, 2022 may not accurately represent adoption of the first booster dose. We therefore omit this period.

Eligibility criteria

We report vaccination rates conditional on eligibility, which require a denominator of the eligible population which changes over time. We estimate this eligible population by first calculating time series for those eligible by age and those eligible by interval since the prior dose.

In practice, there are five criteria for eligibility, of which we only include age and interval:

1. **Age:** older people were eligible for doses earlier than younger people
2. **Interval:** The full series is only accessible after the first dose and an interval of 4 weeks (depending on the manufacturer). The booster dose is only accessible after a full series and an interval of 5-6 months (depending on the date of booster dose).
3. **Medical conditions:** people with certain underlying medical conditions were eligible for doses earlier than people of a similar age without those medical conditions.
4. **Occupation:** some high-risk occupations (such as healthcare providers and teachers) were eligible for doses earlier than people of a similar age who did not work in those occupations.
5. **Long-term care residency:** people who lived in long-term care settings were eligible for doses earlier than people of a similar age who did not live in those settings.

Calculating the eligibility-by-age timeline for boosters is straightforward because all states used the same eligibility dates. CDC began recommending a booster dose for individuals over 65 years in long-term care, anyone over 18 years old with underlying medical conditions, and anyone over 18 in a high-risk occupation in September 2021 (CDC, 2021a). CDC expanded booster eligibility to all people over 65 years in October (CDC, 2021b), all adults in November (CDC, 2021c), all people over 16 years in December (CDC, 2021d), and all people over 12 years in January 2022 (CDC, 2022b).

Calculating the eligibility by age timeline for first doses was more complex because each state used different eligibility dates. Using Census data on population for each state and the age-based

eligibility dates from the COVID-19 US State Policy Database, (Raifman et al., 2020) we calculated how many people were eligible by age for each race in each state by date. We then summed state totals to find the national eligible population. The Census data includes age groups in intervals of five years, so we rounded age requirements to the nearest five years (e.g., when people 16 years old became eligible, this was rounded to people 15 years old).

To find the interval-eligible population for boosters, we lagged the count of full series doses by 180 days (6 months) until January 7, 2022, when CDC changed the recommended interval for boosters to 150 days (5 months) (CDC, 2022c). To find the interval-eligible population for the full series, we lagged the first doses by 28 days (4 weeks). We then defined the eligible population as the minimum of those eligible by age and those eligible by interval.

These calculations yielded a time series of age-eligibility and a time series of interval-eligibility. For the first dose, only age-eligibility is limiting; there is no prior dose so there is no interval requirement. For the full series, only interval-eligibility is limiting; anyone who has a first dose is age-eligible for the full series. However, for boosters, individuals needed to be both of an eligible age *and* have had their full series several months prior. These overlapping criteria are shown in Figure A1.1.

Figure A1.1: Venn diagrams of vaccine eligibility by age and interval for the first dose, full series, and booster.



Over time, the size and overlap between the circles in the Venn diagrams change, as more people become eligible. We estimate the eligible population as the minimum of the age-eligible and interval-eligible populations. This approach works well for the first dose and full series because the overlap is always equal to the smaller population. However, for boosters, this approach overestimates eligibility because it counts everyone who meets the more stringent criteria as

eligible (i.e., everyone in the blue circle above). To more accurately estimate the eligible population (i.e., the overlap between the blue and red circles), we would need information on when people were vaccinated by the intersection of race and age, but these data are not currently available.

We did not include the other eligibility criteria (medical conditions, occupation, and long-term care residency). Estimating the impact on eligibility for these additional criteria requires data on the interaction of all five criteria. This would require individual-level data on vaccination status, which has not been released for privacy reasons.

We believe these compromises are acceptable because age and interval eligibility determined vaccination status for most of the population and because the other criteria were used only early in the rollout for each dose. For instance, booster eligibility for some adults was first granted in September 2021 (CDC, 2021a), and booster eligibility for all adults was granted in November 2021 (CDC, 2021c). Omitting forms of eligibility other than age and interval could only have impacted eligibility estimates for adults between these dates, a period of less than two months.

After calculating the eligible population time series, we estimate the proportion eligible vaccinated for group g and dose d as:

$$ProportionEligibleVaccinated_{g,d} = \frac{DoseCount_{g,d}}{EligiblePopulation_g}$$

Mean vaccination rates

Table 1.1 includes mean vaccination rates. We calculate these mean vaccination rates using the population-weighted mean of Asian, Black, Hispanic, and White vaccination rates. This ensures that the average we calculate is relative to these groups and is not impacted by missing race/ethnicity data.

Relative vaccination rates

The rate of booster uptake shown in Figure 1.3 is relative to the four racial/ethnic groups examined. For each group g and state s we constructed the relative rate:

$$BoosterRate_{s,g} = \frac{ProportionVaccinated_{s,g} \times \sum_g (Population_{s,g})}{\sum_g (ProportionVaccinated_{s,g} \times Population_{s,g})}$$

Rather than have rates relative to the entire population, we used the weighted average of the four population groups to ensure that relative rates were centered on 1.

Equity metric

Figures 1.4 and 1.5 use cumulative data on deaths due to COVID-19 (CDC, 2022a) and vaccinations (CDC, 2022d), to measure vaccine equity in the context differential mortality by race and ethnicity. We calculate an equity metric for each group, equal to the share of vaccinations divided by the share of deaths. We use cumulative data in these calculations to account for deaths during the phase of the pandemic before vaccinations were available.

For group g and dose d we estimated this metric as:

$$EquityMetric_{g,d} = \frac{ShareVaccinations_{g,d}}{ShareDeaths_g} = \frac{\frac{Vaccinations_{g,d}}{\sum_g Vaccinations_{g,d}}}{\frac{Deaths_g}{\sum_g Deaths_g}}$$

We use the sum of the vaccinations/deaths among included groups as denominators for shares ($\sum_g Vaccinations_{g,d}$) rather than all vaccinations ($Vaccinations_d$) to ensure that the ratios displayed are relative to each other and are not biased by missing race/ethnicity data.

This metric can be thought of as a normalized ratio of COVID-19 vaccinations to deaths because it can be written as:

$$EquityMetric_{g,d} = \frac{\sum_g Deaths_g}{\sum_g Vaccinations_{g,d}} \times \frac{Vaccinations_{g,d}}{Deaths_g} = \alpha \frac{Vaccinations_{g,d}}{Deaths_g}$$

Where $\alpha = \frac{\sum_g Deaths_g}{\sum_g Vaccinations_{g,d}}$ is a normalization constant that only depends on the date and the dose (not the group).

Medicaid managed care and pediatric dental emergency department visits

Lawrence Baker

Pardee RAND Graduate School and RAND

Elizabeth L. Munnich

University of Louisville, Kentucky

Ashley M. Kranz

RAND

Abstract

Importance: Millions of economically disadvantaged children depend on Medicaid for dental care, with states differing in whether they deliver these benefits using fee-for-service or capitated managed care payment models. However, there is limited research examining the association between the adoption of managed care and the accessibility of dental services.

Objective: To estimate the relationship between the adoption of managed care for dental services in Florida's Medicaid program on non-traumatic dental emergency department visits and associated charges.

Design: This cohort study used a Callaway and Sant'Anna event-study difference-in-difference design, leveraging Florida Medicaid's staggered adoption of managed care to examine its relationship with pediatric non-traumatic dental emergency department visits and associated charges. Analyses were conducted between May 2023 and April 2024.

Setting: Admission data from all Florida emergency departments from 2010-2014.

Participants: This study includes 34,414 emergency department visits where the patient was aged 17 years or younger, the patient was a Florida resident, Medicaid paid for the visit, and a primary or secondary ICD code was classified as a non-traumatic dental condition.

Exposure: The county of residence transitioned Medicaid dental services from fee-for-service to a fully capitated managed care program managed by a dental plan.

Main Outcomes and Measures: The rate of non-traumatic dental emergency department visits per 100,000 pediatric Medicaid enrollees and the associated mean charges per visit. Non-traumatic dental emergency department visits are a proxy for access to dental care. Data on emergency department visit counts came from Florida's Agency for Health Care Administration (AHCA). Medicaid population denominators were derived from the American Community Survey's 5-year estimates.

Results: 34,414 pediatric non-traumatic dental emergency department visits met inclusion criteria. Over the first 2.5 years of implementation, the adoption of managed care led to an 11.3% [95% CI: 4.0% to 18.4%, $p = 0.002$] increase in non-traumatic dental emergency department visit rates compared to pre-implementation levels. There was no evidence of changes in average charge per visit.

Conclusions and Relevance: Florida Medicaid’s adoption of managed care for pediatric dental services was associated with increased emergency department visits for children, which could be driven by decreased access to dental care.

Introduction

Children enrolled in Medicaid are entitled to comprehensive dental care through the federal Early and Periodic Screening, Diagnostic and Treatment (EPSDT) benefit. Despite the EPSDT benefit, many Medicaid-enrolled children do not routinely access dental care, with only 45% of eligible children receiving any dental services in 2021 (Centers for Medicare and Medicaid Services, 2023). Low rates of utilization stem from multiple sources, including low dentist participation, concerns about reimbursement rates (Chalmers & Compton, 2017), administrative complexity (Logan et al., 2015; Traul, 2023), and long wait times (Zolnikov et al., 2022). Access is particularly limited in rural communities, where there are fewer dentists and practices tend to be smaller and therefore less able to navigate the administrative burden associated with accepting Medicaid (Nasseh et al., 2023; Serban et al., 2022; Spivack et al., 2021).

Some children with non-emergency dental needs seek care at emergency departments (EDs) (Elani et al., 2020). National non-traumatic dental condition (NTDC) ED visit rates average 68.3 per 100,000 Medicaid-enrolled children younger than 15 years old (CareQuest Institute for Oral Health, 2022). NTDC ED visit rates are elevated among Medicaid enrollees, those who are uninsured, and young adults (Akinlotan & Ferdinand, 2020; CareQuest Institute for Oral Health, 2022). EDs typically cannot treat the underlying cause of the NTDC and instead alleviate symptomatic pain, so ED use is considered expensive for the health care system and ineffective for the patient (Akinlotan & Ferdinand, 2020; Rowley et al., 2006).

In an attempt to control costs and to improve access to dental services, many states have transitioned Medicaid dental benefits to fully-capitated payment models, hereafter referred to as managed care (Florida Agency for Health Care Administration, 2013). In these programs, private medical or dental plans take on the financial risk of providing dental services in return for risk-adjusted capitated payments. Some states operate programs in which case management or administrative services are capitated but care is reimbursed under a fee-for-service (FFS) model; these programs are more closely aligned with FFS.

The transition to managed care is ongoing—as of 2018, 18 states (listed in Appendix 2) administered pediatric Medicaid dental benefits through an FFS payment model (Nasseh & Bowblis, 2022) and, since that time, several states have initiated or considered new managed

care programs (NC Oral Health Collaborative, 2022; Oklahoma Health Care Authority, 2022, 2023; Washington State Health Care Authority, 2018).

The theoretical effect of managed care programs is ambiguous. Proponents argue that managed care programs improve coordination between medical and dental services and incentivize the delivery of preventative care to avoid expensive restorative treatment (Sparer, 2012). Critics argue that managed care increases administrative burdens and creates incentives for plans to limit access (Berenson & Rich, 2010). Empirically, medical Medicaid managed care programs have an inconsistent record of improving care or reducing costs (Duggan & Hayford, 2013; MACPAC, 2023b; Sullivan, 2000), but there is limited evidence on the effect of dental Medicaid managed care programs. One study examined whether transitioning Medicaid pediatric dental benefits from FFS to managed care changed service utilization in Indiana, Missouri, and Nebraska compared to states that retained FFS (Nasseh & Bowblis, 2022). Overall, switching to managed care was associated with a 2.6% drop in the share of Medicaid enrollees with a dental claim. However, results varied significantly by state. Dental claim rates dropped sharply in the first two quarters in Indiana before recovering. Reductions were more modest in Nebraska and non-significant in Missouri.

Our study builds on prior work by analyzing how NTDC ED visits changed during the introduction of managed care for Florida Medicaid's pediatric dental services from 2010-2014, a program known as Prepaid Dental Health Plans (PDHPs). Under FFS, all services were billed by dentists to the state according to a fee schedule. Under PDHPs, two dental plans, MCNA Dental and Delta Dental, received a capitated rate from the state and were each responsible for forming a network of dentists, providing care, and negotiating fee schedules. Medicaid enrollees were allocated to one of these plans, which subsequently assigned them to an in-network dentist. Dental plans may have achieved cost containment by negotiating lower rates with dentists, limiting networks to low-cost dentists, reducing utilization, expanding preventative services that reduce the need for restorative services, or identifying administrative efficiencies.

We used the rate of NTDC ED visits as our primary outcome because they directly measure the use of a costly and usually ineffective form of care, and are a proxy for dental care accessibility (Akinlotan & Ferdinand, 2020). When seeking treatment for painful and intractable dental conditions, families must choose whether to visit their dentist or the ED. As accessing a dentist becomes more difficult, more families choose the ED, increasing the rate of NTDC ED visits. We employ an event-study difference-in-differences (DiD) design to estimate changes in the NTDC ED visit rate and the associated charges following the adoption of managed care. We hypothesize that the introduction of managed care disrupted access to dental services because

patients could only receive care from in-network dentists rather than any dentist who accepted Medicaid, increasing NTDC ED visits.

Methods

We followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guideline for cross-sectional studies. The RAND Human Subjects Protection Committee deemed this analysis exempt from additional review.

Data, sample, and variables

We constructed our analytic dataset using data on ED visits and the Medicaid population. Quarterly ED visit and charge data were obtained from Florida's Agency for Healthcare Administration (AHCA). These data cover all ED visits in Florida. Records include patient demographics, self-classified race, county of residence, payer information, diagnoses (up to ten ICD-9 codes), and total charges (Florida Agency for Health Care Administration, 2023b). We obtained and used records from the first quarter of 2010 (2010-Q1) until the second quarter of 2014 (2014-Q2), after which Florida Medicaid made additional policy changes to how it covered dental care. Data on the number of Medicaid enrollees aged 17 years or younger in Florida were extracted from the American Community Survey (ACS) 5-year data (U.S. Census Bureau, 2022) using the tidycensus R package (Walker & Herman, 2023). For additional details on our preparation of population data, see Table A2.1 and Figure A2.1 in Appendix 2.

We used NTDC ED visits as a proxy measure for dental care accessibility. NTDCs encompass conditions like dental caries, abscesses, inflammation, and related pain. Each NTDC ED visit suggests a breakdown in dental care access because these conditions are both preventable and best treated in a dental office. NTDCs have widely been used to study dental health policy changes, including Medicaid expansion (Baicker et al., 2018; Chalmers et al., 2016; Laniado et al., 2017, 2020) and the elimination of Medicaid dental benefits (Salomon et al., 2017; Singhal et al., 2015; N. T. Wallace et al., 2011).

To measure counts of pediatric NTDC ED visits covered by Medicaid, we subset ED visit data using the following inclusion criteria: 1) the patient was age 17 years or younger; 2) the patient was a Florida resident (2.3% of pediatric NTDC visits without a resident Florida county code were excluded); 3) Medicaid paid for the visit; and 4) a primary or secondary ICD-9 code was classified as an NTDC per the Association of State and Territorial Dental Directors' guidelines (Manz, 2021).

We identified when counties adopted managed care using the Florida Medicaid Monthly Enrollment Report from the AHCA (Florida Agency for Health Care Administration, 2023a). Where multiple monthly files were available for the same quarter, the mean was used.

Our primary outcome was the number of NTDC ED visits per 100,000 Medicaid enrollees aged 17 years or younger. Our secondary outcome was the mean charge per NTDC ED visit among this population.

Analytic approach

Our analysis focuses on the shift from FFS to managed care for Florida Medicaid’s pediatric dental services. Most of Florida’s counties (61 of 67) first adopted managed care for pediatric dental services between 2012-Q1 and 2013-Q1. We include these counties in our treatment group. The remaining 6 counties implemented managed care for dental services much earlier, between 2004 and 2007, as part of two separate pilot programs: one for PDHPs and one for a comprehensive managed care system that included medical and dental benefits (Florida Committee on Health Regulation, 2010; OPPAGA, 2016). We use these pilot counties as controls because their payment structures did not change during our 2010-2014 analysis period. We assume that there are no remaining treatment dynamics in control counties because they adopted managed care more than five years before the treatment counties. Table 2.1 shows Medicaid in each county first adopted managed care for pediatric dental care among Medicaid enrollees. Figure A2.2 in the Supplement shows enrollment in managed care dental plans in each treatment county.

Table 2.1: Timing of the introduction of managed care for pediatric dental services in Florida counties

Counties	Adopted managed care for dental services	Treatment/control
Miami-Dade	2004	Control
Broward, Duval	2006	Control
Nassau, Baker, Clay	2007	Control
Indian River, Martin, Okeechobee, Palm Beach, St Lucie	2012-Q1	Treatment
Brevard, Hardee, Highlands, Hillsborough, Manatee, Orange, Osceola, Pasco, Pinellas, Polk, Seminole	2012-Q4	Treatment
All others (45 counties)	2013-Q1	Treatment

We estimate a DiD event study using a two-way fixed effects (TWFE) model with county-quarter observations. We weight the regression by the number of pediatric Medicaid enrollees in each county-quarter. This regression yields average treatment effect on the treated (ATT) estimates for each treatment group in each quarter. We calculate the overall ATT as the weighted average of all post-treatment groups. We construct standard errors and the corresponding pointwise confidence intervals using 100,000 iterations of county-clustered multiplier bootstrapping. We do not add additional controls beyond the treatment and fixed effects required for TWFE, because including covariates that are not orthogonal to treatment can induce bias in event-study designs (Powell, 2022).

Recent DiD literature highlights that TWFE can yield biased estimates when applied to a staggered policy intervention if there are time-varying or heterogeneous effects (Callaway & Sant’Anna, 2021b; Goodman-Bacon, 2021; Wooldridge, 2021). We use a method proposed by Callaway and Sant’Anna (Callaway & Sant’Anna, 2021b) to correct for these biases, implemented with the ‘did’ R package version 2.1.2 (Callaway & Sant’Anna, 2021a).

As robustness checks on our primary outcome results, we estimate several alternative model specifications, which are described in detail in Appendix 2. Specifically, we aggregate the county-quarter observations into a simplified 2x2 DiD model with two time periods (pre- and post-intervention) and two groups (treatment and control). We also present results using NTDC ED visit counts, rather than NTDC ED visit rates, to verify that changes in rates are primarily driven by changes in the number of visits (the numerator) rather than changes in the Medicaid population (the denominator). Since Florida counties vary greatly in size, we use percentage, rather than absolute, changes in counts (Finkelstein, 2007). Finally, because there is no consensus on the optimal approach for adjusting TWFE estimates in the presence of staggered rollouts (de Chaisemartin & D’Haultfœuille, 2023), we present ATTs from three alternative methods (Gardner, 2022; Sun & Abraham, 2021; Wooldridge, 2021).

All analyses were conducted with the R statistical computing language, version 4.2.3 (R Core Team, n.d.), and used $p < 0.05$ as a 2-sided significance threshold.

Results

We analyzed a total of 34,414 NTDC ED visits that met our inclusion criteria. Of these, 10,087 visits occurred in control counties and 24,327 in treatment counties. We provide a comparison of these counties in Table 2.2, focusing on pre-treatment periods from the first quarter of 2010 (2010-Q1) to the fourth quarter of 2011 (2011-Q4).

Table 2.2: Summary statistics for control and treatment counties in pre-treatment quarters.

	Control Counties	Treatment Counties
Observed NTDC ED Visits (2010-Q1 to 2014-Q2)	24,327	10,087
Pre-treatment NTDC Dependent variables		
Quarterly NTDC ED visits per 100,000 pediatric Medicaid Enrollees	123.5	132.7
Mean charge per pediatric NTDC visit	\$823	\$841
Pre-treatment County Characteristics		
Mean population Medicaid enrollees under 18 years old	72,187	15,286
Pre-treatment NTDC ED Visit Characteristics		
Mean Age	7.38	8.59
Sex		
Male	48.6%	51.3%
Female	51.4%	48.7%
Race/Ethnicity		
Hispanic	33.2%	21.5%
Non-Hispanic Asian	0.3%	0.6%
Non-Hispanic Black	48.1%	34.0%
Non-Hispanic White	15.3%	41.1%
Non-Hispanic Other	2.8%	2.1%
Unknown	0.3%	0.6%

NOTES: Includes data for 6 control counties and 61 treatment counties. Except for the first row, the variables shown are the mean for pre-treatment periods (2010-Q1 until 2011-Q4). Control counties are those who received the Pre-paid Dental Health Plan pilot or the Statewide Medicaid Managed Care pilot. The “Non-Hispanic Other” race/ethnicity category includes individuals reported as “Native Hawaiian or Other Pacific Islander” or “Other”. ED: Emergency department.

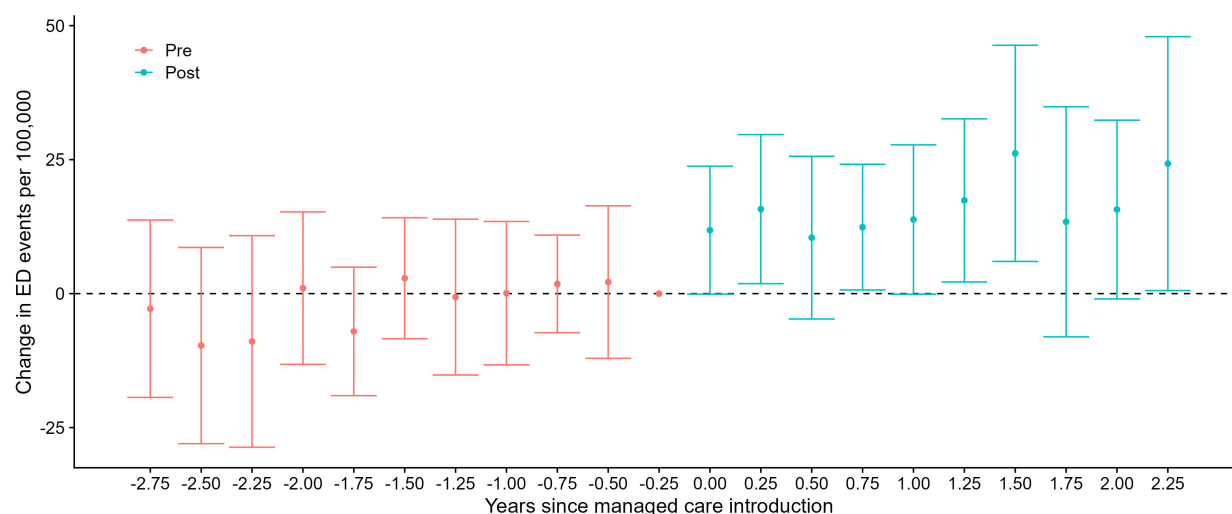
Control counties generally had lower rates of NTDC ED visits per 100,000 enrollees (123.5) compared to treatment counties (132.7). This difference is primarily due to the lower NTDC ED rate in Miami-Dade County. The average charges per NTDC ED visit were similar across both groups, with treatment counties averaging \$841 and control counties \$823. Control counties generally had larger populations (72,187) and a smaller proportion of ED visits for white non-Hispanic residents (15.3%) compared to treatment counties (15,286, 41.1% white non-Hispanic).

Our analysis reveals a large and statistically significant increase in NTDC ED visits among pediatric Medicaid enrollees following the implementation of managed care. Specifically, there was an increase of 15.0 [CI: 5.4 – 24.5, $p = 0.002$] visits per 100,000 enrollees per quarter after managed care was introduced in treatment counties, which translates to an additional 59.8 [CI:

21.4 – 98.194] visits per 100,000 enrollees annually. This represents an 11.3% increase [95% CI: 4.0% to 18.4%] in visits compared to the pre-treatment average in treated counties. These results are similar when we consider only visits with a principal NTDC diagnosis, shown in Table A2.3 in Appendix 2. Additionally, we found no significant association between managed care and the mean charge to Medicaid for NTDC ED visits, with an ATT of -\$49.64 [CI: -\$143.1 – \$45.0, $p = 0.31$].

The quarterly ATTs shown in Figure 2.1 and Appendix Table A2.4 are consistently elevated after managed care was implemented, though most quarterly estimates are not individually statistically significant due to limited sample sizes. Pre-treatment ATTs are non-significant and small relative to post-treatment ATTs, supporting the DiD parallel trends assumption. In contrast, the quarterly ATTs for mean charges display no clear pattern. Although there is a statistically significant decrease in quarters 0 and 0.5, the overall association with charges is statistically insignificant and the quarterly estimates have inconsistent signs, suggesting that this result reflects random variation rather than a true effect.

Figure 2.1: Quarterly event study estimates of the relationship between managed care and NTDC ED visits



NOTES: Data include 67 counties, 1206 county-quarters, and 34,414 NTDC ED visits. Difference-in-differences point estimates and corresponding 95% confidence intervals are shown. Pre- and post-treatment ATTs are constructed using long differences. ATT: Average treatment effect on the treated; ED: Emergency department; NTDC: Non-traumatic dental condition. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To evaluate the robustness of our findings, we estimated several alternative model specifications, with overall ATTs shown in Table 2.3. The ATT for the simplified 2x2 DiD specification was statistically significant and similar in magnitude to the main analysis. This suggests that our primary results are representative of treated counties overall and are not reliant on weighting or temporal aggregation. The ATT from an inverse hyperbolic sine (IHS) count specification was

statistically significant and indicated that managed care we associated with an 8.84% [CI: 2.09% – 15.59%, $p = 0.01$] increase in ED visits. This increase is slightly lower than the 11.3% increase identified in the main specification because it does not account for population changes and compares the effect to post-treatment, rather than pre-treatment, rates. ATTs from the three models using alternative approaches to correct for staggered rollout biases (Gardner, 2022; Sun & Abraham, 2021; Wooldridge, 2021) were consistent in direction and magnitude. Taken together, these findings support the robustness of our main results.

Table 2.3: Comparison of overall difference-in-differences estimates of the relationship between introducing managed care and NTDC ED visits and charges using alternative specifications.

Specification	Quarterly NTDC ED visits per 100,000 pediatric Medicaid Enrollees	Mean charge for NTDC ED visits (\$)	Percentage change in quarterly NTDC ED visits
Main (Callaway and Sant’Anna)	14.951*** [5.352, 24.549]	-49.087 [-143.15, 44.972]	NA
Simplified 2x2	17.738*** [5.6643, 29.812]	13.063 [-102.96, 129.08]	NA
Visit IHS Count	NA	NA	0.0884** [0.0209, 0.1559]
Wooldridge	19.113** [7.517, 30.709]	-27.922 [-106.72, 50.883]	NA
Gardner	15.526*** [6.4491, 24.603]	-20.650 [-128.58, 87.275]	NA
Sun and Abraham	15.156*** [5.2994, 25.013]	-48.324 [-140.98, 44.336]	NA

NOTES: Data include 67 counties, 1206 county-quarters, and 34,414 NTDC ED visits. Difference-in-differences coefficient estimates are shown with standard errors in parentheses and corresponding 95% confidence intervals in brackets. For the main and count inverse hyperbolic sine (IHS) specifications, county-clustered multiplier bootstrap was used to calculate standard errors, for the 2x2 specification no standard error adjustment was used, for other specifications standard errors were clustered at the county level. For event study specifications, overall ATTs are constructed as a weighted average of all post-treatment groups. ATT: Average treatment effect on the treated; ED: Emergency department; NTDC: Non-traumatic dental condition. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Discussion

Florida Medicaid has long struggled to deliver pediatric dental care, with service rates among the lowest in the nation. In 2010, 16% of Florida dentists participated Medicaid (Florida Department of Health, 2011) and only 24% of children enrolled in Florida Medicaid had any dental visit (Centers for Medicare and Medicaid Services, 2023). A decade later, these figures were only slightly improved —22% of dentists participated (Traul, 2023) and 35% of children had a dental visit that year (Centers for Medicare and Medicaid Services, 2023). We examined the relationship between the introduction of fully capitated managed care for dental services and the rate of NTDC ED visits among Medicaid-enrolled children in Florida. Using a DiD specification

we found that, in the first 2.5 years after implementation, the introduction of managed care was associated with a 10% [CI: 3.3% - 16.6%] increase in NTDC ED visits. The average charges for these visits did not change.

We observed an immediate increase in NTDC ED visits following the implementation of managed care, with visits continuing to rise over time. This abrupt increase is counterintuitive given that dental conditions can take years to progress. However, most children enrolled in Florida's Medicaid program do not regularly receive preventive dental care (Centers for Medicare and Medicaid Services, 2023). The immediate change in visits may reflect a substitution toward ED care: children who previously saw a dentist now present to the ED instead. Similar patterns have been observed in other settings. For example, when Medicaid adult emergency dental coverage was eliminated in Maryland, dental ED visits increased by 22% (Cohen et al., 1996). Additionally, EDs are used as substitutes for medical services when access to primary care is limited (Denham et al., 2024). The longer-term increases in NTDC ED visits could be due to decreased preventative care increasing the overall burden of unaddressed dental disease in the population.

Our findings are consistent with prior research, which found that the adoption of managed care for Medicaid dental services was associated with fewer visits to dentists (Nasseh & Bowblis, 2022). There are several reasons why the introduction of managed care could decrease dental care access. One possibility is that some dentists who previously accepted FFS Medicaid may have chosen not to participate in a managed care network. This explanation seems unlikely, as Florida's workforce survey of dentists found no significant reduction in the overall number of dentists accepting Medicaid immediately following the adoption of managed care (Florida Department of Health, 2016).

However, even if the overall number of dentists accepting Medicaid did not decline under managed care, patients likely experienced less flexibility in their choice of dentist. Under FFS, patients could choose any dentist who accepted Medicaid. In contrast, the managed care model used in Florida restricted patients to assigned in-network dentists, although they retained the option to switch between in-network dentists. Surveys of Florida Medicaid patients have shown that confusion around which dentists are in-network is one of the biggest barriers to accessing care (Zolnikov et al., 2022). Enrollees may have struggled to navigate the transition if they were assigned to a new dentist, especially if they lacked transportation options or struggled to trust a new dentist.

Although the data used in this study are relatively old, covering 2010-2014, our findings are relevant to ongoing policy decisions. There is no consensus on the best payment system for

Medicaid's dental benefits, with states approximately evenly split between FFS programs, managed care programs administered by medical plans (carve-in), and managed care programs administered by dental plans (carve-out) (Fontana et al., 2020). As of 2021, 10 states provide Medicaid dental benefits to the majority of enrollees through capitated payments to dental plans (MACPAC, 2023a). As of the end of 2018, 18 states offered pediatric Medicaid dental services FFS (Nasseh & Bowblis, 2022). Since then, several states have initiated or considered managed care programs for dental services. In 2018, Washington State released a request for dental plans as part of implementing a Medicaid managed care program (Washington State Health Care Authority, 2018), before canceling the program less than a year later (Washington State Dental Association, 2019). In 2022, North Carolina convened a taskforce of dentists, Medicaid officials, and academics is investigating whether the state should implement dental managed care (NC Oral Health Collaborative, 2022). In February 2024, Oklahoma transitioned its FFS dental program to managed care (Oklahoma Health Care Authority, 2022, 2023).

In addition, Florida continues to change how it pays for Medicaid dental benefits. In 2018, the state 'carved-out' dental benefits for children and adults, separating them from medical coverage. Whether dental benefits should be managed by dental or medical plans remains contentious, with the AHCA presenting a time series analysis in support of reintegrating dental benefits into medical plans (a 'carve-in') in 2021 (T. Wallace, 2021), which was considered, but not enacted, in the Florida legislature in 2022 (An Act Relating to Medicaid Managed Care, 2022; Sexton, 2022). State program details are provided in Appendix 2.

This study has several limitations. First, NTDC ED visits are relatively uncommon, leading to a modest sample size for our analysis and wide confidence intervals for our ATTs. However, NTDC ED visits are frequently used in research because these visits are typically preventable, indicative of inadequate access to regular dental care, often result in only palliative treatment, and can lead to inappropriate opioid use (Cothron et al., 2021; Okunseri et al., 2015; Singhal et al., 2015). Second, our primary results rely on an assumption that the post-treatment trends in already-treated control counties are an accurate counterfactual for post-treatment trends in treatment counties. We support this assumption by showing that the trends in these groups were similar before policy implementation, verifying that no treatment dynamics remained from pilot implementations five years earlier. Third, our results for charges are based on what ED departments charged, not what was reimbursed by Medicaid. If the proportion of charges that are reimbursed changed alongside the introduction of managed care, then our conclusions about mean charges could be misleading and may not apply to mean reimbursements. Fourth, we rely on Medicaid population estimates from the ACS, rather than enrollment files. We explore the impact of systematic errors in population estimates in Appendix 2, Table A2.2.

Further research should focus on whether the adoption of managed care for dental services changed overall dental and medical costs, and whether managed care delivered the promised cost-savings to states. Finally, there is a need for research on whether managed care dental services are best administered by medical plans or dental plans.

This study highlights the potential unintended consequences of adopting managed care in Medicaid. Introducing managed care was associated with an increase in ED visits for preventable dental conditions, suggesting decreased access to dentists. Managed care policies are attractive because they theoretically enable states to control spending and transfer budgetary risk to the private sector (Perez, 2018). However, if states want to prioritize dental care access for children (Florida Agency for Health Care Administration, 2013), then they should consider retaining FFS payment models.

References

- Akinlotan, M. A., & Ferdinand, A. O. (2020). Emergency department visits for nontraumatic dental conditions: A systematic literature review. *Journal of Public Health Dentistry*, 80(4), 313–326. <https://doi.org/10.1111/jphd.12386>
- American Community Survey. (2022). *Worked Examples for Approximating Standard Errors Using American Community Survey Data*. https://www2.census.gov/programs-surveys/acs/tech_docs/accuracy/2022_ACS_Accuracy_Document_Worked_Examples.pdf
- An Act Relating to Medicaid Managed Care, HB 7047 (2022). https://www.myfloridahouse.gov/Sections/Documents/loaddoc.aspx?FileName=_h7047_.docx&DocumentType=Bill&BillNumber=7047&Session=2022
- Baicker, K., Allen, H. L., Wright, B. J., Taubman, S. L., & Finkelstein, A. N. (2018). The Effect of Medicaid on Dental Care of Poor Adults: Evidence from the Oregon Health Insurance Experiment. *Health Services Research*, 53(4), 2147–2164. <https://doi.org/10.1111/1475-6773.12757>
- Berenson, R. A., & Rich, E. C. (2010). US approaches to physician payment: The deconstruction of primary care. *Journal of General Internal Medicine*, 25(6), 613–618. <https://doi.org/10.1007/s11606-010-1295-z>

- Burbidge, J. B., Magee, L., & Robb, A. L. (1988). Alternative Transformations to Handle Extreme Values of the Dependent Variable. *Journal of the American Statistical Association*, 83(401), 123–127. <https://doi.org/10.2307/2288929>
- Callaway, B., & Sant’Anna, P. (2021a). *did: Difference in Differences* (Version 2.1.2) [Computer software]. <https://bcallaway11.github.io/did/>
- Callaway, B., & Sant’Anna, P. H. C. (2021b). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. <https://doi.org/10.1016/j.jeconom.2020.12.001>
- CareQuest Institute for Oral Health. (2022). *Recent Trends in Hospital Emergency Department Visits for Non-Traumatic Dental Conditions*.
- Centers for Medicare and Medicaid Services. (2023). *Early and Periodic Screening, Diagnostic, and Treatment*. Medicaid.Gov. <https://www.medicaid.gov/medicaid/benefits/early-and-periodic-screening-diagnostic-and-treatment/index.html>
- Chalmers, N., & Compton, R. (2017). Children’s Access to Dental Care Affected by Reimbursement Rates, Dentist Density, and Dentist Participation in Medicaid. *American Journal of Public Health*, 107(10), 1612–1614. <https://doi.org/10.2105/AJPH.2017.303962>
- Chalmers, N., Grover, J., & Compton, R. (2016). After Medicaid Expansion In Kentucky, Use Of Hospital Emergency Departments For Dental Conditions Increased. *Health Affairs*, 35(12), 2268–2276. <https://doi.org/10.1377/hlthaff.2016.0976>
- Cohen, L. A., Manski, R. J., & Hooper, F. J. (1996). Does the elimination of Medicaid reimbursement affect the frequency of emergency department dental visits? *Journal of the American Dental Association* (1939), 127(5), 605–609. <https://doi.org/10.14219/jada.archive.1996.0272>
- Cothron, A., Diep, V. K., Shah, S., Brow, A., Thakkar-Samtani, M., Okunseri, C., Tranby, E. P., & Frantsve-Hawley, J. (2021). A systematic review of dental-related emergency department visits among Medicaid beneficiaries. *Journal of Public Health Dentistry*, 81(4), 280–289. <https://doi.org/10.1111/jphd.12458>
- de Chaisemartin, C., & D’Haultfœuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *The Econometrics Journal*, 26(3), C1–C30. <https://doi.org/10.1093/ectj/utac017>

- Denham, A., Hill, E. L., Raven, M., Mendoza, M., Raz, M., & Veazie, P. J. (2024). Is the emergency department used as a substitute or a complement to primary care in Medicaid? *Health Economics, Policy and Law*, 19(1), 73–91.
<https://doi.org/10.1017/S1744133123000270>
- Duggan, M., & Hayford, T. (2013). Has the Shift to Managed Care Reduced Medicaid Expenditures? Evidence from State and Local-Level Mandates. *Journal of Policy Analysis and Management*, 32(3), 505–535. <https://doi.org/10.1002/pam.21693>
- Elani, H. W., Kawachi, I., & Sommers, B. D. (2020). Changes in emergency department dental visits after Medicaid expansion. *Health Services Research*, 55(3), 367–374.
<https://doi.org/10.1111/1475-6773.13261>
- Finkelstein, A. (2007). The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare*. *The Quarterly Journal of Economics*, 122(1), 1–37.
<https://doi.org/10.1162/qjec.122.1.1>
- Florida Agency for Health Care Administration. (2013, August 6). *Background regarding the provision of Medicaid-covered dental services for children* [Memo].
https://ahca.myflorida.com/content/download/16505/file/The_following_points_are_background_regarding_the_provision_of_Medicaid-covered_dental_services_for_children_.pdf
- Florida Agency for Health Care Administration. (2023a). *Florida Statewide Medicaid Monthly Enrollment Report*. <https://ahca.myflorida.com/medicaid/medicaid-finance-and-analytics/medicaid-data-analytics/medicaid-monthly-enrollment-report,/medicaid/medicaid-finance-and-analytics/medicaid-data-analytics/medicaid-monthly-enrollment-report>
- Florida Agency for Health Care Administration. (2023b, July 5). *Data Dictionary*. Florida Health Finder. <https://quality.healthfinder.fl.gov/Researchers/OrderData/order-data.aspx>
- Florida Committee on Health Regulation. (2010). *Overview of Medicaid Managed Care Programs in Florida* (Issue Brief 2011–221). Florida Senate.
<https://www.flsenate.gov/UserContent/Session/2011/Publications/InterimReports/pdf/2011-221hr.pdf>
- Florida Department of Health. (2011). *Report on the 2009-2010 Florida Workforce Survey of Dentists*.

- Florida Department of Health. (2016). *Report on the 2013-2014 Florida Workforce Survey of Dentists*.
- Fontana, J., Hallum, A., & Lewis, C. (2020). *Medicaid Dental Program Delivery Systems*. Milliman.
- Gardner, J. (2022). *Two-stage differences in differences* (arXiv:2207.05943). arXiv. <https://doi.org/10.48550/arXiv.2207.05943>
- Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254–277. <https://doi.org/10.1016/j.jeconom.2021.03.014>
- Laniado, N., Badner, V. M., & Silver, E. J. (2017). Expanded Medicaid dental coverage under the Affordable Care Act: An analysis of Minnesota emergency department visits. *Journal of Public Health Dentistry*, 77(4), 344–349. <https://doi.org/10.1111/jphd.12214>
- Laniado, N., Brow, A. R., Tranby, E., & Badner, V. M. (2020). Trends in non-traumatic dental emergency department use in New York and New Jersey: A look at Medicaid expansion from both sides of the Hudson River. *Journal of Public Health Dentistry*, 80(1), 9–13. <https://doi.org/10.1111/jphd.12343>
- Logan, H. L., Catalanotto, F., Guo, Y., Marks, J., & Dharamsi, S. (2015). Barriers to Medicaid Participation among Florida Dentists. *Journal of Health Care for the Poor and Underserved*, 26(1), 154–167. <https://doi.org/10.1353/hpu.2015.0000>
- MACPAC. (2023a). *MACStats: Medicaid and CHIP Data Book*. <https://www.macpac.gov/publication/macstats-medicaid-and-chip-data-book-2/>
- MACPAC. (2023b, September 12). *Managed care’s effect on outcomes*. MACPAC. <https://www.macpac.gov/subtopic/managed-cares-effect-on-outcomes/>
- Manz, M. C. (2021). *Recommended Guidelines for Surveillance of Non-Traumatic Dental Care in Emergency Departments*. ASTDD. <https://www.astdd.org/docs/recommended-guidelines-for-surveillance-of-ntdc-in-eds.pdf>
- Nasseh, K., & Bowlblis, J. R. (2022). The effect on dental care utilization from transitioning pediatric Medicaid beneficiaries to managed care. *Health Economics*, 31(6), 1103–1128. <https://doi.org/10.1002/hec.4496>

- Nasseh, K., Fosse, C., & Vujicic, M. (2023). Dentists Who Participate in Medicaid: Who They Are, Where They Locate, How They Practice. *Medical Care Research and Review*, 80(2), 245–252. <https://doi.org/10.1177/10775587221108751>
- NC Oral Health Collaborative. (2022). *Oral Health Transformation Initiative*. <https://oralhealthnc.org/transformation/>
- Oklahoma Health Care Authority. (2022). *SoonerSelect Dental Program Request for Proposals* (8070001412). https://oklahoma.gov/content/dam/ok/en/okhca/docs/about/procurement/soonerselect-dental-8070001412/documents/Dental%20RFP%20Amendment_3_10.27.22%20Final.pdf
- Oklahoma Health Care Authority. (2023, December 15). *About SoonerSelect*. <https://oklahoma.gov/ohca/soonerselect/about.html>
- Okunseri, C., Dionne, R. A., Gordon, S. M., Okunseri, E., & Szabo, A. (2015). Prescription of Opioid Analgesics for Nontraumatic Dental Conditions in Emergency Departments. *Drug and Alcohol Dependence*, 156, 261–266. <https://doi.org/10.1016/j.drugalcdep.2015.09.023>
- OPPAGA. (2016). *Review of Medicaid Dental Services* (Report No. 16-07). Florida Legislature. <https://oppaga.fl.gov/Documents/Reports/16-07.pdf>
- Perez, V. (2018). Does capitated managed care affect budget predictability? Evidence from Medicaid programs. *International Journal of Health Economics and Management*, 18(2), 123–152. <https://doi.org/10.1007/s10754-017-9227-7>
- Powell, D. (2022). *The Labor Supply Consequences of the Opioid Crisis* (SSRN Scholarly Paper 3899329). <https://doi.org/10.2139/ssrn.3899329>
- R Core Team. (n.d.). *R: A language and environment for statistical computing* (Version 4.2.3) [Computer software]. R Foundation for Statistical Computing. <https://www.R-project.org/>
- Rowley, S. T., Sheller, B., Williams, B. J., & Mancl, L. (2006). Utilization of a Hospital for Treatment of Pediatric Dental Emergencies. *Pediatric Dentistry*, 28(1), 10–17.
- Salomon, D., Heidel, R. E., Kolokythas, A., Miloro, M., & Schlieve, T. (2017). Does Restriction of Public Health Care Dental Benefits Affect the Volume, Severity, or Cost of Dental-

- Related Hospital Visits? *Journal of Oral and Maxillofacial Surgery*, 75(3), 467–474.
<https://doi.org/10.1016/j.joms.2016.10.019>
- Serban, N., Anderson, A., Oberst, G., Edupuganti, N., Ramachandran, R., Solipuram, S. R., & Lu, T. (2022). Assessment of Dentist Participation in Public Insurance Programs for Children in the US. *JAMA Network Open*, 5(7), e2221444.
<https://doi.org/10.1001/jamanetworkopen.2022.21444>
- Sexton, C. J. (2022, February 23). Medicaid dental care is a done deal, but differences remain in House, Senate bills. *Florida Politics - Campaigns & Elections. Lobbying & Government*.
<https://floridapolitics.com/archives/499744-medicaid-dental-is-a-done-deal-but-differences-remain-in-house-senate-bills/>
- Singhal, A., Caplan, D. J., Jones, M. P., Momany, E. T., Kuthy, R. A., Buresh, C. T., Isman, R., & Damiano, P. C. (2015). Eliminating Medicaid Adult Dental Coverage In California Led To Increased Dental Emergency Visits And Associated Costs. *Health Affairs*, 34(5), 749–756. <https://doi.org/10.1377/hlthaff.2014.1358>
- Sparer, M. (2012). *Medicaid managed care: Costs, access, and quality of care* (The Synthesis Project). Robert Wood Johnson Foundation.
- Spivack, S. B., Murray, G. F., Rodriguez, H. P., & Lewis, V. A. (2021). Avoiding Medicaid: Characteristics Of Primary Care Practices With No Medicaid Revenue. *Health Affairs (Project Hope)*, 40(1), 98–104. <https://doi.org/10.1377/hlthaff.2020.00100>
- Sullivan, K. (2000). On The ‘Efficiency’ Of Managed Care Plans. *Health Affairs*, 19(4), 139–148. <https://doi.org/10.1377/hlthaff.19.4.139>
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199.
<https://doi.org/10.1016/j.jeconom.2020.09.006>
- Traul, R. (2023). *2019–2020 Workforce Survey of Dentists*. The Florida Department of Health.
- U.S. Census Bureau. (2022). *American Community Survey 5-Year Data (2009-2021)*.
<https://www.census.gov/data/developers/data-sets/acs-5year.html>
- Walker, K., & Herman, M. (2023). *tidycensus: Load US Census Boundary and Attribute Data as “tidyverse” and ‘sf’-Ready Data Frames* (Version 1.4.3) [Computer software].
<https://walker-data.com/tidycensus/index.html>

- Wallace, N. T., Carlson, M. J., Mosen, D. M., Snyder, J. J., & Wright, B. J. (2011). The Individual and Program Impacts of Eliminating Medicaid Dental Benefits in the Oregon Health Plan. *American Journal of Public Health, 101*(11), 2144–2150. <https://doi.org/10.2105/AJPH.2010.300031>
- Wallace, T. (2021, November 2). *Medicaid Dental Updates*. <https://www.myfloridahouse.gov/Sections/Documents/loaddoc.aspx?PublicationType=Committees&CommitteeId=3085&Session=2022&DocumentType=Meeting+Packets&Filename=hhs+11-2-21.pdf>
- Washington State Dental Association. (2019, May 22). *HCA Update: Managed Care Dental Activities are Cancelled*. WSDA. <https://www.wsda.org/newsitems/2019/05/22/hca-update-managed-care-dental-activities-are-cancelled>
- Washington State Health Care Authority. (2018). *State of Washington Request for Proposals 2516* (RFP2516). https://www.hca.wa.gov/assets/program/RFP%202516_MC%20Dental.pdf
- Wooldridge, J. M. (2021). *Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators* (SSRN Scholarly Paper 3906345). <https://doi.org/10.2139/ssrn.3906345>
- Zolnikov, T. R., Garces, K., Masood, A., King, R., Robbins, M., & McGuigan, K. (2022). A mixed methods study reviewing consumer experiences for oral health treatment in Medicaid-eligible children in Florida. *Journal of Public Health Dentistry, 82*(4), 365–371. <https://doi.org/10.1111/jphd.12460>

Appendix 2

Census Medicaid population

County-level populations were estimated using the American Community Survey 5-year data (U.S. Census Bureau, 2022). For each county, we estimated the number of under-18-year-old Medicaid enrollees as the sum of:

- B27010_007: under 18-year-olds with Medicaid only.
- B27010_013: under 18-year-olds with Medicaid and Medicare only.
- B27010_015: under 18-year-olds with another combination of public insurance.

The 5-year data were chosen over 1-year data because the larger sample size improves the accuracy of the population estimate and the 1-year data excludes geographies that have populations smaller than 65,000, including many Florida counties. However, because 5-year data is collected over an extended period (e.g. from 2009-2013), it is unclear if it is representative of a single year.

To identify what year is best represented by the 5-year ACS estimates, we compared them to the 1-year ACS estimates in counties with populations over 65,000. The 5-year estimates were available for collection periods ending 2013-2021 and 1-year estimates were available 2013-2019. We calculated the mean percentage difference in the 5-year and 1-year estimates of the number of Medicaid enrollees under 19 across lags from -5 years to +5 years for each Florida County. We then took the mean of these results across all counties to yield our estimate of the percentage difference, shown in Table A2.1.

Table A2.1: Mean percentage difference between ACS 1-year and ACS 5-year estimates by year offset

Offset for 5-year ACS	Mean percentage difference
-5	7.6%
-4	4.5%
-3	2.5%
-2	-0.1%
-1	-2.0%
0	-3.3%
1	-5.0%
2	-6.9%
3	-8.5%
4	-10.2%
5	-10.8%

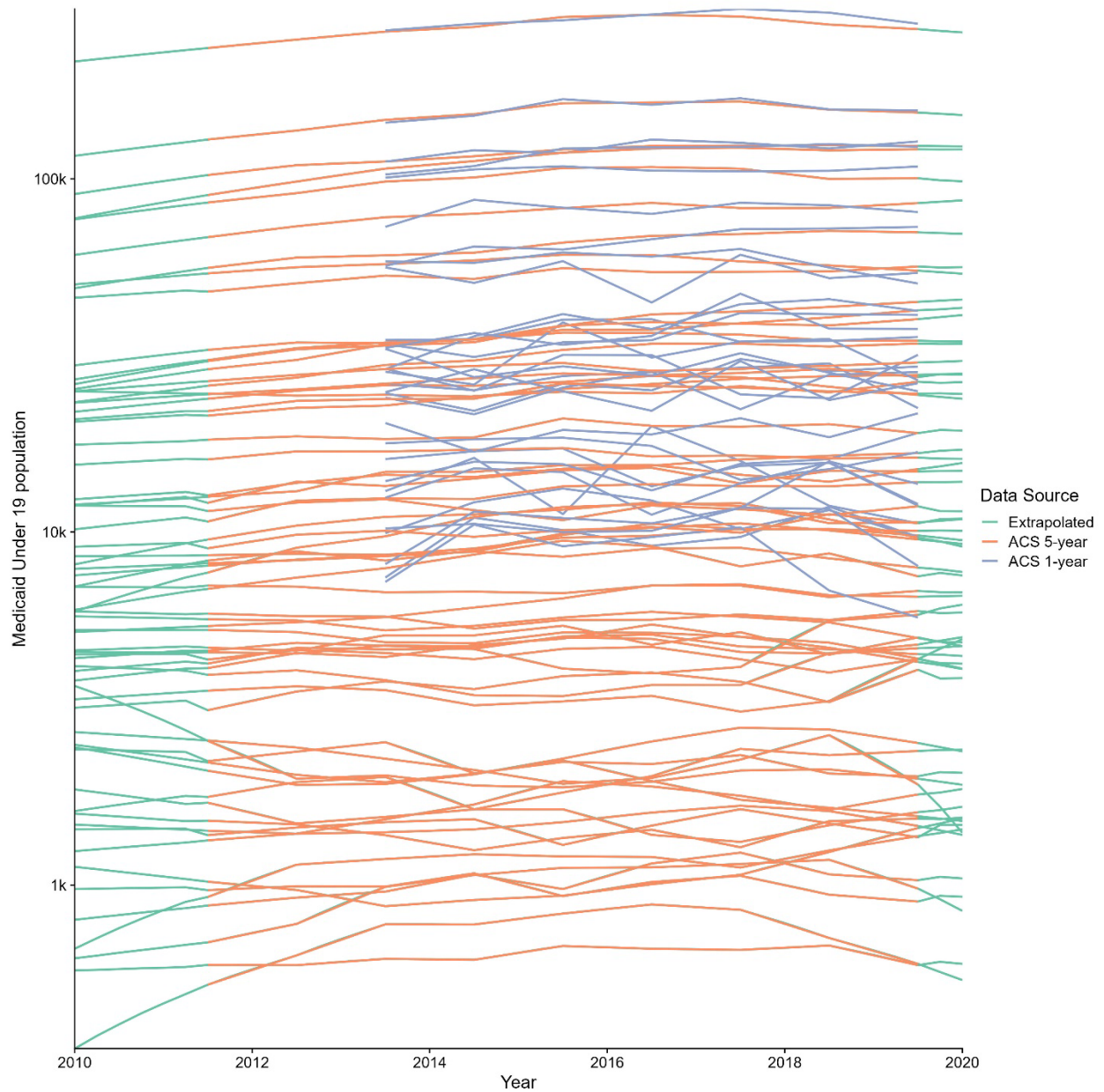
NOTES: Bolded value indicates absolute minimum error. ACS: American Community Survey.

Using a lag of 2 years for the 5-year survey estimates minimized the error with 1-year estimates, which was close to zero (0.1%). For instance, the 2009-2013 survey was chosen to represent 2011. This makes intrinsic sense: 2011 is the midpoint of the survey period, so if trends are approximately linear, then it will be representative of that year.

Lagging the 5-year survey estimates by 2 years provided annual estimates for county populations from 2011 to 2019. Our ED outcome data was for 2010-2014 at a quarterly frequency. To interpolate quarterly values, we assigned the estimates for a year to the third quarter (so 2011 estimates were coded as 2011.5) and then linearly interpolated between observations. Medicaid population variables first became available in the 2009-2013 ACS survey. To extrapolate outside the range of the data, we fitted thin-plate splines with 9 degrees of freedom to each county's observations between 2011 and 2019. We then used the predicted values from these splines for the 2010 data.

Figure A2.1 shows 1-year ACS estimates (blue), offset 5-year ACS estimates (orange), and the interpolated/extrapolated data (green). The interpolated data is obscured by the 5-year estimates because they correspond exactly. Counties with small populations toward the bottom of the plot have no 1-year data because this data is only available for counties with at least 65,000 population.

Figure A2.1: Relationship between ACS 1-year estimates, offset ACS-5 year estimates, and extrapolated data



NOTES: Y-axis is shown on a log scale. All estimates have been offset by 0.5 years (so the 2011 survey is shown in 2011.5), to allow for quarter interpolation. ACS 5-year estimates have additionally been offset by 2 years based on the results in Table A2.1. ACS: American Community Survey.

Population age sample

The ACS reports insured-population data for discrete age groups, in our case, for children aged 0 – 17 years. This does not exactly match with the population affected by Florida’s managed care policy, which applies to all enrollees aged 0 – 20 years. To ensure that our rate numerator and denominator use the same population, we limit our emergency department visit sample to visits from Medicaid-enrolled children aged 0 – 17 years. Therefore, our results apply only to children aged 0 – 17 years, rather than all enrollees aged 0 – 20 years.

Robustness analyses

As robustness checks on our primary outcome results, we estimate several alternative model specifications. Specifically, we aggregate the county-quarter observations into a simplified 2x2 DiD model with two time periods (pre- and post-intervention) and two groups (treatment and control). In this specification, we exclude the transition quarters from 2012-Q1 to 2012-Q4 when managed care programs were implemented in some, but not all, treatment counties. This simplified approach does not require population weighting or aggregation of time-specific ATTs and serves as a straightforward check on our main results. No standard error clustering correction was used, since observations are already aggregated.

We also present results using NTDC ED visit counts, rather than NTDC ED visit rates, to verify that changes in rates are driven by changes in the number of visits (the numerator) rather than changes in the Medicaid population (the denominator). Since Florida counties vary greatly in size, we compare percentage changes in counts, rather than absolute changes in counts (Finkelstein, 2007). To do this, we use the inverse hyperbolic sine (IHS) transformation of NTDC ED visit counts as the outcome variable. As with log transformations, regression coefficients from IHS-transformed models can be interpreted as approximate percentage changes. However, unlike the log transformation, the IHS transformation is defined at zero (Burbidge et al., 1988). As in the main specification, we used the two-way fixed effects (TWFE) approach recommended by Callaway and Sant’Anna (Callaway & Sant’Anna, 2021b) and multiplier bootstrapping for standard errors.

There are several methods to correct for staggered treatment bias in TWFE by excluding invalid group-time comparisons. We chose the method proposed by Callaway and Sant’Anna (Callaway & Sant’Anna, 2021b) because it imposes a less stringent parallel trends assumption than alternatives while still generating pre-treatment ATTs to evaluate parallel trends (de Chaisemartin & D’Haultfœuille, 2023). Because there is no consensus on the optimal approach for adjusting TWFE estimates in the presence of staggered rollouts (de Chaisemartin & D’Haultfœuille, 2023), we present ATTs from three alternative methods as a robustness check

(Gardner, 2022; Sun & Abraham, 2021; Wooldridge, 2021). For these specifications, shown in Table 2.3, standard errors were clustered at the county level.

Population variation

ACS population estimates contain uncertainty because they are based on a population sample. The ACS reports a margin of error (MoE) for each population value. To identify whether population uncertainty impacts our results, we perform our primary analysis with low and high population values based on these MoEs, which are equivalent to 90% confidence intervals. We estimate the MoE of sums as the root sum of squares of constituent MoEs.(American Community Survey, 2022) Results from these analyses are shown in Table A2.2.

Table A2.2: Comparison of ACS population estimates

Population	Quarterly NTDC ED visits per 100,000 pediatric Medicaid Enrollees	Pre-treatment mean in treatment counties	Percentage change
ACS High	14.172*** [5.1178, 23.226]	125.252	11.31%
ACS point estimate	14.951*** [5.352, 24.549]	132.677	11.27%
ACS Low	15.790*** [5.669, 25.9119]	141.038	11.20%

NOTES: Difference-in-differences coefficient estimates are shown with corresponding 95% confidence intervals in brackets. ATT: Average treatment effect on the treated; ED: Emergency department; NTDC: Non-traumatic dental condition. ***p < 0.01, **p < 0.05, *p < 0.1

When we use the low population estimates the rate denominator is smaller, so the overall rate effect is larger. The converse is true for high population estimates. However, the percentage change relative to the pre-treatment mean in treated counties is similar for all these analyses, because the denominator impacts the pre-treatment as well as post-treatment rates. We therefore believe that the interpretation of our results is relatively robust to systematic biases in population estimates.

Principal diagnoses

Our main specification uses ED visits that have either a principal or secondary NTDC diagnosis. Secondary NTDC ED visits may be less strongly associated with the adoption of managed care than principal visits. To test this, we subset our data to only visits with a principal NTDC diagnosis, dropping 22.1% of our original sample which only has a secondary NTDC diagnosis code. We then rerun our main specification for our primary outcome. The results are shown in Table A2.3.

Table A2.3: Comparison of primary vs primary and secondary diagnosis codes

Sample	Quarterly NTDC ED visits per 100,000 pediatric Medicaid Enrollees	Mean ED visit rate in treatment counties before treatment	Percentage change
Primary and secondary visits	14.951*** [5.352, 24.549]	132.67	11.27%
Primary visits only	12.849*** [3.531, 22.166]	103.89	12.37%

NOTES: Data include 67 counties, 1206 county-quarters, and 34,414 NTDC ED visits. Difference-in-differences coefficient estimates are shown and corresponding 95% confidence intervals are in brackets. Overall estimates are constructed as a weighted average of all post-treatment groups. ED: Emergency department; NTDC: Non-traumatic dental condition. ***p < 0.01, **p < 0.05, *p < 0.1

The absolute change in ED visit rates is smaller for the specification with only primary visits, but this is because it is a smaller sample of all visits. When these rate changes are compared as percentages of the pre-treatment mean in treated counties, the change is slightly larger when only considering principal visits. This makes intrinsic sense: if the adoption of managed care is impacting NTDC ED visits, then it ought to have a slightly larger effect on primary visits than on secondary visits. These results corroborate our main analysis, providing additional evidence that NTDC ED visits are associated with the adoption of managed care.

State Medicaid policies

Nasseh and Bowblis, used Medicaid data from 2014-2018 to categorize states as fee-for-service (FFS) if the percentage of pediatric dental claims which were FFS was at or near 100% (Nasseh & Bowblis, 2022). As of 2018, they categorized 18 states as being fee-for-service:

Alabama, Alaska, Connecticut, Delaware, Hawaii, Massachusetts, Maryland, Maine, Montana, North Carolina, North Dakota, New Hampshire, Oklahoma*, South Carolina, South Dakota, Tennessee, Virginia and Washington State.

*Oklahoma switched from FFS to a capitated dental managed care plan in February 2024 (Oklahoma Health Care Authority, 2022, 2023)

MACPAC collects data on the percentage of enrollees in different forms of managed care programs by state. As of 2021: 14 states provided provide Medicaid dental benefits to some enrollees through capitated dental managed care plans, of which 10 provide dental benefits to the majority of their enrollees (MACPAC, 2023a). The states in which Medicaid dental services are provided through capitated dental managed care plans to some enrollees are:

Arkansas[†], California, Florida[†], Idaho[†], Iowa[†], Louisiana[†], Michigan, Nebraska[†], Nevada[†], Oregon, Rhode Island, Tennessee[†], Texas[†], Utah[†].

[†]Denotes that the majority of enrollees are covered by capitated dental managed care plans.

Quarterly event study estimates

Table A2.4: Overall and quarterly event study estimates of the relationship between introducing managed care and NTDC ED visits and charges.

Quarter	Quarterly NTDC ED visits per 100,000 pediatric Medicaid Enrollees	Mean Charge for NTDC ED visits (\$)
Overall	14.951*** [5.3527, 24.549]	-49.087 [-143.15, 44.972]
-2.75	-2.818 [-19.368, 13.732]	0.16802 [-134.48, 134.82]
-2.5	-9.6953 [-28.003, 8.6125]	-35.267 [-194.54, 124.01]
-2.25	-8.9239 [-28.662, 10.815]	-38.08 [-193.55, 117.39]
-2	1.028 [-13.196, 15.252]	-3.4569 [-162.4, 155.48]
-1.75	-7.0499 [-19.038, 4.9379]	-101.89 [-317.28, 113.51]
-1.5	2.8707 [-8.4186, 14.16]	-66.881 [-208.03, 74.268]
-1.25	-0.64422 [-15.185, 13.896]	-73.452 [-192.85, 45.947]
-1	0.084213 [-13.3, 13.469]	0.67945 [-124.9, 126.26]
-0.75	1.8102 [-7.2976, 10.918]	-52.364 [-156.67, 51.942]
-0.5	2.1501 [-12.074, 16.374]	2.3011 [-87.276, 91.878]
-0.25	0 [NA, NA]	0 [NA, NA]
0	11.844* [-0.094183, 23.782]	-142.3** [-260.86, -23.739]
0.25	15.765** [1.8573, 29.673]	-64.726 [-203.36, 73.912]
0.5	10.444 [-4.7319, 25.62]	-141.06** [-249.81, -32.307]
0.75	12.406** [0.68098, 24.132]	-29.886 [-142.9, 83.132]
1	13.83* [-0.10528, 27.765]	39.956 [-116.22, 196.13]

1.25	17.39** [2.1745, 32.606]	50.996 [-95.066, 197.06]
1.5	26.174** [6.0034, 46.344]	-117.16 [-311.48, 77.157]
1.75	13.402 [-8.0646, 34.869]	137.93 [-397.53, 673.4]
2	15.69* [-0.98638, 32.366]	22.435 [-244.18, 289.05]
2.25	24.261** [0.56779, 47.955]	-63.99 [-240.93, 112.96]

NOTES: Data include 67 counties, 1206 county-quarters, and 34,414 NTDC ED visits. Difference-in-differences coefficient estimates are shown and corresponding 95% confidence intervals are in brackets. Overall estimates are constructed as a weighted average of all post-treatment groups. Pre- and post-treatment ATTs are constructed using long differences. ATT: Average treatment effect on the treated; ED: Emergency department; NTDC: Non-traumatic dental condition. ***p < 0.01, **p < 0.05, *p < 0.1

County plan enrollment

Figure A2.2: Enrollment in Pre-paid Dental Health Plans by medical Medicaid coverage type and county



NOTES: Pre-paid Dental Health Plans were mandatory for all Medicaid enrollees under 21 years of age, irrespective of the medical coverage, so enrollees of all medical plan types were transitioned. CMC: Comprehensive managed care; FFS: Fee for service; PCCM: primary care case management

Blood Biomarker Testing for Alzheimer's Disease in Primary Care

Lawrence Baker

Pardee RAND Graduate School and RAND

Abstract

Introduction: Medicare began covering disease-modifying therapies for Alzheimer's disease in July 2023, making them available across the United States. However, a limited supply of dementia specialists may limit the US health care system's ability to prescribe and monitor these treatments. Blood biomarker testing in primary care settings could help by screening out patients without Alzheimer's pathology before a specialist referral, potentially improving the use of limited specialist resources. However, the cost implications of this approach are unclear.

Methods: This study employs a simulation model of Alzheimer's disease diagnosis and treatment from 2025 to 2044. The model incorporates health care system capacities, patient decision-making, and disease progression. Capacity data are derived from the Area Health Resources Files, while disease prevalence is based on data from the US Census and Health and Retirement Study. This study aims to estimate the effect of adopting blood biomarkers in primary care on patient waiting times, direct medical spending, indirect medical and care costs associated with Alzheimer's disease progression, and quality-adjusted life years for patients and their caregivers.

Results: In a scenario where there is moderate demand for disease-modifying therapies, the adoption of blood biomarker testing reduced wait times by 64% (9.5 vs 26.5 months), equivalent to increasing specialist capacity by 35%. The number of treated patients increased by 15%. However, costs also increased over the 20-year simulation by \$49.2 billion, with \$39.2 billion attributable to Medicare. These increased costs were the result of treating more patients and the high price of disease-modifying therapies (\$26,500 annually) and biomarker tests (\$750 per test). At these prices, blood biomarkers were not cost-effective (>\$150,000 per quality-adjusted life year). However, they could become cost-effective if test or drug prices fall, or if future disease-modifying therapies prove more effective at slowing dementia progression.

Conclusions: This study highlights the tradeoffs surrounding the potential use of Alzheimer's disease blood biomarkers in primary care settings. The adoption of blood biomarkers could dramatically reduce wait times and increase access to disease-modifying therapies. However, this would substantially increase costs paid by Medicare and would not be cost-effective.

Introduction

In 2023, the Food and Drug Administration (FDA) granted traditional approval to lecanemab, one of a new generation of disease-modifying therapies that slow the progression of Alzheimer's disease (Food and Drug Administration, 2023). Concurrently, the Centers for Medicare and Medicaid Services (CMS) announced that Medicare would cover lecanemab (Centers for Medicare and Medicaid Services, 2023), making it available to amyloid-positive Medicare and Medicaid enrollees with mild cognitive impairment or mild dementia (Centers for Medicare and Medicaid Services, 2022). In 2024, donanemab, which has a similar mechanism of action, was granted coverage in the same population. These drugs may be the first of many similar therapies that help to address the clinical progression of Alzheimer's disease and the associated costs (Cummings, Zhou, et al., 2023).

The total cost of care for Alzheimer's disease and related dementias in the US was estimated to be \$305 billion in 2020, increasing to \$1.4 trillion in 2050 (Nandi et al., 2024). These costs are largely due to long-term care requirements, including nursing homes, where patients with dementia occupy half all beds, professional home care, and the forgone wages of informal caregivers (Alzheimer's Association, 2020).

The growing availability of Alzheimer's disease-modifying therapies poses two major challenges. First, their widespread adoption will likely increase health care spending, particularly for Medicare. As of January 2025, disease-modifying therapies are priced between \$26,500-\$32,000 annually (Arbanas et al., 2023; Belluck, 2024), and CMS estimates \$3.5 billion in spending on Alzheimer's disease-modifying therapies and associated costs in 2025, approximately 0.3% of all Medicare spending (Herman & Cohrs Zhang, 2024).

Second, the U.S. health care system may lack adequate capacity to diagnose, prescribe, and monitor the use of Alzheimer's disease-modifying therapies. Diagnosing Alzheimer's disease is complex, because it shares symptoms with other forms of dementia, and requires multiple forms of testing including cognitive assessments, brain imaging, and biomarker analysis. In 2025, there will be 63 million individuals aged 65 years and over in the US (US Census Bureau, 2023b), of which approximately 6.6 million will have Alzheimer's dementia (Matthews et al., 2019), and 14.3 million will have mild cognitive impairment (Rajan et al., 2021).

Several studies have warned that this influx of potential patients may overwhelm the US health care system, leading to wait times of several years (Liu et al., 2024; Mattke & Hanson, 2022). These long wait times are primarily driven by a lack of dementia specialists, such as neurologists, geriatricians, and geriatric psychiatrists (Liu et al., 2024). Anecdotal evidence supports these shortage concerns: in early 2024, memory clinics reported 9-month wait times

(Bowman Rogers, 2024; Saltzman, 2024). Since Alzheimer's disease-modifying therapies are most effective when given during the early stages of the disease, there is a critical need for timely patient identification and treatment.

The adoption of Alzheimer's disease blood biomarkers in primary care is one potential solution to limited specialist capacity. While cognitive assessments like the Montreal Cognitive Assessment (MoCA), are used in primary care to distinguish patients with mild cognitive impairment or dementia from the healthy population, they cannot identify an underlying Alzheimer's disease etiology (Lonie et al., 2009). As a result, many patients without Alzheimer's disease pathology are referred to specialists. Blood tests for Alzheimer's disease biomarkers could complement cognitive assessments in primary care, reducing unnecessary specialist referrals and effectively increasing specialist capacity.

This study uses a simulation model to explore the impact of adopting primary care Alzheimer's disease blood biomarker testing on wait times, health outcomes, and costs to the US health care system.

Background

Diagnosing Alzheimer's disease

Dementia describes a group of symptoms affecting memory, language, and problem-solving that interfere with daily life. Alzheimer's disease is the most common cause of dementia, accounting for 60-80% of all dementia cases (Alzheimer's Association, 2021). Other causes of dementia include vascular dementia, Lewy body dementia, and frontotemporal dementia. Many patients have multiple types of dementia simultaneously. Alzheimer's disease is defined by three key features: β amyloid deposits, pathologic tau protein, and subsequent neurodegeneration, known as AT(N) (Jack et al., 2018). After symptoms begin, patients typically live for about a decade - spending roughly half that time with mild cognitive impairment, followed by progressive decline, and 2-3 years of advanced disease marked by loss of independence (Vermunt et al., 2019). Early diagnosis and intervention are therefore critical for extending patient independence.

Diagnosing Alzheimer's Disease and related dementias requires evaluating both clinical symptoms and biological markers. The clinical diagnosis of dementia or mild cognitive impairment is based on gradual-onset symptoms that impair memory, reasoning, visuospatial abilities, or language, ultimately impacting daily function (Albert et al., 2011; McKhann et al., 2011). Before confirming Alzheimer's disease, clinicians must rule out other potential causes like medical conditions, nutritional deficiencies, and other types of neurodegeneration using AT(N) biomarkers.

The diagnostic pathway for Alzheimer's disease typically begins in primary care when patients or families report cognitive changes during routine care like the Medicare annual wellness visit. Primary care providers (PCPs) conduct initial assessments using tools like the AD8 or MoCA. If these screenings indicate potential cognitive impairment, PCPs may refer patients to dementia specialists - neurologists, geriatricians, or geriatric psychiatrists. Although Medicare covers and encourages brief cognitive assessments during annual wellness visits, their effectiveness remains uncertain. The United States Preventative Services Task Force found insufficient evidence to recommend cognitive screening for the general population. (US Preventive Services Task Force, 2020).

After referral, specialists first rule out other causes of cognitive decline, such as vitamin B12 deficiency or hypothyroidism, if not already done in primary care (Hampel et al., 2022). The specialist then performs a comprehensive evaluation including a detailed clinical history, structural brain imaging, and, in atypical presentations, neurocognitive assessments. To confirm the presence of Alzheimer's biomarkers and determine eligibility for disease-modifying therapies, specialists use either amyloid positron emission tomography (PET) imaging or cerebrospinal fluid (CSF) testing. Once infusions with disease-modifying therapies begin, specialists must monitor patients with regular magnetic resonance imaging (MRI) scans to check for potential complications like amyloid-related imaging abnormalities (ARIA), which can include hemorrhages or edema.

Alzheimer's disease-modifying therapies

As of December 2024, two FDA-approved Alzheimer's disease-modifying therapies, lecanemab and donanemab, are covered by Medicare provided that clinicians participate in a CMS-facilitated registry. Both drugs work by binding to amyloid protofibrils and reducing the volume of amyloid plaques in the brain (Cummings, Apostolova, et al., 2023; Söderberg et al., 2024). According to the AT(N) hypothesis, early reduction of amyloid plaques should slow neurodegeneration. Clinical trials show both drugs effectively clear amyloid, with most treated patients becoming amyloid-negative after 18 months (Sims et al., 2023; van Dyck et al., 2023). While these treatments slowed disease progression by 27-29% on the Clinical Dementia Rating – Sum of Boxes (CDR-SB) scale (Iwatsubo, 2023; Sims et al., 2023; van Dyck et al., 2023), debate continues about whether this improvement is clinically meaningful (Cummings, 2023), especially considering that approximately 3% of patients experience severe side effects requiring urgent care (Sarkisian et al., 2024). Treatment effectiveness varies by genetic profile: ApoE4 heterozygotes show less benefit than non-carriers, while ApoE4 homozygotes experience disease progression similar to placebo groups and face higher risks of ARIA (Cummings, Apostolova, et al., 2023; Sims et al., 2023; van Dyck et al., 2023)

The high cost of disease-modifying therapies raises significant concerns about health care spending, particularly for Medicare. These drugs carry substantial annual list prices of \$26,500-\$32,000 (Arbanas et al., 2023; Belluck, 2024). When including necessary diagnostic testing and monitoring, Alzheimer's disease-modifying therapies could increase Medicare spending by \$2-5 billion annually (Arbanas et al., 2023), with CMS projecting \$550 million of spending in 2024 and \$3.5 billion in 2025 (Herman & Cohrs Zhang, 2024). The health benefits of these therapies may not be commensurate with their high price; an independent health technology assessment estimated the incremental cost-effectiveness ratio of lecanemab at \$236,000 per quality-adjusted life year (QALY), far above typical cost-effectiveness thresholds in the US of \$100,000 - \$150,000 per QALY (Lin et al., 2023).

Despite predictions of blockbuster spending, the uptake of Alzheimer's disease-modifying therapies has been low. As of February 2024, only approximately 2,000 patients were receiving lecanemab in the US. There are multiple reasons for low uptake: including the limited number of physicians who are willing to prescribe these therapies, patient concerns about side effects, and the relatively high copays required by Medicare part B.

Lecanemab and donanemab are only the first of a wave of similar therapies (Osaka et al., 2024). As of 2024, seven additional biologic disease-modifying therapies and thirteen small molecule disease-modifying therapies were in phase III clinical trials, with numerous others in earlier development stages (Cummings et al., 2024). While currently available therapies may have limited adoption, future treatments could offer better results, fewer complications, or reduced costs that drive greater demand. This makes it essential to prepare for the eventual widespread adoption of disease-modifying therapies.

Blood biomarkers

Blood biomarkers can identify the AT(N) pathology characteristic of Alzheimer's disease, serving the same diagnostic role as amyloid PET imaging or CSF testing. Compared to these methods, blood biomarkers are less invasive, can be conducted without specialized training, and are potentially cheaper. These tests measure various proteins in blood plasma, including β -amyloid, phosphorylated-tau, neurofilament light, and glial fibrillary acidic protein (Hansson et al., 2022). In a relatively homogeneous population of cognitively impaired individuals, the most recently developed blood biomarker assays have excellent concordance with amyloid PET, with some even outperforming CSF (Barthélemy et al., 2024).

While blood biomarker testing is currently used to screen participants for clinical trials, it has not yet entered routine clinical practice and is not covered by Medicare. Of the 16 assays under development as of 2023, three have received FDA Breakthrough Device Designation (Hampel et

al., 2022). Before blood biomarkers can be widely adopted in primary care settings, several challenges must be addressed: standardizing procedures, ensuring consistent performance across laboratories, and validating results in diverse clinical populations (Angioni et al., 2022; Hampel et al., 2022; Hansson, 2021; Hansson et al., 2022, 2023; Teunissen et al., 2022). Initially, blood biomarker testing might help primary care providers determine whether to refer to a specialist, but it may eventually replace PET and CSF testing altogether (Hampel et al., 2023; Hansson et al., 2023; Teunissen et al., 2022). However, since biomarker tests alone cannot diagnose Alzheimer's disease, cognitive assessments and specialist involvement will remain necessary (Hansson et al., 2022). Without Medicare coverage, patients are unlikely to use blood biomarker testing due to high costs – approximately \$1,250 for commercially available tests (Anderson & Pierce, 2022). Medicare coverage would likely eliminate patient costs since laboratory testing usually has no cost sharing. While Medicare pricing for blood biomarker testing remains under review, preliminary estimates suggest a combined amyloid and tau blood biomarker test will cost the program \$750 in 2025 (Centers for Medicare and Medicaid Services, 2024b).

Other simulation models of blood biomarker testing

Two prior simulation models have investigated the use of Alzheimer's disease blood biomarker testing in primary care. One US study examined the effect of adopting Alzheimer's disease blood biomarker testing in primary care, finding that they could dramatically reduce wait times and, if priced at \$100, were cost-saving (Mattke et al., 2020). However, this study did not consider the costs or benefits of treatment, a key component in the cost-effectiveness of diagnostic tools that affect treatment uptake. Another study performed an economic analysis of using blood biomarker tests in Sweden, (Aye et al., 2024) finding that if disease-modifying therapies were priced at €5000 (\$5,100), blood biomarker tests were cost-effective and increased the number of patient referrals. This model did not consider specialist capacity constraints and investigated rule-in testing for uncertain cases, which would increase demand for specialist services.

Methods

Model overview

This study expands on prior research that modeled US health care system capacity and wait times for Alzheimer's disease care (Liu et al., 2024). This updated model includes more detailed disease progression tracking, economic costs, and scenarios for using Alzheimer's disease blood biomarkers in primary care.

As shown in Figure 3.1, the model consists of four interconnected components:

A system dynamics component that tracks patient flow through the clinical pathway, accounting for health states, diagnostic accuracy, and clinical capacity

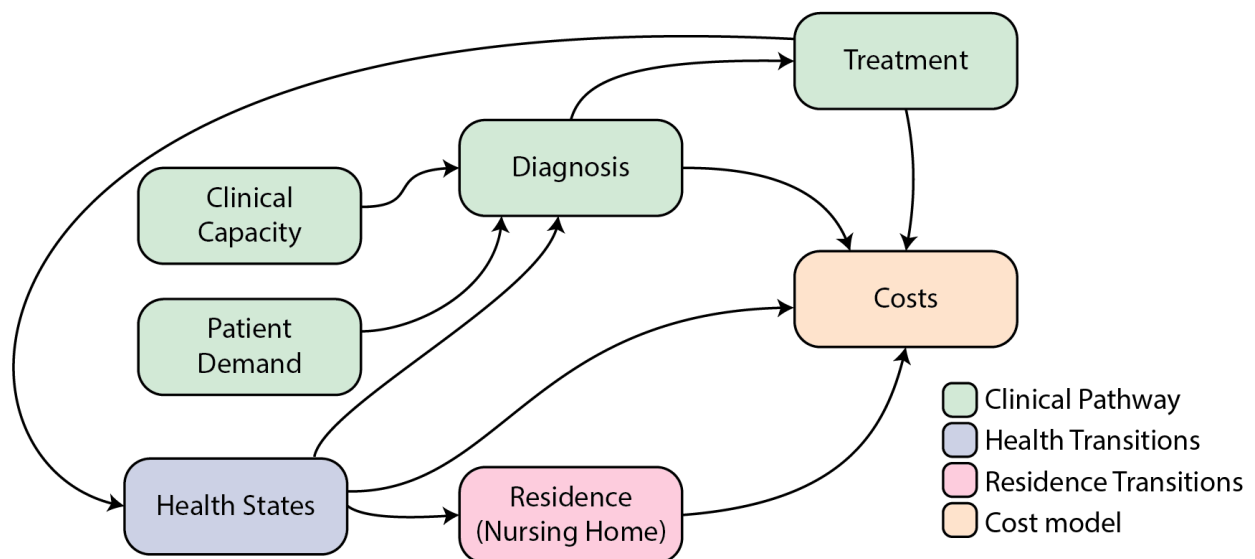
A demographic-based transition model that simulates progression through cognitive states (normal cognition, mild cognitive impairment, mild, moderate, and severe dementia due to Alzheimer's disease, and cognitive impairment due to other causes) by age and sex

A residential transition model that tracks movement between living situations (community, residential care, and nursing homes) based on age and disease status

A cost component that calculates health care resource usage, medical and care costs by health state, and residential care expenses, while also QALYs

The model generates results for each US state separately, then combines them for national projections, capturing regional differences in health care capacity and population age distribution. Each simulation runs deterministically over 20 years (2025-2044).

Figure 3.1: Simulation model structure



Clinical pathway

Figure 3.2 illustrates the clinical pathway that tracks patients from the initial detection of cognitive impairment through Alzheimer's diagnosis and treatment. The clinical pathway includes five component types:

- **Patient populations:** Groups awaiting testing or evaluation, such as individuals eligible for cognitive assessment but not yet screened.

- **Healthcare system resources:** Clinical staff and facilities that conduct tests or provide treatment, with state-specific monthly capacity limits.
- **Clinical decisions:** Test outcomes that guide next steps, accounting for imperfect sensitivity and specificity to patient health states.
- **Patient decisions:** Aggregate behavioral choices, such as the proportion of referred patients who follow through with specialist visits.
- **Patient exits:** Points where individuals leave the clinical pathway, though their health states continue to be tracked until death.

The model uses monthly time steps to simulate patient movement through the pathway, with queues forming at health care resources when demand exceeds capacity. Some health care system resources are required at multiple points in the clinical pathway. For instance, specialists are required for evaluations, biomarker reviews, and treatment monitoring. Patients who test negative may choose to return for testing in subsequent years and so may be tested multiple times, even if their initial tests show negative results.

Data overview

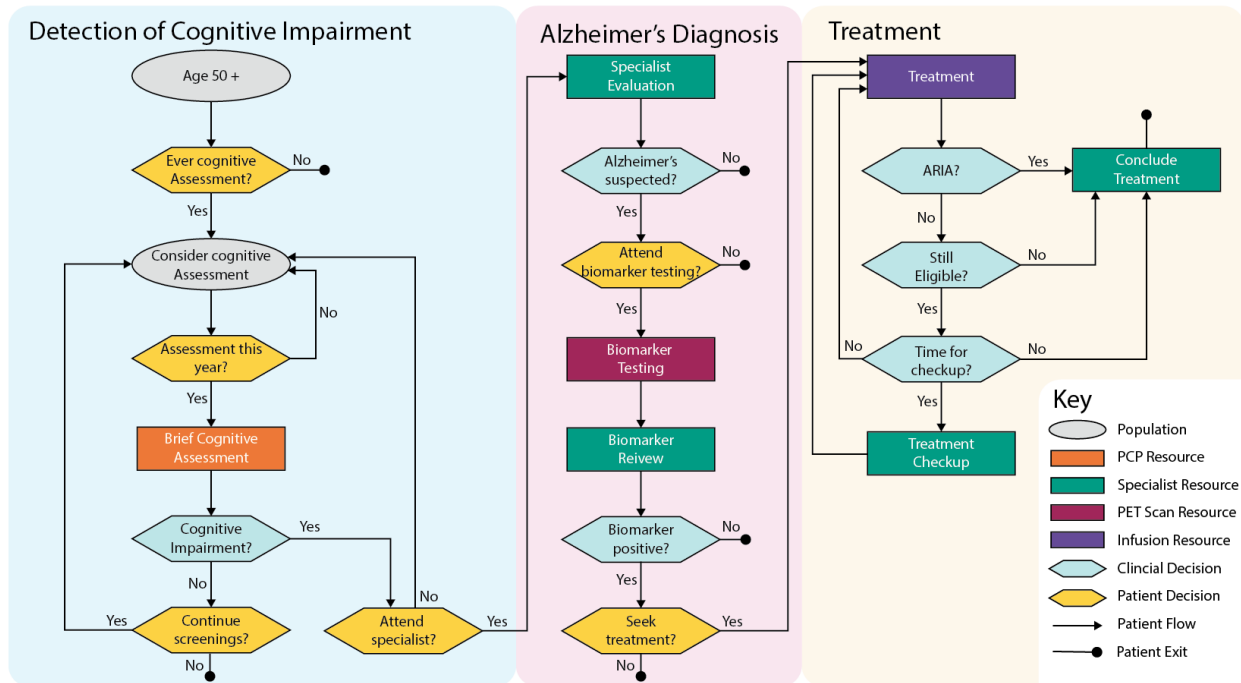
Table 3.1 provides an overview of the data sources used in each of the model components, which are explained in more detail in subsequent sections and Appendix 3.

Table 3.1 Data and parameter overview

Model component	Input	Description	Main sources
Clinical pathway	Population estimates	Prevalent population age 50+ in 2025, and incident population turning 50 each year 2026-2044 from the Census	(US Census Bureau, 2020) (US Census Bureau, 2017)
Clinical pathway	Health system capacity	Estimates of the number of primary care physicians, dementia specialists, PET scanners, and infusion capacity from the Area Health Resources File	(Health Resources and Services Administration, 2023a) (Liu et al., 2024)
Clinical pathway	Demand	Estimates of how likely patients are to attend cognitive screening and subsequent visits.	Expert elicitation
Clinical pathway	Test parameters	Sensitivity and specificity of clinical tests from the literature	Roalf (2013), Abd Razak (2019) Nakamura (2018) Salloway (2017)
Clinical pathway	Treatment effects and side effects	Clinical trial data for lecanemab, treatment persistence estimated using donanemab trial data	(Cummings, Apostolova, et al., 2023) (van Dyck et al., 2023)
Health state transitions	Health state prevalence	Age-specific prevalence data from the Health and Retirement Study. Continuous cognitive scores were used to assign individuals between mild, moderate, and severe dementia.	(Hudomiet et al., 2022) (Davis et al., 2018) (Yuan et al., 2021)
Health state transitions	Health state mortality	National vital statistics lifetables, combined with health state hazard ratios from the literature.	(Arias & Xu, 2022)
Health state transitions	Health state transition probabilities	Literature probabilities, modified to match prevalence data.	(Davis et al., 2018)
Residence transitions	Residence prevalence and transition probabilities	Analysis of National Health and Aging Trends Study data between 2011-2021. Transition probabilities were estimated through longitudinal analysis of individual patients.	(Kasper et al., 2013) (NHATS, 2023)
Cost model	Direct costs	Medicare payment rates for office visits, and imaging, infusions. Prices were modified by average price multipliers to match other payers. Drug list prices used for all payers	(Arbanas et al., 2023) (Centers for Medicare and Medicaid Services, 2024a)
Cost model	Health state costs	Average indirect medical costs, caregiver time costs, and home care costs attributable to Alzheimer's disease. Split into rates for mild, moderate, and severe dementia using surveys of dementia patients.	(Nandi et al., 2024) (Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023)
Cost model	Residence state costs	Average costs are taken from Genworth's cost of care 2023. Residence probability varies by health state, but costs conditional on residence are assumed to be fixed.	(Genworth, 2023)
Cost model	Health state quality of life	Quality of life estimates used in QALY calculations from a systematic review. Caregiver and side-effect disutility based on estimates used in a prior study	(Landeiro et al., 2020) (Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023)
Cost model	Insurance prevalence	The proportion of patients with Medicare, Medicaid, Private, or dual-eligible coverage.	(Cha & Cohen, 2022)
Cost model	Payer cost splits	The proportion of costs paid by Medicare, Medicaid, Private plans, or OOP for each cost and coverage type.	(MACPAC, 2013) (MedPAC & MACPAC, 2024)

NOTES: QALY: Quality-adjusted life year; OOP: Out-of-pocket.

Figure 3.2: Flow diagram of the clinical pathway



NOTES: ARIA: Amyloid related imaging abnormality; PCP: Primary-care provider; PET: Positron emission tomography

Clinical pathway data and parameters

Population estimates by state, sex, and single year of age are drawn from the Census (US Census Bureau, 2020) and extrapolated into future years using the growth rates from the national population projections (US Census Bureau, 2017). State-level health care workforce data from the Area Health Resources Files (AHRF) is used to estimate health system capacities (Health Resources and Services Administration, 2023a), using methods from prior work (Liu et al., 2024), which are included in the appendix. These capacities are then projected forward using growth rates from Health Resources and Services Administration health workforce projections (Health Resources and Services Administration, 2023b).

The analysis assumes a baseline patient demand reflecting moderate adoption of Alzheimer's disease-modifying therapies. While not intended to be predictive, demand parameters are based on expert feedback, collected February – March 2023 (Liu et al., 2024), to explore a hypothetical scenario where treatment demand exceeds health system capacity. The model assumes 70% of eligible patients might receive a cognitive assessment in their lifetime, consistent with established screening programs for breast, cervical, and colorectal cancer (Amboree et al., 2024; Mattke et al., 2020). However, annual cognitive assessment rates are set much lower, reflecting

the limited frequency of cognitive assessments at Medicare annual wellness visits (Morgan et al., 2021). Among patients willing to undergo cognitive assessment, the assumed annual rates are: 30% for those over 65 with cognitive impairment, 6% for those over 65 without cognitive impairment, and 5% for patients aged 50-64 with cognitive impairment. Patients under 65 without cognitive impairment are assumed to receive no assessments. The analysis also includes a low-demand scenario to examine the impact of blood biomarker testing when specialist capacity is not a limiting factor, parameters for this scenario are included in Appendix 3.

Clinical tests are defined by their positive states and corresponding sensitivity and specificity values, detailed in Appendix 3. PCPs are assumed to use the MoCA as a cognitive assessment in primary care to differentiate the cognitively normal population from patients with mild cognitive impairment and dementia (Abd Razak et al., 2019; Roalf et al., 2013), though in reality, they may use a broad range of different assessments. Specialists are assumed to be accurate at differentiating cognitive impairment and dementia from cognitively healthy patients but rely on amyloid PET scans or CSF testing to confirm Alzheimer's pathology (Salloway et al., 2017).

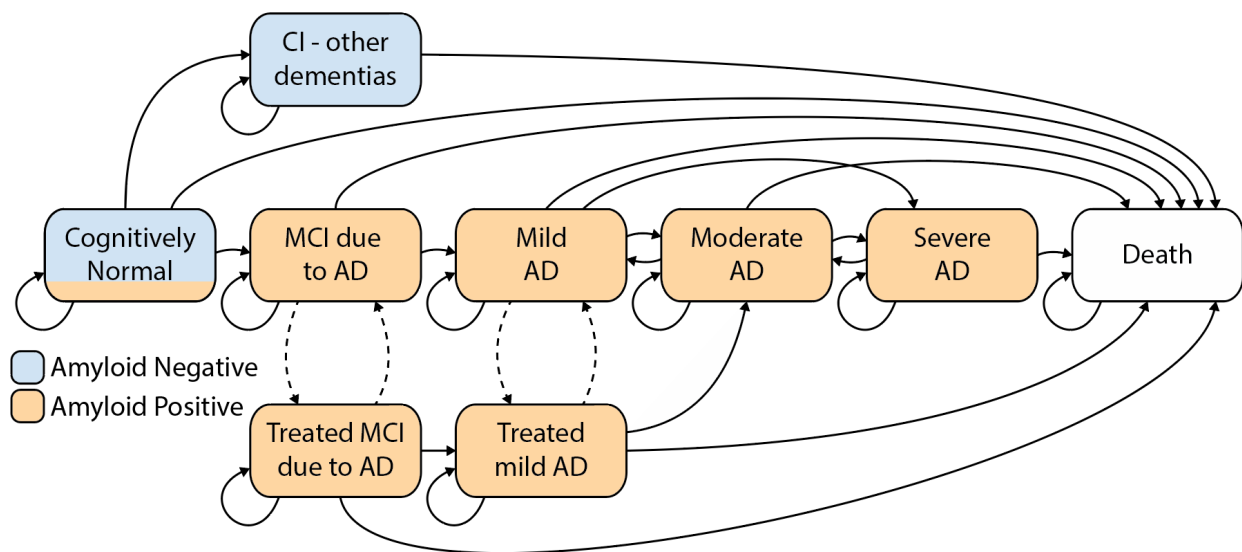
Modelling of lecanemab treatment and side effects is based on the Clarity AD phase III trial data and appropriate use recommendations (Cummings, Apostolova, et al., 2023; van Dyck et al., 2023). The treatment protocol involves 36 biweekly lecanemab infusions over 18 months, with a chance of an adverse event leading to treatment discontinuation and potential hospitalization (Arbanas et al., 2023). Patients with mild cognitive impairment or mild dementia who were treated with lecanemab were assumed to progress to more severe dementia stages 27% slower than untreated patients. Based on donanemab trial data (Sims et al., 2023), we assume that treatment effects persist on average for 4 years after the end of treatment (Shcherbinin et al., 2022), or until a patient develops moderate dementia. Additional details on the clinical pathway, how patients are represented, and model inputs are given in Appendix 3.

Health states

A transition model represents the true underlying health states, which are then imperfectly observed through clinical testing. As shown in Figure 3.3, there are 9 mutually exclusive health states encompassing: a cognitively normal state, states representing Alzheimer's disease progression, cognitive impairment from other conditions, and a death state. Treatment is modeled through two treated health states, which have reduced progression to subsequent dementia states. Each state has an associated amyloid positivity, indicated by fill color in Figure 3.3, which determines positive or negative results for blood biomarkers testing and PET scans. Among cognitively normal individuals, 20% are assumed to be amyloid positive (Jansen et al., 2015), representing preclinical Alzheimer's dementia.

Health state prevalence and transition probabilities are sex- and age-specific and were derived from multiple sources: cognitive scores calculated using the HRS (Hudomiet et al., 2022), National Vital Statistics lifetables (Arias & Xu, 2022), and population-level prevalence for mild, moderate, and severe dementia (Davis et al., 2018; Yuan et al., 2021). Transitions are applied annually. Further details on our methodology, plots of health state prevalence by age and sex, and transition matrices are included in Appendix 3.

Figure 3.3: Health state transition model



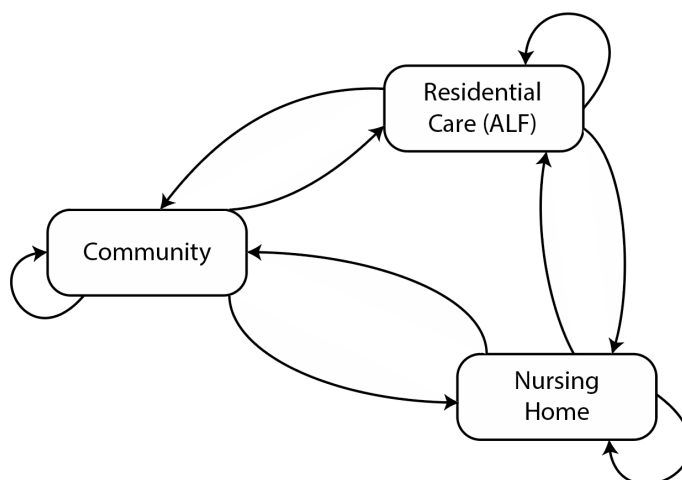
NOTES: Dashed arrows indicate a treatment transition. Arrows from treated to untreated states are due to treatment waning, which is assumed to take four years on average after treatment concludes. AD: Alzheimer's Disease

Residence transitions

A significant portion of costs for Alzheimer's Disease and related dementias are associated with long-term care: nursing homes, assisted living facilities, home health aides, and unpaid caregiver time. Unlike medical costs, the cost of long-term care costs are covered largely by Medicaid (for eligible enrollees) or paid out-of-pocket (OOP) by patients and their families. The model tracks patient residence using three states, as shown in Figure 3.4: community living, residential care (including assisted living facilities), and nursing homes. Patients can move between any of these states, including returning to community living from nursing homes or residential care (Callahan et al., 2015).

Each residence state's prevalence and transition probabilities vary by sex and health state, based on data from the National Health and Aging Trends Study (NHATS) and imputed cognitive status (Kasper et al., 2013; NHATS, 2023). Appendix 3 contains additional methodological details, residence prevalence plots, and residence transition probability plots.

Figure 3.4: Residence state transition model



NOTES: ALF: Assisted living facility

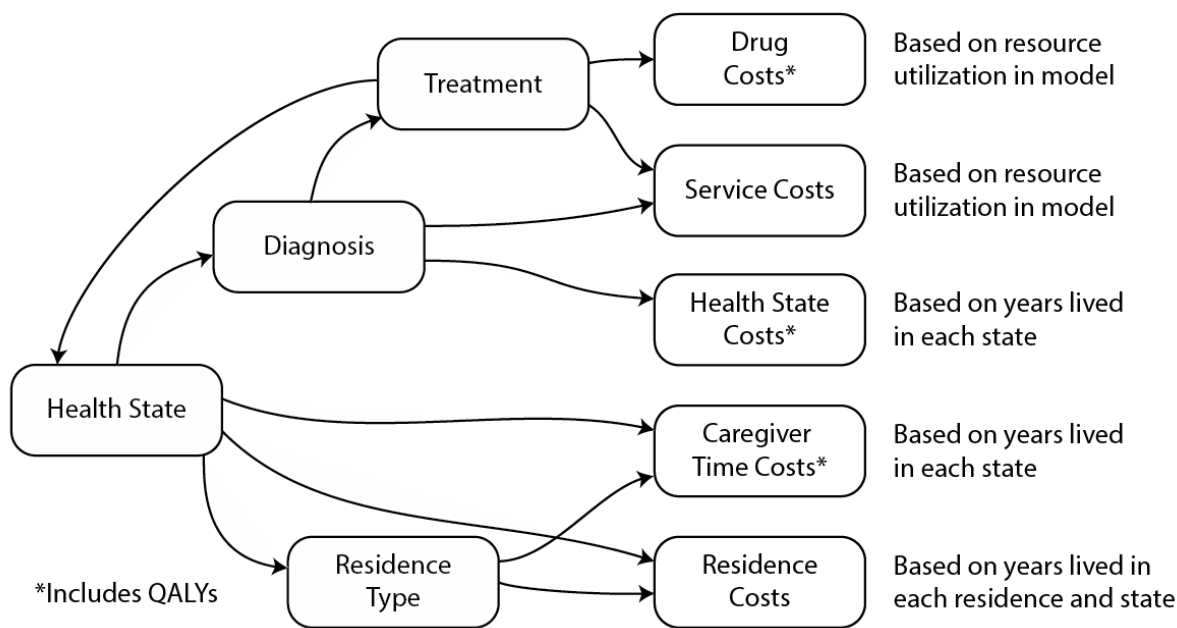
Cost model

The cost model estimates spending across four main US health care system payers (Medicaid, Medicare, private plans, and OOP costs paid by patients) in different scenarios. As shown in Figure 3.5, the model includes five cost components:

- **Drug costs** track direct medical spending for disease-modifying therapies by calculating treatment duration from the clinical pathway and applying monthly unit costs based on manufacturer prices, which are assumed to be the same for all payers.
- **Medical service costs** cover direct medical spending on services beyond drug costs, including primary care and specialist visits, biomarker testing, infusions, MRI scans, and hospital visits for side effects. These costs are calculated by tracking service usage and applying unit costs from lecanemab cost studies (Arbanas et al., 2023) and average Medicare payment rates (Centers for Medicare and Medicaid Services, 2024a).
- **Health state costs** represent indirect medical costs from dementia-related loss of function, primarily inpatient costs due to increased hospitalization risk, based on recent HRS data (Nandi et al., 2024). Other indirect costs, such as lost wages for the patient, are not included.
- **Residence costs** encompass direct costs for home health care, residential care, and nursing home care. Each residence and health state combination has assigned annual costs. Home health costs derive from recent HRS respondent studies (Nandi et al., 2024) while residential and nursing home costs reflect market rates (Genworth, 2023).

- **Caregiver costs** measure unpaid caregiver time valued as forgone wages. Caregiver time requirements vary by health state and residence type. Forgone future wage increases for caregivers are not included. Caregiver costs are categorized as OOP expenses.

Figure 3.5: Cost model structure



NOTES: QALY: Quality-adjusted life year

Costs are initially categorized into nine types: drug, physician, inpatient, outpatient, home care, nursing care, residential care, blood biomarker tests, and caregiver time. For each cost type, the model determines the proportion of the population with each insurance type (private, Medicaid only, Medicare only, dual eligible) and identifies what fraction of costs are covered by payers under each insurance type. Caregiver time costs are assumed to be 100% out-of-pocket and are valued based on lost wages (Nandi et al., 2024). This analysis is conducted separately for patients above and below age 65. Type-specific cost multipliers are applied to each payer to account for price variations between payers (Congressional Budget Office, 2022). Cost multipliers are given in Appendix 3.

QALY changes are calculated by assigning quality of life (QoL) values to patients and caregivers for each health state (Landeiro et al., 2020; Lin et al., 2023; Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023), with additional disutility applied for patients experiencing severe side effects (Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023). Both costs and QALYs are discounted at 3% annually. All costs are expressed in 2024 dollars, adjusted using a health care expenditure index (U.S. Bureau of Economic Analysis, 1947).

Details on cost assignment are given in Appendix 3, along with parameter values, coinsurance rates, QoL, and relative prices by payer.

Validation

We validate inputs by comparing model estimates for 2025 to external estimates for the number of individuals with dementia, the number of individuals in nursing homes and residential care, age at death, and health care spending on Alzheimer's disease. Validation comparisons are shown in Appendix 3.

Scenarios

The main analysis examines 5 alternative blood biomarker testing scenarios under baseline demand conditions, as shown in Table 3.2. In each scenario, blood biomarker tests are only used on patients who have a cognitive impairment indicated by a brief cognitive assessment. If a patient has multiple cognitive assessments throughout the simulation, then a blood biomarker test will be conducted in each one where they test positive. The model also explores additional scenarios by varying four critical parameters: drug cost, blood biomarker test cost, drug effectiveness, and specialist capacity. The same set of scenarios were conducted for donanemab, but since they produced results very similar to lecanemab, they are not reported separately. Details of donanemab modeling are included in Appendix 3.

Table 3.2 Baseline scenario list

Scenario	Sensitivity	Specificity	Notes
Status quo	-	-	Status quo, blood biomarker testing is not adopted.
Low-accuracy blood biomarker testing	0.8	0.5	Due to issues with robustness in different lab settings, poor performance in diverse populations, and/or poor generalizability to a largely cognitively normal population, blood biomarker tests are less accurate than current studies indicate (Hampel et al., 2023).
Current-accuracy blood biomarker testing	0.89	0.69	Blood biomarker tests are adopted which have the same accuracy as in currently commercially available assays in validation samples (Nakamura et al., 2018).
High accuracy blood biomarker testing	0.9	0.87	Highly accurate blood biomarker tests that outperform CSF testing are adopted in primary care (Barthélemy et al., 2024).
High-accuracy blood biomarker testing, replacing PET	0.9	0.87	Highly accurate blood biomarker tests have become well-validated and can entirely replace other biomarker testing, removing the need for amyloid PET scans, CSF, or the associated specialist visits.

Outcomes

Model outcomes include average wait time, total patients treated, QALYs, and total cost. Wait times and patient treatment numbers are reported as absolute values, with treated patients counted only if they receive clinical benefit. QALY and cost values are presented as differences from the status quo scenario (which assumes no blood biomarker adoption), representing the effect of blood biomarkers within the simulation. All outcomes cover the full 20-year simulation period. Appendix 3 provides additional details on outcome calculations.

For each scenario, an incremental cost-effectiveness ratio is calculated relative to the status quo, based on marginal costs and QALYs. The status quo scenario includes two cost-effectiveness ratios for lecanemab: one considering only drug price, aligned with other analyses (Lin et al., 2023), and another incorporating drug price plus administration costs, side effect costs, and costs for Alzheimer’s disease pathology confirmation visits and tests. These additional services are required to confirm Alzheimer’s pathology for lecanemab treatment eligibility. The analysis uses a \$150,000/QALY threshold to define cost-effectiveness (R. W. Dubois, 2016), though some experts advocate for a lower threshold of \$100,000/QALY (Vanness et al., 2021).

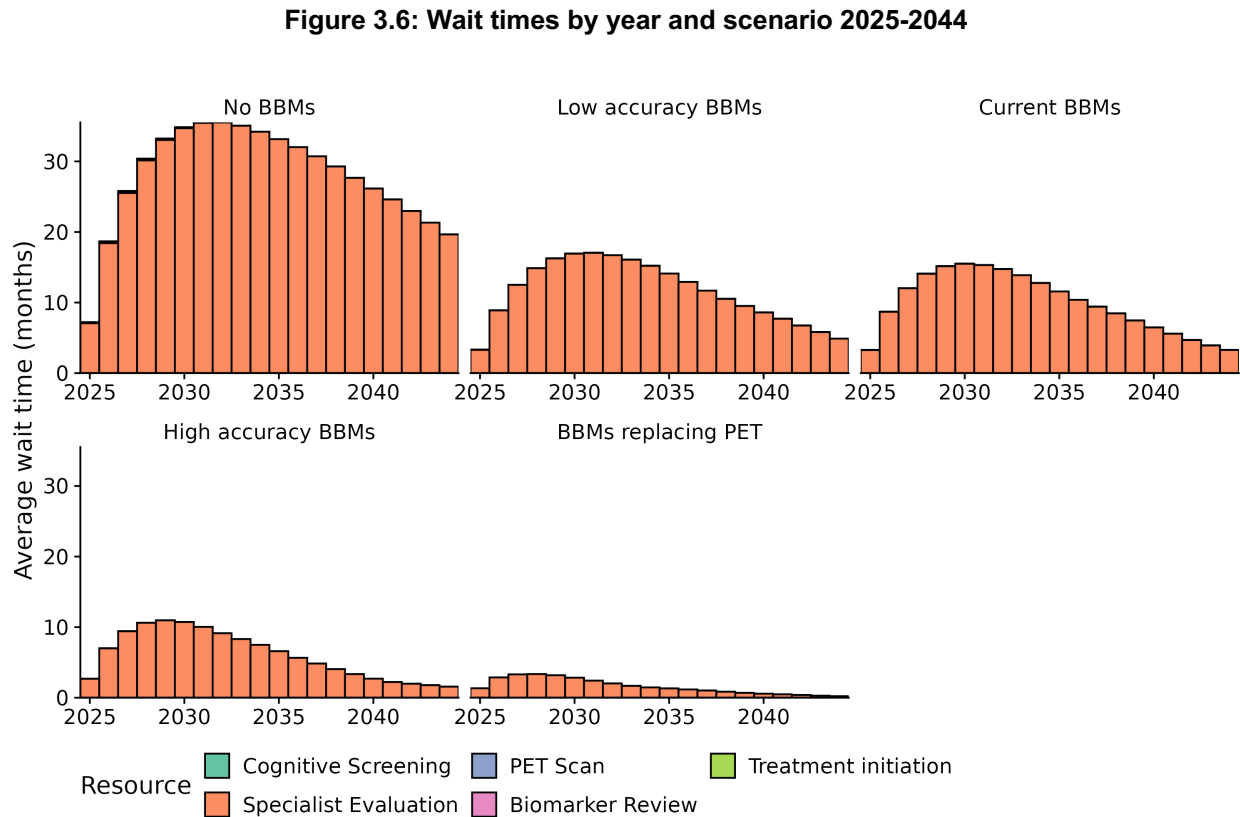
Results

Wait times and patients treated

Figure 3.6 illustrates annual average wait times across different blood biomarker adoption scenarios. Because the initial eligible population (ages 50-90) is much larger than the yearly

influx of new 50-year-olds, and only a portion of eligible patients receive primary care assessment each year, substantial queues form in the first few years. However, once most of the initial population has been assessed by specialists, wait times decrease in all scenarios, regardless of blood biomarker adoption. While this figure shows combined wait times for all visits, specialist appointments are the rate-limiting step in every scenario, so queues for the specialist evaluation dominate overall wait times. This finding aligns with prior analyses (Liu et al., 2024; Mattke et al., 2020; Mattke & Hanson, 2022).

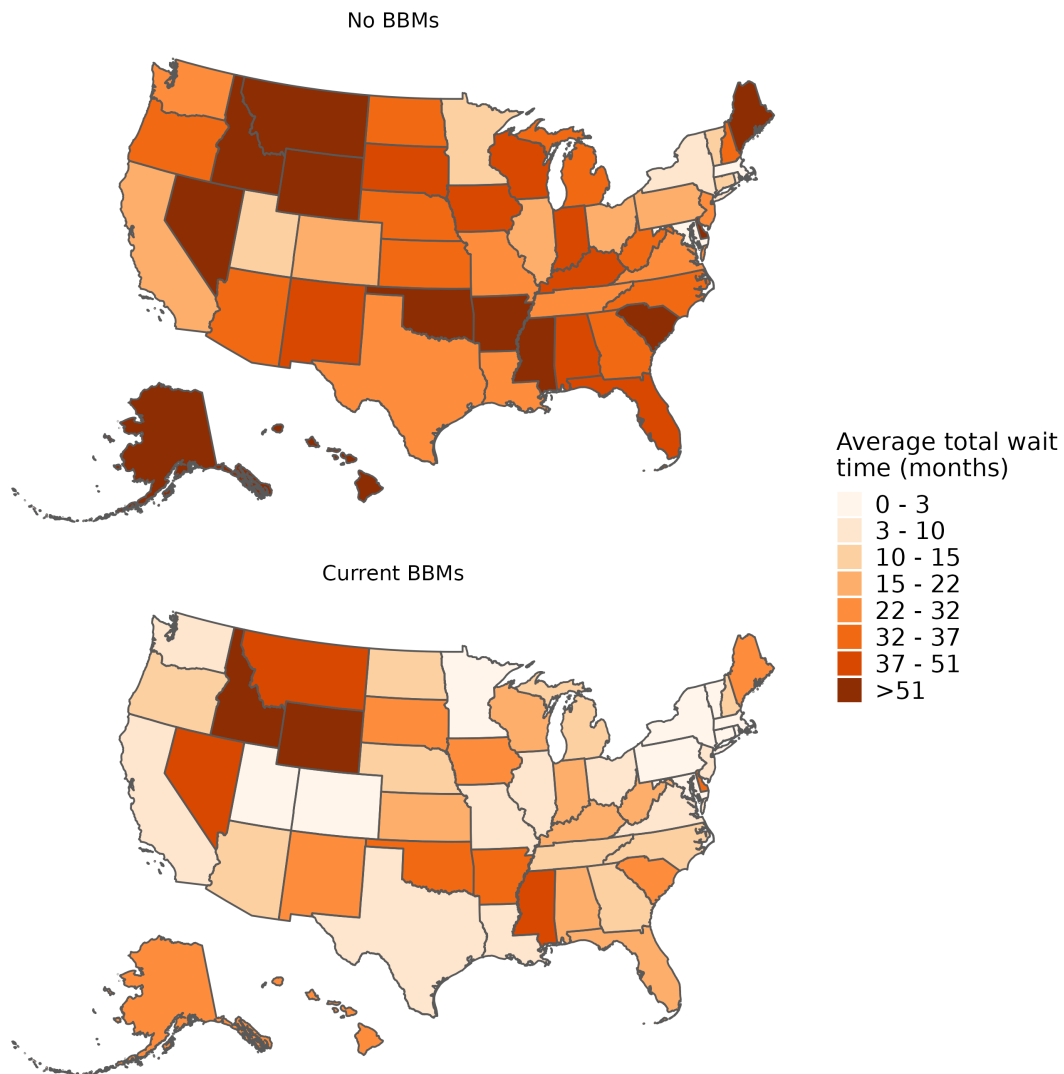
Blood biomarker testing adoption dramatically decreases wait times to approximately half of those in the status quo scenario. Adopting current-accuracy blood biomarker tests reduced average wait times by 64% (9.5 months vs 26.5 months). The reduction in wait times from adopting current-accuracy blood biomarker tests is approximately equivalent to increasing specialist capacity by 35%. More accurate blood biomarker tests yield larger gains, and if blood biomarker testing can replace PET and CSF, wait times for treatment could be almost eliminated at this level of demand.



NOTES: Figure includes wait times for all resources, but because the specialist is the rate-limiting step, all wait times shown are for the specialist evaluation. BBM: Blood biomarker; PET: Positron emission tomography

Blood biomarker testing's impact on wait times varies significantly by state, as shown in Figure 3.7, which compares average wait times (2025-2044) between the no blood-biomarker testing (status quo) and current-accuracy blood biomarker testing scenarios. States in New England and the Mid-Atlantic region, which have a relatively high specialist capacity, show minimal wait times even without blood biomarker testing. However, states in the South and Midwest, where specialists are scarcer, face wait times exceeding two years in scenarios without blood biomarker testing.

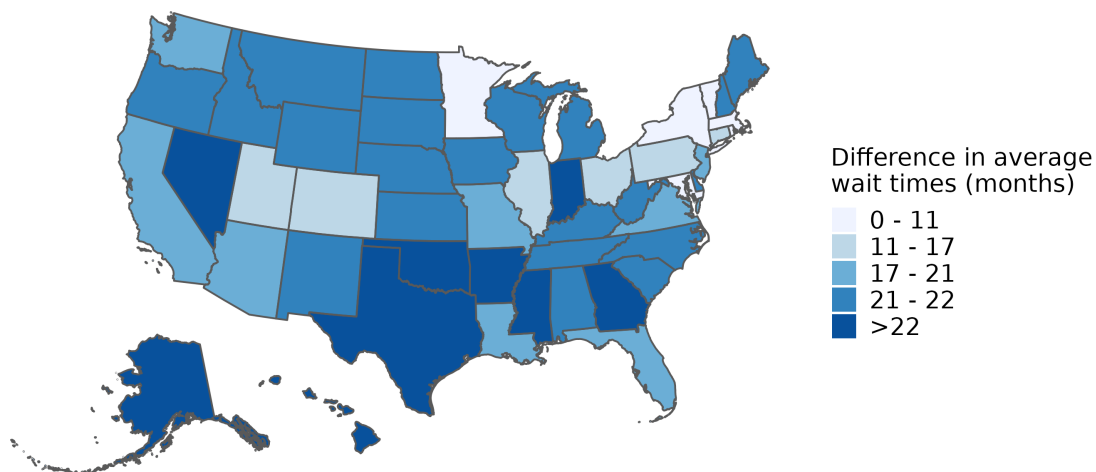
Figure 3.7: Total wait times by US state 2025-2044



NOTES: Average total wait time 2025-2044. Cut points were chosen at equally spaced quantiles. BBM: Blood biomarker.

Blood biomarker testing implementation reduces wait times nationwide, though several states continue to experience multi-year queues. States like Idaho, Montana, Wyoming, Nevada, and Mississippi still face specialist shortages even after adopting blood biomarker testing. Figure 3.8 illustrates the wait time reductions achieved by implementing current-accuracy blood biomarker testing compared to the status quo. The improvements follow a bimodal pattern: most states see wait times decrease by 17-23 months, while states that initially had short wait times see them nearly eliminated.

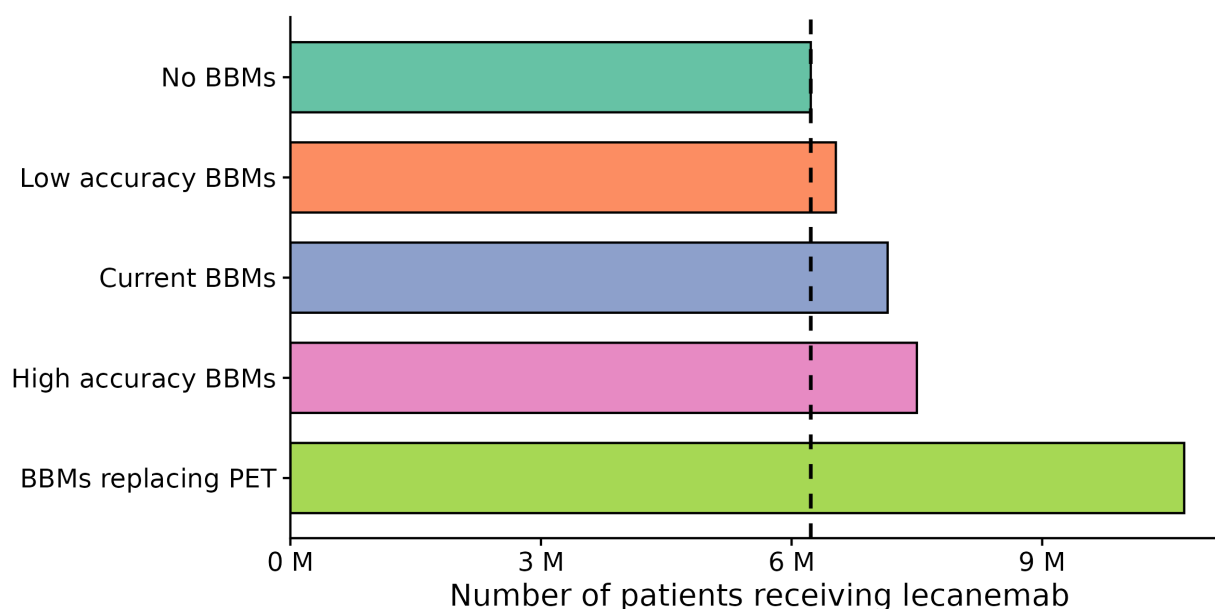
Figure 3.8: Difference in average wait times by US state 2025-2044



NOTES: Difference in average total wait time 2025-2044 between the status quo and current-accuracy blood biomarker testing scenarios. Positive numbers represent reductions in wait times when adopting blood biomarker testing. Cut points were chosen at equally spaced quantiles, and fewer categories were used due to the tight bimodal distribution of results.

Figure 3.9 shows how different scenarios affect the number of patients receiving treatment. Typically, introducing additional tests that screen out patients reduces the overall number of patients treated. However, this pattern changes when testing occurs before the bottleneck of specialist assessment. When more testing happens in primary care, specialists see a higher proportion of positive cases, enabling more referrals to treatment. Tests with higher specificity further increase the number of treated patients by reducing false positive referrals to specialists. Adopting current-accuracy blood biomarker tests increased treated patients by 15% (7.15 million vs 6.23 million). When highly accurate blood biomarker tests replace PET and CSF, the number of treated patients increases by 72% compared to the status quo (10.7 million vs 6.2 million). This result does not hold in situations with low patient demand and no specialist queues. When specialists are readily available, adding screening tests that exclude patients reduces the total number of patients seen by a specialist and therefore the number of treated patients.

Figure 3.9: Number of treated patients by scenario, 2025-2044



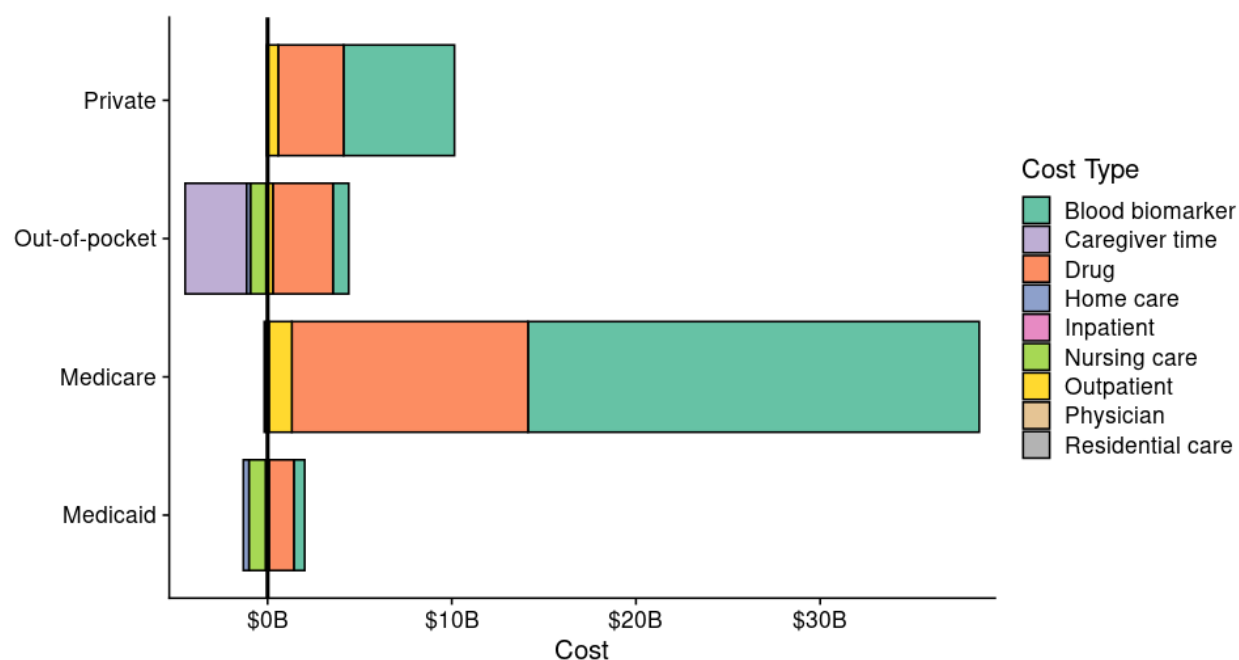
NOTES: Dashed line represents the number of patients treated in the status quo scenario. BBM: Blood biomarker; PET: Positron emission tomography

Cost-effectiveness and economic outcomes

Figure 3.10 shows the cost breakdown for the current-accuracy blood biomarker testing scenario relative to the status quo over 20 years. Negative cost values represent cost savings. Blood biomarkers can be costly both because of the test price (assumed \$750) and because they increase the number of people treated with lecanemab (costing \$26,500 annually). At these prices, the expenditure on blood biomarker tests and disease-modifying therapies substantially exceeds savings from reduced or delayed nursing home stays and unpaid caregiving time.

The costs and benefits of blood biomarker testing are distributed unevenly across payers. Medicare and private insurers bear the primary burden, covering most drug and blood biomarker expenses. The modest savings from reduced care needs benefit Medicaid, patients, and caregivers. Over 20 years, the adoption of blood biomarker tests could cost \$49.2 billion, with Medicare paying net costs of \$38.5 billion, private insurers \$10.1 billion, and Medicaid \$0.7 billion. Out-of-pocket costs remain nearly unchanged, with total savings of \$0.07 billion.

Figure 3.10: Cost breakdown by payer and type for current-accuracy blood biomarkers, 2025-2044

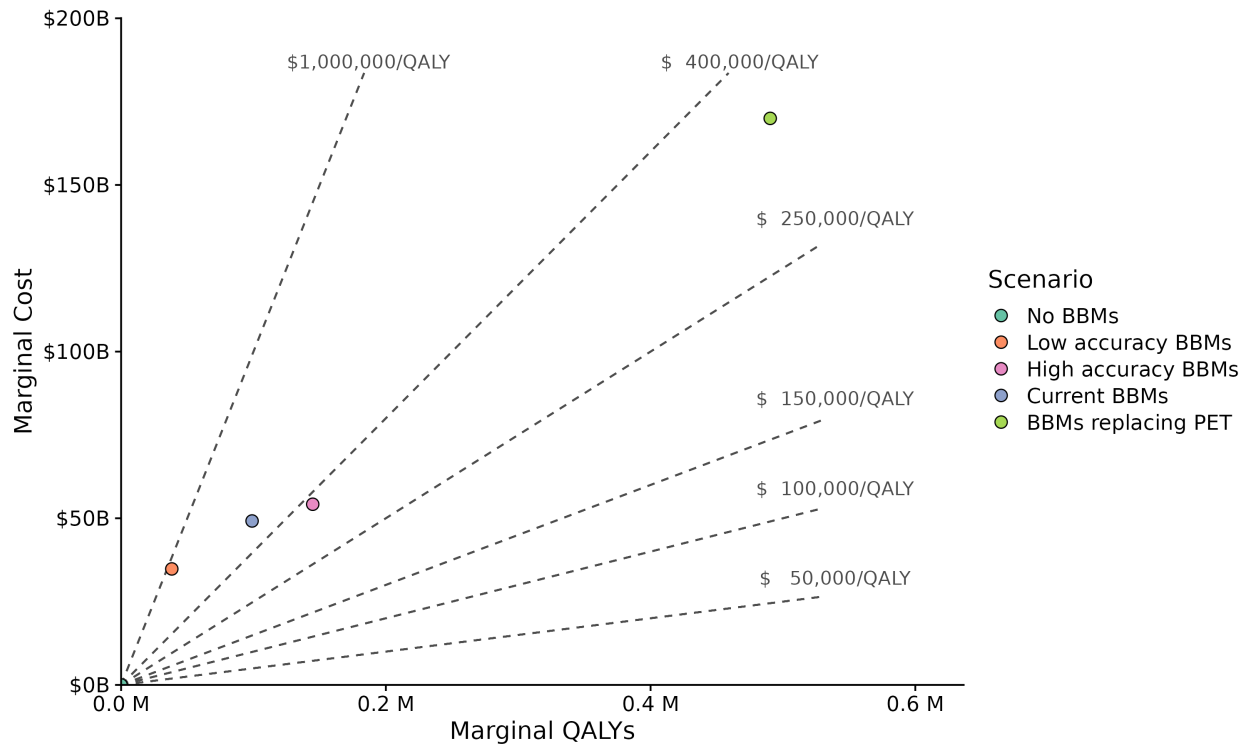


NOTES: Y-axis in units of billions of USD. USD: United States Dollars

In the status quo scenario, we estimate the incremental cost-effectiveness of lecanemab to be \$279,000 per QALY. When we include service costs directly related to lecanemab treatment, such as confirmatory biomarker testing, infusion costs, monitoring costs, and side effects, the cost-effectiveness worsens to \$416,000 per QALY. Cost-effectiveness was similar for donanemab, \$277,000 per QALY without service costs and \$422,000 per QALY with service costs.

Figure 3.11 displays marginal costs and QALYs for each scenario compared to the status quo, with radial lines indicating different cost-effectiveness thresholds. More cost-effective interventions show a higher ratio of QALYs to costs, positioning them in the bottom right corner of the plot. In no scenario is blood biomarker testing cost-effective at the typical \$150,000 per QALY threshold. While reducing false positives generates some savings, these are overwhelmed by increased drug costs due to both expanded treatment populations and high blood biomarker testing expenses. Scenarios involving broader treatment coverage, such as substituting PET scans with high-accuracy blood biomarker testing, incur much higher marginal treatment costs than other scenarios.

Figure 3.11: Cost-effectiveness by scenario, 2025-2044



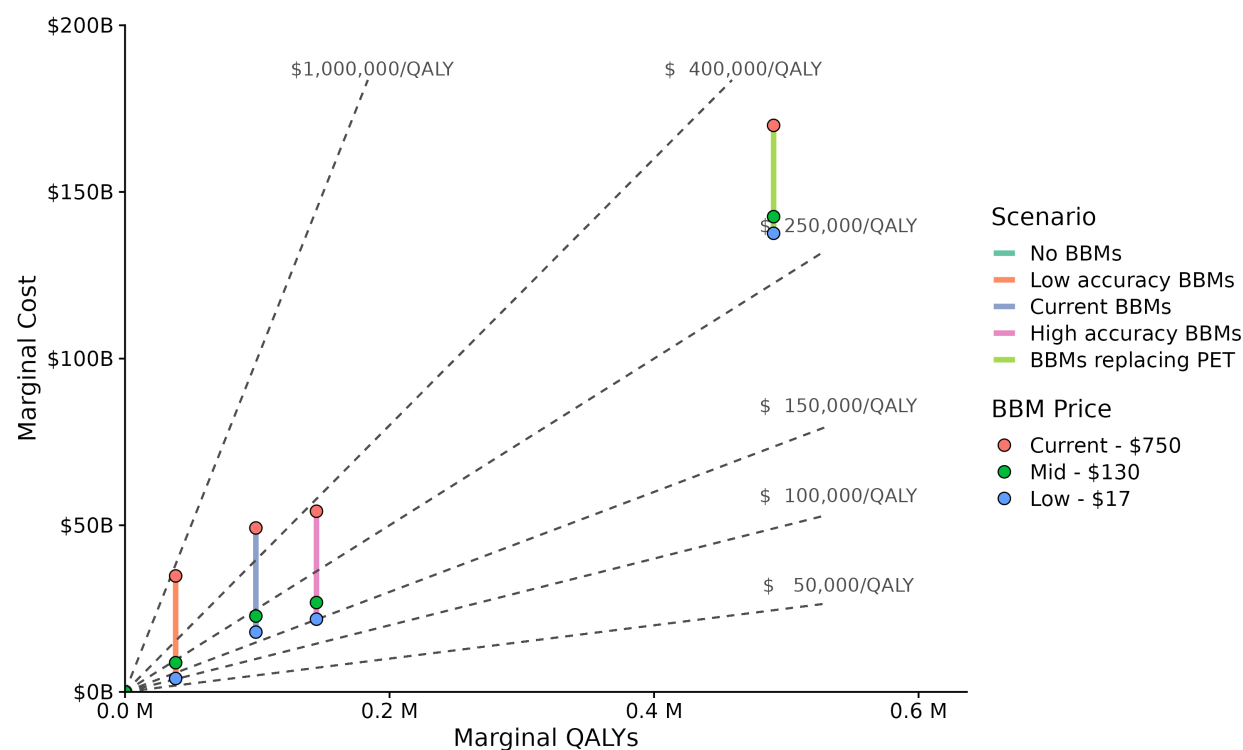
NOTES: X-axis in units of millions of quality-adjusted life years. Y-axis in units of billions of USD. BBM: Blood biomarker; QALY: Quality-adjusted life years. PET: Positron emission tomography; USD: United States Dollars

Alternative cost-effectiveness scenarios

Alternative scenarios demonstrate how the cost-effectiveness of blood biomarker testing responds to changes in prices and treatment efficacy. These scenarios vary costs for lecanemab and blood biomarker tests and drug effectiveness from a placebo to an ideal therapy that completely halts dementia progression. Figures 3.10, 3.11, and 3.12 present scatter plots showing marginal costs and QALYs for these scenarios. Points within the same blood biomarker adoption scenario are connected by color-coded lines.

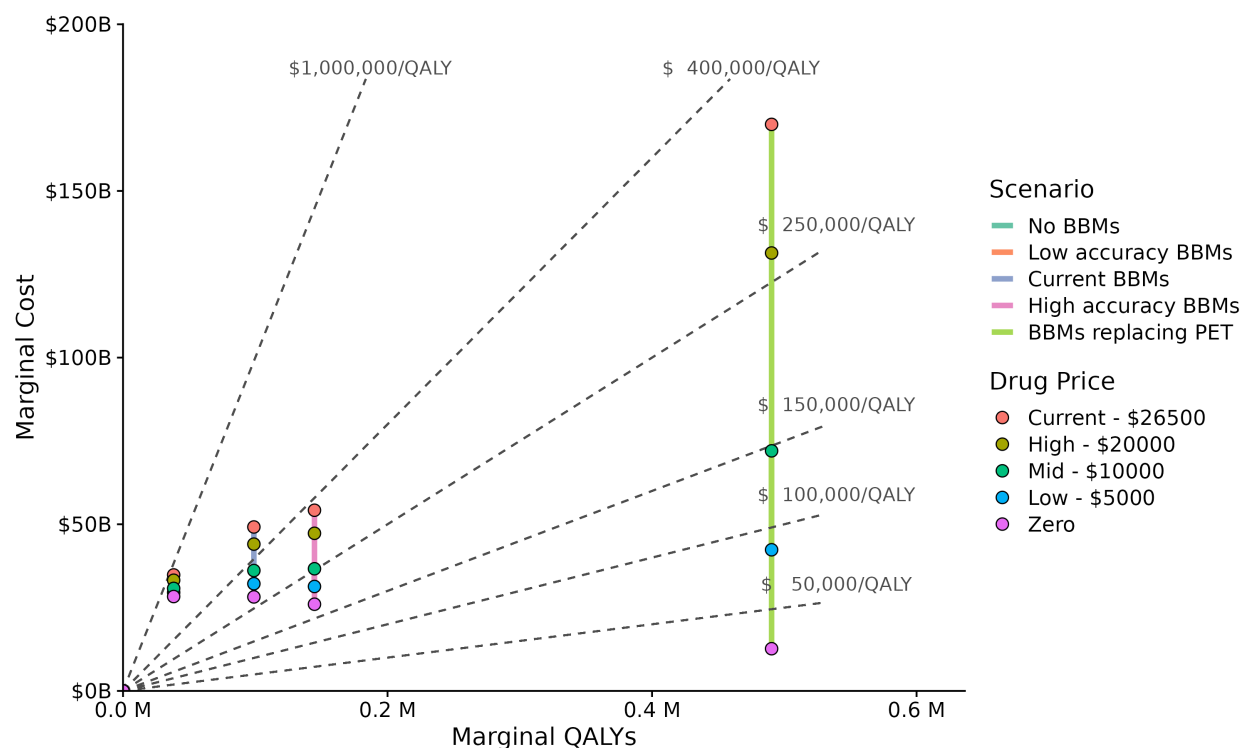
As shown in Figure 3.12, blood biomarker test price reductions lead to similar absolute cost reductions in all scenarios since each involves roughly equal testing volumes. However, blood biomarker test price changes have less impact on cost-effectiveness in scenarios with higher treatment rates, where drug costs dominate total spending. Conversely, in scenarios with fewer additional treated patients, blood biomarker test pricing is more significant.

Figure 3.12: Cost-effectiveness by scenario, varying blood biomarker price, 2025-2044



NOTES: X-axis in units of millions of quality-adjusted life years. Y-axis in units of billions of USD. BBM: Blood biomarker; QALY: Quality-adjusted life years. PET: Positron emission tomography; USD: United States Dollars

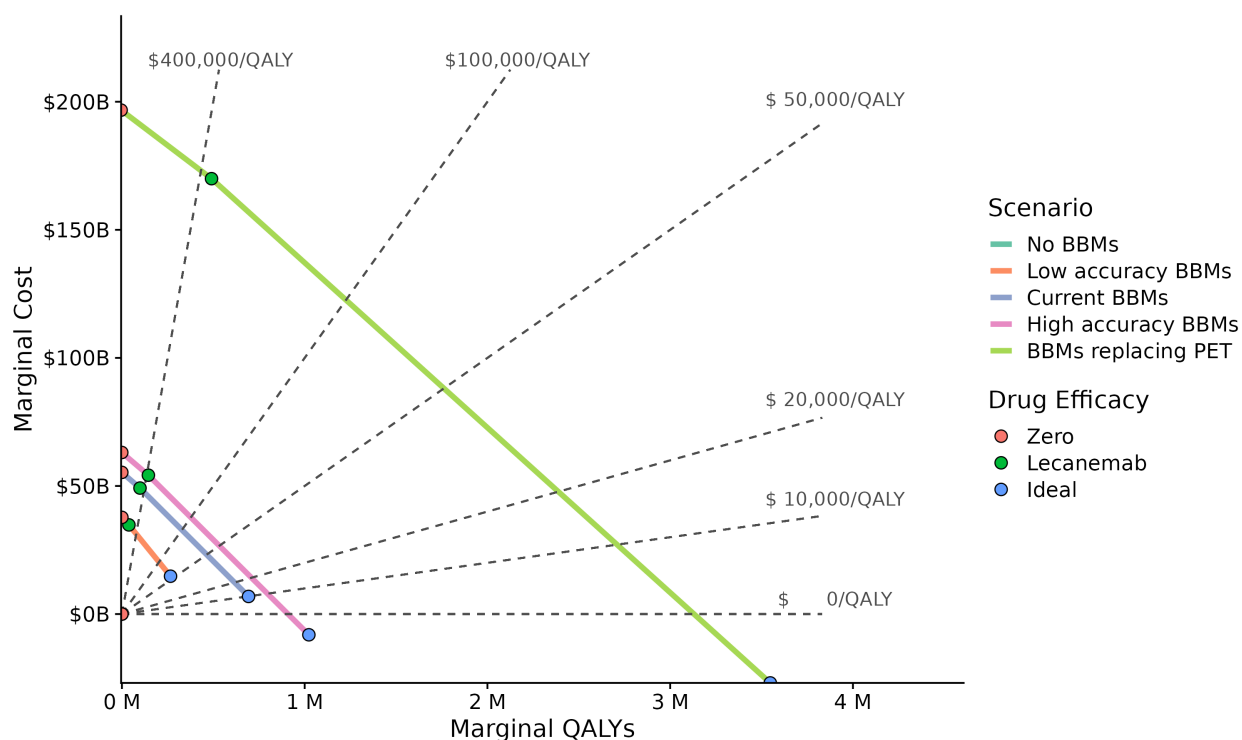
Figure 3.13: Cost-effectiveness by scenario, varying drug price, 2025-2044



NOTES: X-axis in units of millions of quality-adjusted life years. Y-axis in units of billions of USD. BBM: Blood biomarker; QALY: Quality-adjusted life years. PET: Positron emission tomography; USD: United States Dollars

Conversely, reducing drug costs has the greatest impact in scenarios with increased patient treatment numbers. As shown in Figure 3.13, when disease-modifying therapy prices drop sufficiently, blood biomarker tests can be cost-efficient if they replace PET scans. Figure 3.14 demonstrates that enhanced drug effectiveness could have an even more significant impact than cost reduction. A hypothetical ideal drug preventing Alzheimer's disease progression indefinitely would achieve cost savings (-\$5,400/QALY) through both reduced care costs and increased QALYs. Consequently, interventions expanding access to such a drug would be cost-effective.

Figure 3.14: Cost-effectiveness by scenario, varying drug effectiveness, 2025-2044



NOTES: X-axis in units of millions of quality-adjusted life years. Y-axis in units of billions of USD. BBM: Blood biomarker; QALY: Quality-adjusted life years. PET: Positron emission tomography; USD: United States Dollars

Discussion

This simulation model of the US health care system found that using blood biomarker tests in primary care to assess Alzheimer's Disease could substantially reduce overall wait times for disease-modifying therapies by decreasing false-positive referrals. In the baseline demand scenario, the wait time reduction was equivalent to a 35% increase in specialist capacity. Using more accurate blood biomarker tests and replacing PET scans produced even greater wait time reductions. States with significant specialist shortages, particularly in the South and Midwest, saw the largest improvements in wait times.

Other strategies to reduce wait times would be more difficult to implement. Training additional specialists would require years, and many currently available training positions remain unfilled - less than half of geriatric post-residency fellowships were filled in 2023 (National Resident Matching Program, 2023). Another strategy to overcome limited specialist availability, shifting treatment management to primary care, would be more challenging with lecanemab and donanemab. These drugs have a severe side effect profile and require frequent monitoring MRIs,

usually undertaken by interdisciplinary teams of neurologists, geriatricians, nurses, and neuroradiologists in memory clinics (Turk et al., 2024).

In contrast, blood biomarker tests are well-suited for primary care implementation, because they require minimal PCP training and the blood draw could be part of the same visit as a brief cognitive assessment. Beyond reducing wait times, primary care triage using blood biomarker testing could increase the number of treated patients by ensuring specialists see a higher proportion of patients with Alzheimer's disease pathology. Testing blood biomarkers only in patients who show signs of cognitive impairment aligns with the International Working Group's stance that Alzheimer's disease should be diagnosed exclusively in people with cognitive symptoms, rather than screening the general population (B. Dubois et al., 2021).

Blood biomarker testing could provide additional benefits beyond those examined in this study, including helping patients make care and financial plans earlier and directing those with non-Alzheimer's cognitive impairment toward more appropriate care. However, current evidence for such benefits is limited. A clinical trial of a similar intervention, cognitive screening in the general population, found no impact on health care utilization, diagnosis rates, or advance care planning (Fowler et al., 2020). Further research is needed to determine whether blood biomarker testing can deliver these potential benefits.

There are several prerequisites before blood biomarker tests can be implemented in primary care. Test performance must first be validated in representative primary care populations with prospective cut points (Hampel et al., 2022; Hansson, 2021; Teunissen et al., 2022). Additionally, standardized testing kits must be mass-produced, and there needs to be a proliferation of laboratories capable of processing them (Hampel et al., 2023). PCPs need educational materials outlining when blood biomarker tests should be used, how to interpret results, how to communicate results with patients, and when specialist referral is warranted (Hansson et al., 2022). Finally, CMS needs to approve coverage and issue guidance on how testing be incorporated into existing clinical workflows.

CMS has discretion in how they cover blood biomarker tests. They could already choose to cover the four tests with an FDA breakthrough designation using the Transitional Coverage for Emerging Technologies pathway (Farmer et al., 2024). CMS can also choose not to cover tests even if they do receive traditional approval from the FDA because CMS approval criteria ("reasonable and necessary") differ from FDA review criteria ("safe and effective") (Daval & Kesselheim, 2023). CMS has taken a step towards coverage by adding several Alzheimer's disease blood biomarker tests to the Clinical Laboratory Fee Schedule for CY 2025 (Centers for Medicare and Medicaid Services, 2024b). Through coverage with evidence determination, CMS

could implement specific usage requirements, such as requiring evidence of cognitive impairment before use or mandating registry entry to build evidence on blood biomarker test accuracy in diverse populations.

Blood biomarker test implementation carries substantial costs that must be factored into coverage decisions. The major cost drivers include high test prices, expanded treatment access, and therapies that are not cost-effective. The financial impact of adopting blood biomarkers, and disease-modifying therapies in general, is unevenly distributed: while patients, caregivers, and Medicaid benefit from improved quality of life and reduced long-term care expenses, the Medicare program, and by extension taxpayers, bear most of the costs. In addition, high costs create incentives for some payers to restrict access to both blood biomarker tests and disease-modifying therapies. Some Medicare Advantage, employer, and state Medicaid plans have added requirements in addition to those imposed by traditional Medicare to restrict access to disease-modifying therapies including specialty-specific prescribing restrictions and multiple treatment reauthorization requirements (Aetna, 2023; Husky Health, 2023; United Healthcare, 2023).

CMS faces a complex decision regarding whether to cover blood biomarker testing in primary care settings. Although Alzheimer's disease-modifying therapies are covered by Medicare, specialist shortages may lead to de facto rationing of treatment. Memory clinics reported wait times of up to 9 months in early 2024 (Bowman Rogers, 2024; Saltzman, 2024). On the other hand, making blood biomarker testing widely available would incur substantial costs for relatively limited patient benefit.

CMS could use its substantial market power and role as a price-setter for laboratory tests to influence prices and increase the cost-effectiveness of blood biomarker testing. If spending on Alzheimer's disease-modifying therapies is significant, then CMS could use the nascent Drug Price Negotiation Program to reduce prices – Part B drugs are included from 2027 (Sullivan, 2023).

CMS could influence test prices through the Clinical Laboratory Fee Schedule. Prices for new tests are set by comparing them to prices for existing tests and reagent costs (MedPAC, 2024). The choice of comparator test significantly impacts pricing - Alzheimer's disease blood biomarker tests could be compared to expensive cerebrospinal fluid tests measuring the same proteins, or to less costly blood tests for similar biomarkers. The most recent fee schedule determination has set prices for the most accurate Alzheimer's disease blood biomarker tests to \$750 (Centers for Medicare and Medicaid Services, 2024b), far higher than the \$130 recommended by an industry and academic consortium (Global CEO Initiative, 2024). Other, potentially less accurate, Alzheimer's disease blood biomarker assays that do not test for both

amyloid and tau have lower fee schedule prices. Medicare's efficient pricing of laboratory services is crucial. Setting prices too low will result in inadequate test availability while setting prices too high will lead to excess spending since Medicare laboratory tests have no cost-sharing requirements.

In the future, Alzheimer's disease care and treatment may shift toward the asymptomatic preclinical stage. The Alzheimer's Association working group has proposed redefining Alzheimer's disease based solely on biomarkers, rather than combining biomarkers with symptoms (Jack Jr. et al., 2024). This new definition would enable the treatment of preclinical Alzheimer's disease, requiring widespread amyloid screening. Blood tests represent the only biomarker detection method that could feasibly scale to screen the general population (Jack Jr. et al., 2024). However, the International Working Group opposes this redefinition, noting that many people with Alzheimer's biomarkers never develop symptoms. They argue these individuals should be considered "at risk" for developing Alzheimer's disease rather than being diagnosed with the disease itself (B. Dubois et al., 2024). CMS should consider how they will impact these potential applications when they make coverage decisions.

Limitations

This study has several limitations. While Alzheimer's disease involves the gradual accumulation of amyloid plaques and pathologic tau, leading to neurodegeneration, the health state model uses discrete disease stages that approximate these dynamics by increasing the progression probability with age. Although an individual-level microsimulation would more accurately represent Alzheimer's disease progression, simulating enough individuals to accurately estimate queue times would be computationally expensive.

The model excludes variables that could influence treatment effectiveness, disease progression, and health care access, including race, ApoE4 status, education, and income. Given that disease progression is central to calculating a therapy's effect on QALYs, microsimulation-based studies may provide more accurate QALY and cost-effectiveness estimates (Tahami Monfared, Ye, Sardesai, Folse, Chavan, Aruffo, et al., 2023). Instead, this study's contribution is modeling the effect of dynamics that are not usually included in cost-effectiveness analyses, such as constraints on treatment capacity, imperfect testing, and patient attrition.

Tests were assumed to be independent of one another, although their results could be correlated. This assumption may overstate the value of repeated testing, as tests may consistently misclassify the same patients. The model also assumed binary positive or negative test results, whereas clinical tests typically produce continuous measures. These continuous measures provide more information but also introduce uncertainty in clinical decision-making. For

example, some blood biomarker tests employ multiple cut points to classify patients into low, intermediate, and high likelihood of amyloid positivity, enabling a more nuanced triage system for patient referrals (Hu et al., 2022). In addition, the model assumes all patients over 65 years of age have the same likelihood of receiving testing given their health status, there may be more efficient distribution strategies like limiting testing to patients over 70.

The clinical model assumes that all physicians use the same tests, when there may be a range of different tests used, especially for brief cognitive assessments in primary care. These tests may be less accurate than the MoCA and therefore could lead to an overestimation of primary care triage accuracy and an understatement of blood biomarker testing value.

The cost model includes several simplifications of the US health care system. The cost model uses coinsurance rates rather than the deductibles and copays that most patients face. Additionally, certain insurance types are omitted, including uninsurance, Veterans' health coverage, Medigap, and Medicare Advantage (MA) plans. Individuals with these insurance types are assigned to other payers or accounted for through patient decisions - for example, uninsured individuals are assumed to never receive cognitive assessments. Medigap premiums and resulting cost savings to patients are excluded, based on the assumption that aggregate costs are bounded by plan profitability and medical loss ratios.

The model does not include all variation in state Medicaid programs. For instance, only some state Medicaid programs cover home- and community-based services (Gonçalves et al., 2020), and Medicaid payments for dual-eligibles for Medicare-covered services vary by state (MACPAC, 2013).

The model includes forgone caregiver wages and direct disutility for both patients and caregivers, but excludes long-term changes in labor market earnings, caregiver health costs, and the cost of lost leisure time (Coe et al., 2018). This likely results in underestimated indirect costs.

Finally, the model treats provider, patient, and payer decision-making as exogenous. In practice, these actors might respond to changing circumstances, such as primary care providers decreasing referral rates due to long wait times, or patients increasing demand for more effective therapies. Without modeling these endogenous feedback loops directly, this model has limited predictive utility and primarily serves to describe dynamics.

Conclusion

This study highlights tradeoffs for the potential use of Alzheimer's disease blood biomarker testing in primary care settings. The adoption of these tests could significantly reduce specialist wait times and increase access to disease-modifying therapies. However, blood biomarker testing

in primary care imposes high costs on Medicare and is not cost-effective when tests are priced at \$750 and disease-modifying therapies cost \$26,500 annually. If negotiation or innovation produces more affordable or effective treatments or tests, the cost-effectiveness of this approach may improve. Policymakers and payers must weigh the potential benefits against the significant costs and uncertainties associated with the widespread use of blood biomarker testing in primary care. As the rollout of disease-modifying therapies continues information on patient demand, long-term drug effectiveness, and health care system constraints, will be crucial in guiding evidence-based decisions on the use of blood biomarker tests for Alzheimer's disease.

References

- Abd Razak, M. A., Ahmad, N. A., Chan, Y. Y., Mohamad Kasim, N., Yusof, M., Abdul Ghani, M. K. A., Omar, M., Abd Aziz, F. A., & Jamaluddin, R. (2019). Validity of screening tools for dementia and mild cognitive impairment among the elderly in primary health care: A systematic review. *Public Health*, 169, 84–92.
<https://doi.org/10.1016/j.puhe.2019.01.001>
- Aetna. (2023). *Lecanemab-irmb (Leqembi)—Medical Clinical Policy Bulletins*. Aetna.
https://www.aetna.com/cpb/medical/data/1000_1099/1026.html
- Albert, M. S., DeKosky, S. T., Dickson, D., Dubois, B., Feldman, H. H., Fox, N. C., Gamst, A., Holtzman, D. M., Jagust, W. J., Petersen, R. C., Snyder, P. J., Carrillo, M. C., Thies, B., & Phelps, C. H. (2011). The diagnosis of mild cognitive impairment due to Alzheimer’s disease: Recommendations from the National Institute on Aging-Alzheimer’s Association workgroups on diagnostic guidelines for Alzheimer’s disease. *Alzheimer’s & Dementia: The Journal of the Alzheimer’s Association*, 7(3), 270–279.
<https://doi.org/10.1016/j.jalz.2011.03.008>
- Alzheimer’s Association. (2019). 2019 Alzheimer’s disease facts and figures. *Alzheimer’s & Dementia*, 15(3), 321–387. <https://doi.org/10.1016/j.jalz.2019.01.010>
- Alzheimer’s Association. (2020). 2020 Alzheimer’s disease facts and figures. *Alzheimer’s & Dementia: The Journal of the Alzheimer’s Association*. <https://doi.org/10.1002/alz.12068>
- Alzheimer’s Association. (2021). 2021 Alzheimer’s disease facts and figures. *Alzheimer’s & Dementia: The Journal of the Alzheimer’s Association*, 17(3), 327–406.
<https://doi.org/10.1002/alz.12328>
- Alzheimer’s Association. (2023). 2023 Alzheimer’s disease facts and figures. *Alzheimer’s & Dementia: The Journal of the Alzheimer’s Association*, 19(4), 1598–1695.
<https://doi.org/10.1002/alz.13016>
- Amboree, T. L., Montealegre, J. R., Parker, S. L., Garg, A., Damgacioglu, H., Schmeler, K. M., Chiao, E. Y., Hill, E. G., Sonawane, K., Deshmukh, A. A., & Adsul, P. (2024). National Breast, Cervical, and Colorectal Cancer Screening Use in Federally Qualified Health Centers. *JAMA Internal Medicine*, 184(6), 671–679.
<https://doi.org/10.1001/jamainternmed.2024.0693>

- American Hospital Association. (2018). *Trendwatch Chartbook 2018, Trends in Hospital Financing*. <https://www.aha.org/system/files/2018-05/2018-chartbook-table-4-4.pdf>
- American Association of Nurse Practitioners. (2022, May). *Nurse Practitioners in Primary Care*. <https://www.aanp.org/advocacy/advocacy-resource/position-statements/nurse-practitioners-in-primary-care>
- Anderson, J., & Pierce, C. (2022). PrecivityAD for Diagnosis of Alzheimer Disease. *American Family Physician*, 105(1), 79–81.
- Angioni, D., Delrieu, J., Hansson, O., Fillit, H., Aisen, P., Cummings, J., Sims, J. R., Braunstein, J. B., Sabbagh, M., Bittner, T., Pontecorvo, M., Bozeat, S., Dage, J. L., Largent, E., Mattke, S., Correa, O., Gutierrez Robledo, L. M., Baldivieso, V., Willis, D. R., ... EU/US/CTAD Task Force. (2022). Blood Biomarkers from Research Use to Clinical Practice: What Must Be Done? A Report from the EU/US CTAD Task Force. *The Journal of Prevention of Alzheimer's Disease*, 9(4), 569–579. <https://doi.org/10.14283/jpad.2022.85>
- Arbanas, J. C., Damberg, C. L., Leng, M., Harawa, N., Sarkisian, C. A., Landon, B. E., & Mafi, J. N. (2023). Estimated Annual Spending on Lecanemab and Its Ancillary Costs in the US Medicare Program. *JAMA Internal Medicine*. <https://doi.org/10.1001/jamainternmed.2023.1749>
- Arias, E., & Xu, J. (2022). United States Life Tables, 2019. *National Vital Statistics Reports: From the Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System*, 70(19), 1–59.
- Association of American Medical Colleges. (2021). *Number of People per Active Physician by Specialty, 2021*. AAMC. <https://www.aamc.org/page-not-found>
- Aye, S., Handels, R., Winblad, B., & Jönsson, L. (2024). Optimising Alzheimer's Disease Diagnosis and Treatment: Assessing Cost-Utility of Integrating Blood Biomarkers in Clinical Practice for Disease-Modifying Treatment. *The Journal of Prevention of Alzheimer's Disease*. <https://doi.org/10.14283/jpad.2024.67>
- Barthélemy, N. R., Salvadó, G., Schindler, S. E., He, Y., Janelidze, S., Collij, L. E., Saef, B., Henson, R. L., Chen, C. D., Gordon, B. A., Li, Y., La Joie, R., Benzinger, T. L. S., Morris, J. C., Mattsson-Carlsson, N., Palmqvist, S., Ossenkoppele, R., Rabinovici, G. D., Stomrud, E., ... Hansson, O. (2024). Highly accurate blood test for Alzheimer's disease

- is similar or superior to clinical cerebrospinal fluid tests. *Nature Medicine*, 30(4), 1085–1095. <https://doi.org/10.1038/s41591-024-02869-z>
- Beck, A., Page, C., Buche, J., Rittman, D., & Gaiser, M. (2018). *Estimating the Distribution of the U.S. Psychiatric Subspecialist Workforce*. University of Michigan Behavioral Health Workforce Research Center. https://www.healthworkforceta.org/wp-content/uploads/2023/07/BHWRC_Estimating-Distribution-of-US-Psychiatrist.pdf
- Belluck, P. (2024, July 2). New Drug Approved for Early Alzheimer’s. *The New York Times*. <https://www.nytimes.com/2024/07/02/health/alzheimers-treatment-kisunla-donanemab.html>
- Bowman Rogers, M. (2024, January). *Rising Leqembi Prescriptions Are Straining Clinic Capacity*. ALZFORUM. <https://www.alzforum.org/news/research-news/rising-leqembi-prescriptions-are-straining-clinic-capacity>
- Callahan, C. M., Tu, W., Unroe, K. T., LaMantia, M. A., Stump, T. E., & Clark, D. O. (2015). Transitions in Care in a Nationally Representative Sample of Older Americans with Dementia. *Journal of the American Geriatrics Society*, 63(8), 1495–1502. <https://doi.org/10.1111/jgs.13540>
- Centers for Medicare and Medicaid Services. (2022, April 7). *Monoclonal Antibodies Directed Against Amyloid for the Treatment of Alzheimer’s Disease*. Medicare Coverage Database. <https://www.cms.gov/medicare-coverage-database/view/ncd.aspx?ncdid=375&ncdver=1>
- Centers for Medicare and Medicaid Services. (2023, July 6). *Statement: Broader Medicare Coverage of Leqembi Available Following FDA Traditional Approval*. Cms.Gov. <https://www.cms.gov/newsroom/press-releases/statement-broader-medicare-coverage-leqembi-available-following-fda-traditional-approval>
- Centers for Medicare and Medicaid Services. (2024a). *Physician Fee Schedule*. Cms.Gov. <https://www.cms.gov/medicare/physician-fee-schedule/search>
- Centers for Medicare and Medicaid Services. (2024b, December 5). *2024-12-05-Medicare Learning Network Connects*. Cms.Gov. <https://www.cms.gov/training-education/medicare-learning-network/newsletter/2024-12-05-mlnc>
- Cha, A., & Cohen, R. (2022). *Demographic Variation in Health Insurance Coverage: United States, 2021*. National Center for Health Statistics (U.S.). <https://doi.org/10.15620/cdc:121554>

- Coe, N. B., Skira, M. M., & Larson, E. B. (2018). A Comprehensive Measure of the Costs of Caring for a Parent: Differences According to Functional Status. *Journal of the American Geriatrics Society*, 66(10), 2003–2008. <https://doi.org/10.1111/jgs.15552>
- Coffman, J., Chan, K., & Bates, T. (2015). *Profile of the Licensed Practical Nurse/Licensed Vocational Nurse Workforce, 2008 and 2013*. UCSF Health Workforce Research Center on Long-Term Care.
- Congressional Budget Office. (2022). *The Prices That Commercial Health Insurers and Medicare Pay for Hospitals' and Physicians' Services*. CBO. <https://www.cbo.gov/system/files/2022-01/57422-medical-prices.pdf>
- Crowell, V., Reyes, A., Zhou, S. Q., Vassilaki, M., Gsteiger, S., & Gustavsson, A. (2023). Disease severity and mortality in Alzheimer's disease: An analysis using the U.S. National Alzheimer's Coordinating Center Uniform Data Set. *BMC Neurology*, 23(1), 302. <https://doi.org/10.1186/s12883-023-03353-w>
- Cummings, J. (2023). Meaningful benefit and minimal clinically important difference (MCID) in Alzheimer's disease: Open peer commentary. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, 9(3), e12411. <https://doi.org/10.1002/trc2.12411>
- Cummings, J., Apostolova, L., Rabinovici, G. D., Atri, A., Aisen, P., Greenberg, S., Hendrix, S., Selkoe, D., Weiner, M., Petersen, R. C., Salloway, S., & For the Alzheimer's Disease and Related Disorders Therapeutics Work Group. (2023). Lecanemab: Appropriate Use Recommendations. *The Journal of Prevention of Alzheimer's Disease*, 10(3), 362–377. <https://doi.org/10.14283/jpad.2023.30>
- Cummings, J., Zhou, Y., Lee, G., Zhong, K., Fonseca, J., & Cheng, F. (2023). Alzheimer's disease drug development pipeline: 2023. *Alzheimer's & Dementia (New York, N. Y.)*, 9(2), e12385. <https://doi.org/10.1002/trc2.12385>
- Cummings, J., Zhou, Y., Lee, G., Zhong, K., Fonseca, J., & Cheng, F. (2024). Alzheimer's disease drug development pipeline: 2024. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, 10(2), e12465. <https://doi.org/10.1002/trc2.12465>
- Daval, C. J. R., & Kesselheim, A. S. (2023). Authority of Medicare to Limit Coverage of FDA-Approved Products: Legal and Policy Considerations. *JAMA Internal Medicine*, 183(9), 999–1004. <https://doi.org/10.1001/jamainternmed.2023.3961>

- Davis, M., O'Connell, T., Johnson, S., Cline, S., Merikle, E., Martenyi, F., & Simpson, K. (2018). Estimating Alzheimer's Disease Progression Rates from Normal Cognition Through Mild Cognitive Impairment and Stages of Dementia. *Current Alzheimer Research*, 15(8), 777–788. <https://doi.org/10.2174/1567205015666180119092427>
- DiBenedetti, D. B., Slota, C., Wronski, S. L., Vradenburg, G., Comer, M., Callahan, L. F., Winfield, J., Rubino, I., Krasa, H. B., Hartry, A., Wieberg, D., Kremer, I. N., Lappin, D., Martin, A. D., Frangiosa, T., Biggar, V., & Hauber, B. (2020). Assessing what matters most to patients with or at risk for Alzheimer's and care partners: A qualitative study evaluating symptoms, impacts, and outcomes. *Alzheimer's Research & Therapy*, 12, 90. <https://doi.org/10.1186/s13195-020-00659-6>
- Dubois, B., Villain, N., Frisoni, G. B., Rabinovici, G. D., Sabbagh, M., Cappa, S., Bejanin, A., Bombois, S., Epelbaum, S., Teichmann, M., Habert, M.-O., Nordberg, A., Blennow, K., Galasko, D., Stern, Y., Rowe, C. C., Salloway, S., Schneider, L. S., Cummings, J. L., & Feldman, H. H. (2021). Clinical diagnosis of Alzheimer's disease: Recommendations of the International Working Group. *The Lancet. Neurology*, 20(6), 484–496. [https://doi.org/10.1016/S1474-4422\(21\)00066-1](https://doi.org/10.1016/S1474-4422(21)00066-1)
- Dubois, B., Villain, N., Schneider, L., Fox, N., Campbell, N., Galasko, D., Kivipelto, M., Jessen, F., Hanseeuw, B., Boada, M., Barkhof, F., Nordberg, A., Froelich, L., Waldemar, G., Frederiksen, K. S., Padovani, A., Planche, V., Rowe, C., Bejanin, A., ... Frisoni, G. B. (2024). Alzheimer Disease as a Clinical-Biological Construct—An International Working Group Recommendation. *JAMA Neurology*, 81(12), 1304–1311. <https://doi.org/10.1001/jamaneurol.2024.3770>
- Dubois, R. W. (2016). Cost–effectiveness thresholds in the USA: Are they coming? Are they already here? *Journal of Comparative Effectiveness Research*, 5(1), 9–12. <https://doi.org/10.2217/cer.15.50>
- Farmer, S. A., Ashby, L. M., & Blum, J. D. (2024). Medicare's New Pathway for Transitional Coverage for Emerging Technologies. *JAMA Health Forum*, 5(11), e243901. <https://doi.org/10.1001/jamahealthforum.2024.3901>
- Food and Drug Administration. (2023, July 7). *FDA Converts Novel Alzheimer's Disease Treatment to Traditional Approval*. FDA.Gov; FDA. <https://www.fda.gov/news-events/press-announcements/fda-converts-novel-alzheimers-disease-treatment-traditional-approval>

- Fowler, N. R., Perkins, A. J., Gao, S., Sachs, G. A., & Boustani, M. A. (2020). Risks and Benefits of Screening for Dementia in Primary Care: The Indiana University Cognitive Health Outcomes Investigation of the Comparative Effectiveness of Dementia Screening (IU CHOICE) Trial. *Journal of the American Geriatrics Society*, 68(3), 535–543. <https://doi.org/10.1111/jgs.16247>
- Genworth. (2023). *Cost of Long Term Care by State*. Genworth. <https://www.genworth.com/aging-and-you/finances/cost-of-care>
- Global CEO Initiative. (2024, October 25). *CY 2025 Clinical Laboratory Fee Schedule Preliminary Determinations: Category 1 CPT Codes and Assays for Fluid-Based Amyloid Beta and Tau Protein Biomarkers*. <https://www.alzbiomarkerhub.org/s/CEOi-CMS-BBM-Reimbursement-Comment-Letter-10-25-2024-131.pdf>
- Gonçalves, J., Weaver, F., & Konetzka, R. T. (2020). Measuring State Medicaid Home Care Participation and Intensity Using Latent Variables. *Journal of Applied Gerontology*, 39(7), 731–744. <https://doi.org/10.1177/0733464818786396>
- Hampel, H., Au, R., Mattke, S., van der Flier, W. M., Aisen, P., Apostolova, L., Chen, C., Cho, M., De Santi, S., Gao, P., Iwata, A., Kurzman, R., Saykin, A. J., Teipel, S., Vellas, B., Vergallo, A., Wang, H., & Cummings, J. (2022). Designing the next-generation clinical care pathway for Alzheimer’s disease. *Nature Aging*, 2(8), 692–703. <https://doi.org/10.1038/s43587-022-00269-x>
- Hampel, H., Hu, Y., Cummings, J., Mattke, S., Iwatsubo, T., Nakamura, A., Vellas, B., O’Bryant, S., Shaw, L. M., Cho, M., Batrla, R., Vergallo, A., Blennow, K., Dage, J., & Schindler, S. E. (2023). Blood-based biomarkers for Alzheimer’s disease: Current state and future use in a transformed global healthcare landscape. *Neuron*, 111(18), 2781–2799. <https://doi.org/10.1016/j.neuron.2023.05.017>
- Hansson, O. (2021). Biomarkers for neurodegenerative diseases. *Nature Medicine*, 27(6), 954–963. <https://doi.org/10.1038/s41591-021-01382-x>
- Hansson, O., Blennow, K., Zetterberg, H., & Dage, J. (2023). Blood biomarkers for Alzheimer’s disease in clinical practice and trials. *Nature Aging*, 3(5), 506–519. <https://doi.org/10.1038/s43587-023-00403-3>
- Hansson, O., Edelmayer, R. M., Boxer, A. L., Carrillo, M. C., Mielke, M. M., Rabinovici, G. D., Salloway, S., Sperling, R., Zetterberg, H., & Teunissen, C. E. (2022). The Alzheimer’s

- Association appropriate use recommendations for blood biomarkers in Alzheimer's disease. *Alzheimer's & Dementia*, 18(12), 2669–2686. <https://doi.org/10.1002/alz.12756>
- Health Resources and Services Administration. (2023a). *Area Health Resource Files*. Data.HRSA.Gov. <https://data.hrsa.gov/data/download>
- Health Resources and Services Administration. (2023b). *Workforce Projections*. Data.HRSA.Gov. <https://data.hrsa.gov/topics/health-workforce/workforce-projections>
- Herman, B., & Cohrs Zhang. (2024, April 11). Medicare expects to spend \$3.5 billion on new Alzheimer's drug in 2025. *STAT*. <https://www.statnews.com/2024/04/11/medicare-will-spend-billions-on-alzheimers-drug-leqembi-eisai-biogen/>
- Hu, Y., Kirmess, K. M., Meyer, M. R., Rabinovici, G. D., Gatsonis, C., Siegel, B. A., Whitmer, R. A., Apgar, C., Hanna, L., Kanekiyo, M., Kaplow, J., Koyama, A., Verbel, D., Holubasch, M. S., Knapik, S. S., Connor, J., Contois, J. H., Jackson, E. N., Harpstrite, S. E., ... West, T. (2022). Assessment of a Plasma Amyloid Probability Score to Estimate Amyloid Positron Emission Tomography Findings Among Adults With Cognitive Impairment. *JAMA Network Open*, 5(4), e228392. <https://doi.org/10.1001/jamanetworkopen.2022.8392>
- Hudomiet, P., Hurd, M. D., & Rohwedder, S. (2022). Trends in inequalities in the prevalence of dementia in the United States. *Proceedings of the National Academy of Sciences*, 119(46), e2212205119. <https://doi.org/10.1073/pnas.2212205119>
- Husky Health. (2023). *Amyloid Beta-Directed Monoclonal Antibodies for Alzheimer's Disease* (Provider Policies and Procedures). https://www.huskyhealthct.org/providers/provider_postings/policies_procedures/Amyloid_Beta_Directed_Monoclonal_Antibodies_for_Alzheimer_Policy.pdf
- Iwatsubo, T. (2023). Clinical Implementation of Lecanemab: Challenges, Questions and Solutions. *The Journal of Prevention of Alzheimer's Disease*, 10(3), 353–355. <https://doi.org/10.14283/jpad.2023.41>
- Jack, C. R., Bennett, D. A., Blennow, K., Carrillo, M. C., Dunn, B., Haeberlein, S. B., Holtzman, D. M., Jagust, W., Jessen, F., Karlawish, J., Liu, E., Molinuevo, J. L., Montine, T., Phelps, C., Rankin, K. P., Rowe, C. C., Scheltens, P., Siemers, E., Snyder, H. M., ... Silverberg, N. (2018). NIA-AA Research Framework: Toward a biological definition of Alzheimer's disease. *Alzheimer's & Dementia*, 14(4), 535–562. <https://doi.org/10.1016/j.jalz.2018.02.018>

- Jack Jr., C. R., Andrews, J. S., Beach, T. G., Buracchio, T., Dunn, B., Graf, A., Hansson, O., Ho, C., Jagust, W., McDade, E., Molinuevo, J. L., Okonkwo, O. C., Pani, L., Rafii, M. S., Scheltens, P., Siemers, E., Snyder, H. M., Sperling, R., Teunissen, C. E., & Carrillo, M. C. (2024). Revised criteria for diagnosis and staging of Alzheimer's disease: Alzheimer's Association Workgroup. *Alzheimer's & Dementia*, 20(8), 5143–5169. <https://doi.org/10.1002/alz.13859>
- Jansen, W. J., Ossenkoppele, R., Knol, D. L., Tijms, B. M., Scheltens, P., Verhey, F. R. J., Visser, P. J., & and the Amyloid Biomarker Study Group. (2015). Prevalence of Cerebral Amyloid Pathology in Persons Without Dementia: A Meta-analysis. *JAMA*, 313(19), 1924–1938. <https://doi.org/10.1001/jama.2015.4668>
- Kaiser Family Foundation. (2019). *Medicaid-to-Medicare Fee Index* [KFF]. <https://www.kff.org/medicaid/state-indicator/medicaid-to-medicare-fee-index/>
- Kasper, J. D., Freedman, V. A., & Spillman, B. (2013). *Classification of Persons by Dementia Status in the National Health and Aging Trends Study* (Johns Hopkins University School of Public Health Technical Paper #5). https://www.nhats.org/sites/default/files/inline-files/DementiaTechnicalPaperJuly_2_4_2013_10_23_15.pdf
- KFF. (2017, June 20). Medicaid's Role in Nursing Home Care. *Kaiser Family Foundation*. <https://www.kff.org/infographic/medicaids-role-in-nursing-home-care/>
- Lam, J., Jun, H., Cho, S. K., Hanson, M., & Mattke, S. (2021). Projection of budgetary savings to US state Medicaid programs from reduced nursing home use due to an Alzheimer's disease treatment. *Alzheimer's & Dementia : Diagnosis, Assessment & Disease Monitoring*, 13(1), e12159. <https://doi.org/10.1002/dad2.12159>
- Landeiro, F., Mughal, S., Walsh, K., Nye, E., Morton, J., Williams, H., Ghinai, I., Castro, Y., Leal, J., Roberts, N., Wace, H., Handels, R., Lecomte, P., Gustavsson, A., Roncancio-Diaz, E., Belger, M., Jhuti, G. S., Bouvy, J. C., Potashman, M. H., ... on behalf of the ROADMAP consortium. (2020). Health-related quality of life in people with predementia Alzheimer's disease, mild cognitive impairment or dementia measured with preference-based instruments: A systematic literature review. *Alzheimer's Research & Therapy*, 12(1), 154. <https://doi.org/10.1186/s13195-020-00723-1>
- Lin, G., Whittington, M., Wright, A., Agboola, F., Herron-Smith, S., Pearson, S., & Rind, D. (2023). *Lecanemab for Early Alzheimer's Disease—Final Evidence Report*. Institute for Clinical and Economic Review. <https://icer.org/wp->

content/uploads/2023/04/ICER_Alzheimers-Disease_Final-Report_For-Publication_04172023.pdf

- Liu, J. L., Baker, L., Chen, A., Wang, J., & Girosi, F. (2024). *Modeling Early Detection and Geographic Variation in Health System Capacity for Alzheimer's Disease—Modifying Therapies*. RAND Corporation. https://www.rand.org/pubs/research_reports/RRA2643-1.html
- Liu, J. L., Hlavka, J. P., Hillestad, R., & Mattke, S. (2017). *Assessing the Preparedness of the U.S. Health Care System Infrastructure for an Alzheimer's Treatment*. RAND Corporation. https://www.rand.org/pubs/research_reports/RR2272.html
- Lonie, J. A., Tierney, K. M., & Ebmeier, K. P. (2009). Screening for mild cognitive impairment: A systematic review. *International Journal of Geriatric Psychiatry*, 24(9), 902–915. <https://doi.org/10.1002/gps.2208>
- MACPAC. (2013). Medicaid Coverage of Premiums and Cost Sharing for Low-Income Medicare Beneficiaries. In *Report to Congress on Medicaid and CHIP*. <https://www.macpac.gov/wp-content/uploads/2013/03/Medicaid-Coverage-of-Premiums-and-Cost-Sharing-for-Low-Income-Medicare-Beneficiaries.pdf>
- MACPAC. (2023). *Estimates of Medicaid Nursing Facility Payments Relative to Costs* [Issue Brief]. <https://www.macpac.gov/wp-content/uploads/2023/01/Estimates-of-Medicaid-Nursing-Facility-Payments-Relative-to-Costs-1-6-23.pdf>
- Matthews, K. A., Xu, W., Gaglioti, A. H., Holt, J. B., Croft, J. B., Mack, D., & McGuire, L. C. (2019). Racial and ethnic estimates of Alzheimer's disease and related dementias in the United States (2015–2060) in adults aged ≥ 65 years. *Alzheimer's & Dementia*, 15(1), 17–24. <https://doi.org/10.1016/j.jalz.2018.06.3063>
- Mattke, S., Cho, S. K., Bittner, T., Hlávka, J., & Hanson, M. (2020). Blood-based biomarkers for Alzheimer's pathology and the diagnostic process for a disease-modifying treatment: Projecting the impact on the cost and wait times. *Alzheimer's & Dementia : Diagnosis, Assessment & Disease Monitoring*, 12(1), e12081. <https://doi.org/10.1002/dad2.12081>
- Mattke, S., & Hanson, M. (2022). Expected wait times for access to a disease-modifying Alzheimer's treatment in the United States. *Alzheimer's & Dementia*, 18(5), 1071–1074. <https://doi.org/10.1002/alz.12470>

- McKhann, G. M., Knopman, D. S., Chertkow, H., Hyman, B. T., Jack, C. R., Kawas, C. H., Klunk, W. E., Koroshetz, W. J., Manly, J. J., Mayeux, R., Mohs, R. C., Morris, J. C., Rossor, M. N., Scheltens, P., Carrillo, M. C., Thies, B., Weintraub, S., & Phelps, C. H. (2011). The diagnosis of dementia due to Alzheimer's disease: Recommendations from the National Institute on Aging-Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease. *Alzheimer's & Dementia: The Journal of the Alzheimer's Association*, 7(3), 263–269. <https://doi.org/10.1016/j.jalz.2011.03.005>
- MedPAC. (2024). *Clinical Laboratory Services Payment System* (Payment Basics).
- MedPAC & MACPAC. (2024). *Data book: Beneficiaries dually eligible for Medicare and Medicaid*. https://www.macpac.gov/wp-content/uploads/2024/01/Jan24_MedPAC_MACPAC_DualsDataBook-508.pdf
- Morgan, K. M., Marcotte, L. M., Zhou, L., & Liao, J. M. (2021). Annual Wellness Visits in the Era of Value-Based Care: National Trends in Use, 2011–2018. *Journal of General Internal Medicine*, 36(9), 2894–2896. <https://doi.org/10.1007/s11606-020-06032-5>
- Nakamura, A., Kaneko, N., Villemagne, V. L., Kato, T., Doecke, J., Doré, V., Fowler, C., Li, Q.-X., Martins, R., Rowe, C., Tomita, T., Matsuzaki, K., Ishii, K., Arahata, Y., Iwamoto, S., Ito, K., Tanaka, K., Masters, C. L., & Yanagisawa, K. (2018). High performance plasma amyloid- β biomarkers for Alzheimer's disease. *Nature*, 554(7691), 249–254. <https://doi.org/10.1038/nature25456>
- Nandi, A., Counts, N., Bröker, J., Malik, S., Chen, S., Han, R., Klusty, J., Seligman, B., Tortorice, D., Vigo, D., & Bloom, D. E. (2024). Cost of care for Alzheimer's disease and related dementias in the United States: 2016 to 2060. *Npj Aging*, 10(1), 1–8. <https://doi.org/10.1038/s41514-024-00136-6>
- National Commission on Certification of Physician Assistants. (2020). *2019 Statistical Profile of Certified Physician Assistants: An Annual Report of the National Commission on Certification of Physician Assistants*. https://www.nccpa.net/wp-content/uploads/2020/11/2019-Recently-Certified-Report-final_compressed.pdf
- National Post-acute and Long-term Care Study. (2023, December 12). *Biennial Overview of Post-acute and Long-term Care in the United States*. National Center for Health Statistics. <https://www.cdc.gov/nchs/npals/webtables/overview.htm>

- National Resident Matching Program. (2023). *Match Results Statistics*.
<https://www.nrmp.org/wp-content/uploads/2023/11/2023-MPSM-Match-Results-Statistics-Report.pdf>
- NHATS. (2023). *National Health and Aging Trends Study* (Produced with funding from the National Institute on Aging (U01AG032947).) [Dataset]. www.nhats.org
- OECD. (2023). *OECD Statistics*. OECD.Stat. <https://stats.oecd.org/>
- Osaka, H., Nishida, K., & Kanazawa, T. (2024). Beyond lecanemab: Examining Phase III potential in Alzheimer’s therapeutics. *Psychiatry and Clinical Neurosciences Reports*, 3(1), e185. <https://doi.org/10.1002/pcn5.185>
- Petersen, R. C., Lopez, O., Armstrong, M. J., Getchius, T. S. D., Ganguli, M., Gloss, D., Gronseth, G. S., Marson, D., Pringsheim, T., Day, G. S., Sager, M., Stevens, J., & Rae-Grant, A. (2018). Practice guideline update summary: Mild cognitive impairment: Report of the Guideline Development, Dissemination, and Implementation Subcommittee of the American Academy of Neurology. *Neurology*, 90(3), 126–135.
<https://doi.org/10.1212/WNL.0000000000004826>
- Rajan, K. B., Weuve, J., Barnes, L. L., McAninch, E. A., Wilson, R. S., & Evans, D. A. (2021). Population estimate of people with clinical Alzheimer’s disease and mild cognitive impairment in the United States (2020–2060). *Alzheimer’s & Dementia*, 17(12), 1966–1975. <https://doi.org/10.1002/alz.12362>
- Roalf, D. R., Moberg, P. J., Xie, S. X., Wolk, D. A., Moelter, S. T., & Arnold, S. E. (2013). Comparative accuracies of two common screening instruments for classification of Alzheimer’s disease, mild cognitive impairment, and healthy aging. *Alzheimer’s & Dementia: The Journal of the Alzheimer’s Association*, 9(5), 529–537.
<https://doi.org/10.1016/j.jalz.2012.10.001>
- Salloway, S., Gamez, J. E., Singh, U., Sadowsky, C. H., Villena, T., Sabbagh, M. N., Beach, T. G., Duara, R., Fleisher, A. S., Frey, K. A., Walker, Z., Hunjan, A., Escovar, Y. M., Agronin, M. E., Ross, J., Bozoki, A., Akinola, M., Shi, J., Vandenberghe, R., ... Curtis, C. (2017). Performance of [18F]flutemetamol amyloid imaging against the neuritic plaque component of CERAD and the current (2012) NIA-AA recommendations for the neuropathologic diagnosis of Alzheimer’s disease. *Alzheimer’s & Dementia: Diagnosis, Assessment & Disease Monitoring*, 9, 25–34. <https://doi.org/10.1016/j.dadm.2017.06.001>

- Saltzman, J. (2024, February 13). *Biogen Alzheimer's drug launch off to slow start*. Boston Globe. <https://www.bostonglobe.com/2024/02/13/business/biogen-leqembi-alzheimers-eisai-christopher-a-viebacher/>
- Santo, L., & Kang, K. (2023). *National Hospital Ambulatory Medical Care Survey: 2019 National Summary Tables*. National Center for Health Statistics (U.S.). <https://doi.org/10.15620/cdc:123251>
- Sarkisian, C. A., Romanov, A., & Mafi, J. N. (2024). Talking With Patients About the New Anti-amyloid Alzheimer Disease Medications. *Annals of Internal Medicine*, 177(2), 246–248. <https://doi.org/10.7326/M23-3377>
- Shcherbinin, S., Evans, C. D., Lu, M., Andersen, S. W., Pontecorvo, M. J., Willis, B. A., Gueorguieva, I., Hauck, P. M., Brooks, D. A., Mintun, M. A., & Sims, J. R. (2022). Association of Amyloid Reduction After Donanemab Treatment With Tau Pathology and Clinical Outcomes: The TRAILBLAZER-ALZ Randomized Clinical Trial. *JAMA Neurology*, 79(10), 1015–1024. <https://doi.org/10.1001/jamaneurol.2022.2793>
- Sims, J. R., Zimmer, J. A., Evans, C. D., Lu, M., Ardayfio, P., Sparks, J., Wessels, A. M., Shcherbinin, S., Wang, H., Monkul Nery, E. S., Collins, E. C., Solomon, P., Salloway, S., Apostolova, L. G., Hansson, O., Ritchie, C., Brooks, D. A., Mintun, M., Skovronsky, D. M., & TRAILBLAZER-ALZ 2 Investigators. (2023). Donanemab in Early Symptomatic Alzheimer Disease: The TRAILBLAZER-ALZ 2 Randomized Clinical Trial. *JAMA*, 330(6), 512–527. <https://doi.org/10.1001/jama.2023.13239>
- Söderberg, L., Johannesson, M., Gkanatsiou, E., Nygren, P., Fritz, N., Zachrisson, O., Rachalski, A., Svensson, A.-S., Button, E., Dentoni, G., Osswald, G., Lannfelt, L., & Möller, C. (2024). Amyloid-beta antibody binding to cerebral amyloid angiopathy fibrils and risk for amyloid-related imaging abnormalities. *Scientific Reports*, 14(1), 10868. <https://doi.org/10.1038/s41598-024-61691-2>
- Spackman, D. E., Kadiyala, S., Neumann, P. J., Veenstra, D. L., & Sullivan, S. D. (2012). Measuring Alzheimer Disease Progression with Transition Probabilities: Estimates from NACC-UDS. *Current Alzheimer Research*, 9(9), 1050–1058.
- Sullivan, S. D. (2023). Medicare Drug Price Negotiation in the United States: Implications and Unanswered Questions. *Value in Health*, 26(3), 394–399. <https://doi.org/10.1016/j.jval.2022.11.015>

- Tahami Monfared, A. A., Ye, W., Sardesai, A., Folse, H., Chavan, A., Aruffo, E., & Zhang, Q. (2023). A Path to Improved Alzheimer's Care: Simulating Long-Term Health Outcomes of Lecanemab in Early Alzheimer's Disease from the CLARITY AD Trial. *Neurology and Therapy*, 12(3), 863–881. <https://doi.org/10.1007/s40120-023-00473-w>
- Tahami Monfared, A. A., Ye, W., Sardesai, A., Folse, H., Chavan, A., Kang, K., & Zhang, Q. (2023). Estimated Societal Value of Lecanemab in Patients with Early Alzheimer's Disease Using Simulation Modeling. *Neurology and Therapy*, 12(3), 795–814. <https://doi.org/10.1007/s40120-023-00460-1>
- Teunissen, C. E., Verberk, I. M. W., Thijssen, E. H., Vermunt, L., Hansson, O., Zetterberg, H., van der Flier, W. M., Mielke, M. M., & Del Campo, M. (2022). Blood-based biomarkers for Alzheimer's disease: Towards clinical implementation. *The Lancet. Neurology*, 21(1), 66–77. [https://doi.org/10.1016/S1474-4422\(21\)00361-6](https://doi.org/10.1016/S1474-4422(21)00361-6)
- Turk, K. W., Knobel, M. D., Nothorn, A., Friedman, G., Noah, H., Campbell, B., Anderson, D. C., Charidimou, A., Mills, A., Coronel, V., Pierre, N., Reynolds, B. V., Wagner, C., Varga, L. M., Roefaro, J., Triantafylidis, L., & Budson, A. E. (2024). An Interprofessional Team for Disease-Modifying Therapy in Alzheimer Disease Implementation. *Neurology. Clinical Practice*, 14(6), e200346. <https://doi.org/10.1212/CPJ.0000000000200346>
- United Healthcare. (2023). *Leqembi (Lecanemab-Irmb) Commercial Medical Benefit Drug Policy* (2023D00125A). <https://www.uhcprovider.com/content/dam/provider/docs/public/policies/comm-medical-drug/leqembi.pdf>
- U.S. Bureau of Economic Analysis. (1947, January 1). *Personal consumption expenditures: Health care*. FRED, Federal Reserve Bank of St. Louis; FRED, Federal Reserve Bank of St. Louis. <https://fred.stlouisfed.org/series/DHLCRG3Q086SBEA>
- U.S. Bureau of Labor Statistics. (2022). *Registered Nurses: Occupational Outlook Handbook*. Bureau of Labor Statistics. <https://www.bls.gov/ooh/healthcare/registered-nurses.htm>
- US Census Bureau. (2017). *2017 National Population Projections Tables*. Census.Gov. <https://www.census.gov/data/tables/2017/demo/popproj/2017-summary-tables.html>
- US Census Bureau. (2020). *Sex by Single-Year Age* [Dataset]. Decennial Census, DEC Demographic and Housing Characteristics. <https://data.census.gov/table/DECENNIALDHC2020.PCT12?q=PCT12&d=DEC>

- US Census Bureau. (2023a, July 19). *People Ages 65 and Older Were Most Likely to Hold More Than One Health Insurance Plan*. Census.Gov. <https://www.census.gov/library/stories/2023/07/multiple-health-coverage-plans-in-2021.html>
- US Census Bureau. (2023b, November). *2023 National Population Projections Tables: Main Series*. Census.Gov. <https://www.census.gov/data/tables/2023/demo/popproj/2023-summary-tables.html>
- US Government Accountability Office. (2022). *Markets Remained Concentrated through 2020, with Increases in the Individual and Small Group Markets* (GAO-23-105672). GAO. <https://www.gao.gov/assets/gao-23-105672.pdf>
- US Preventive Services Task Force. (2020). Screening for Cognitive Impairment in Older Adults: US Preventive Services Task Force Recommendation Statement. *JAMA*, 323(8), 757–763. <https://doi.org/10.1001/jama.2020.0435>
- van Dyck, C. H., Swanson, C. J., Aisen, P., Bateman, R. J., Chen, C., Gee, M., Kanekiyo, M., Li, D., Reyderman, L., Cohen, S., Froelich, L., Katayama, S., Sabbagh, M., Vellas, B., Watson, D., Dhadda, S., Irizarry, M., Kramer, L. D., & Iwatsubo, T. (2023). Lecanemab in Early Alzheimer’s Disease. *New England Journal of Medicine*, 388(1), 9–21. <https://doi.org/10.1056/NEJMoa2212948>
- Vanness, D. J., Lomas, J., & Ahn, H. (2021). A Health Opportunity Cost Threshold for Cost-Effectiveness Analysis in the United States. *Annals of Internal Medicine*, 174(1), 25–32. <https://doi.org/10.7326/M20-1392>
- Vermunt, L., Sikkes, S. A. M., van den Hout, A., Handels, R., Bos, I., van der Flier, W. M., Kern, S., Ousset, P.-J., Maruff, P., Skoog, I., Verhey, F. R. J., Freund-Levi, Y., Tsolaki, M., Wallin, Å. K., Olde Rikkert, M., Soininen, H., Spuru, L., Zetterberg, H., Blennow, K., ... Groups, I. study. (2019). Duration of preclinical, prodromal, and dementia stages of Alzheimer’s disease in relation to age, sex, and APOE genotype. *Alzheimer’s & Dementia*, 15(7), 888–898. <https://doi.org/10.1016/j.jalz.2019.04.001>
- Yuan, J., Maserejian, N., Liu, Y., Devine, S., Gillis, C., Massaro, J., & Au, R. (2021). Severity Distribution of Alzheimer’s Disease Dementia and Mild Cognitive Impairment in the Framingham Heart Study. *Journal of Alzheimer’s Disease: JAD*, 79(2), 807–817. <https://doi.org/10.3233/JAD-200786>

Appendix 3

Model description: Clinical pathway

The clinical pathway model represents patients as groups sharing similar characteristics rather than as individuals. This design choice enables the model to efficiently handle the entire US population over age 50, approximately 125 million people (US Census Bureau, 2023b).

The clinical pathway is comprised of a series of interconnected units that allow patients to flow between them. Each unit contains a data frame of the patients within it, each row in that data frame represents a specific patient group. Groups are defined by: the number of patients, their distribution across health states, queue position, age, sex, US state, and residence type. These units can be flexibly combined to enable complex behavior, such as multiple testing. For instance, after receiving a negative test result, patients may either exit the clinical pathway or return to the pool of those seeking cognitive assessment, allowing for the possibility of repeated testing over time. Since the model's computational complexity scales with the number of groups rather than individual patients, it is practical to simulate large populations.

Test Units represent clinical tests within the health system. Each unit has a capacity (the number of tests that can be performed each timestep), a sensitivity, a specificity, and a set of health states that should test positive (detailed in Table A3.2). The testing capacity is determined by available resources, such as PET scanners. When multiple testing procedures require the same resource (for example, specialist physicians who perform dementia evaluations, treatment initiation, and side effect monitoring), they share a common capacity limit. In these cases, test units positioned later in the clinical pathway receive priority.

Patient groups entering a Test Unit join the queue at the end (represented as the final row in the data frame). During each monthly timestep, the system processes groups from the front of the queue until reaching the resource's capacity limit. Any groups not processed remain in the queue for future timesteps. The testing process generates both positive and negative results, including false positives and false negatives based on the test's sensitivity and specificity parameters. These results determine the patients' subsequent pathway progression in the following timestep.

Treatment Units operate on a similar principle to Test Units but serve a different function in the clinical pathway. Rather than conducting diagnostic tests, these units modify patients' health states. When patients arrive at a Treatment Unit in an appropriate health state (such as mild cognitive impairment), they are transitioned to a corresponding treated state (such as treated mild cognitive impairment). This treated state is associated with slower disease progression in the transition model. However, treatment is only beneficial for patients in specific health states -

patients who are cognitively normal or who have advanced to severe dementia do not experience benefits from the treatment intervention.

Pool Units in the clinical pathway represent groups of patients who are in the process of making health care decisions. There is only one pool unit in the clinical pathway: patients who are eligible to receive a primary care cognitive assessment. Each timestep, a fixed proportion of the eligible population leaves the pool to attend their primary care visit. For instance, if there are 100,000 people in the pool, and the monthly rate of attendance is 2%, then each timestep 2,000 will leave the pool to attend the visit. This attendance rate translates to an average testing frequency - in this case, patients would receive cognitive assessment once every 50 months on average (the reciprocal of the 2% monthly rate). The model allows the proportion attending the visit to vary by age (to account for Annual Wellness Visit eligibility), and health status (to allow for the fact that symptomatic individuals may be more likely to request a cognitive assessment). Pool transition probabilities are given in Table A3.1.

Outflow Units track patients who exit the main clinical pathway, whether due to successful treatment completion or their decision to discontinue cognitive testing. Although these patients have left the active treatment flow, the model continues to monitor their status and progression through different health states.

The clinical pathway also incorporates patient decisions, such as whether to proceed with a specialist referral. When patients encounter either clinical tests or make a decision, their group is split into two new groups, which each progress to different parts of the pathway. Since the model treats group sizes as continuous values, these divisions occur proportionally - for example, when a group of 23 patients splits evenly, it creates two groups of 11.5 patients each. This deterministic splitting process means the entire model operates deterministically.

As the simulation progresses, each clinical test or patient decision point increases the total number of groups by one. To prevent unlimited growth in the number of groups, the model includes an aggregation mechanism: groups that share identical characteristics are combined. For instance, if there are three separate groups of 74-year-old men from Michigan waiting for specialist appointments (with sizes of 100, 20, and 3 patients), they would be consolidated into a single group of 123 patients.

Model description: Health state and residence transition models

The model employs transition matrices to simulate changes in both health states and residence status. Due to computational constraints, these transitions are calculated annually rather than monthly. During this yearly update, each group's current health state distribution is multiplied by

the appropriate transition matrix. The model incorporates two distinct sets of transition matrices: health transition matrices and residence transition matrices.

For health transitions, the model uses 100 different matrices, accounting for both sex (male and female) and age (50-99 years). Residence transitions utilize 200 different matrices that account for age (50-99 years) and dementia severity (none, mild, moderate, or severe). Example transition matrices for both health and residence status can be found in Table A3.4.

Model description: Cost model

At the end of the simulation, the model generates annual logs that track two key metrics: the total person-years lived in each health state and the frequency of health system resource utilization. These metrics are calculated separately for patients above and below age 65. Direct medical costs are computed by multiplying observed resource utilization by corresponding unit prices (detailed in Table A3.5). The model also accounts for indirect costs using health state-specific annual rates (shown in Table A3.6), including indirect medical expenses, caregiver time costs, and formal care expenses. These calculations yield total costs, which are categorized into nine types: drug, physician, inpatient, outpatient, home care, nursing care, residential care, blood biomarker tests, and caregiver time.

The model assigns costs to different payers (Medicare, Medicaid, out-of-pocket, and private insurance) through a multi-step process. First, costs are allocated to insurance types based on the age distribution of patients (over and under 65) and their insurance coverage category (private insurance, Medicaid only, Medicare only, or dual eligible). Next, these costs are distributed among payers according to average coinsurance rates specific to both the cost type and insurance type. For example, in Medicare Part B drug coverage, Medicare covers 80% of costs while patients are responsible for the remaining 20% as out-of-pocket expenses.

The complete breakdown of insurance prevalence and cost-sharing arrangements is illustrated in Figure A3.5. The model also accounts for price variations across payers, as different insurers may pay different rates for the same services. For instance, private insurers typically pay higher rates than Medicare for outpatient services and physician procedures. These price differentials are incorporated using relative price multipliers, which are detailed in Table A3.8.

The model calculates Quality-Adjusted Life Years (QALYs) using a method similar to health state cost calculations. It multiplies the total years spent in each health state by a corresponding quality of life (specified in Table A3.7). Both costs and QALYs are subject to a 3% annual discount rate.

To evaluate the effectiveness of different scenarios, the model determines marginal costs and QALYs by comparing each scenario to a status quo baseline where no blood biomarker testing is performed. The incremental cost-effectiveness ratio is then computed by dividing the change in costs by the change in QALYs.

Clinical pathway details

Lecanemab and donanemab are currently indicated for patients aged 50-90 (Sims et al., 2023; van Dyck et al., 2023), so the clinical pathway begins with the initial prevalent population aged 50-90 and the incident population aged 50 for each subsequent timestep. When patients reach age 90 they exit the clinical pathway. Some patients exit the clinical pathway immediately and never receive a cognitive assessment. This fraction represents people who do not want a cognitive assessment, who are uninsured, who live in an area where there are too few providers to offer cognitive assessments, or who are linked to providers who have decided not to offer cognitive assessments. Those who are willing and able to receive a cognitive assessment enter a separate population and each month a fixed proportion of this population seeks an assessment. This proportion is higher among patients who are aged 65 and over, due to access to the Medicare annual wellness visit, and among those in cognitively impaired health states, since assessments are often done in response to memory complaints (Alzheimer's Association, 2019).

Patients who show impairment on a brief cognitive assessment are referred to a specialist. These assessments, such as the Mini-Mental State Examination (MMSE) or MoCA have relatively low specificities and are not designed to distinguish Alzheimer's disease pathology from other dementias (Lonie et al., 2009), so many of those referred will not have Alzheimer's disease. Most patients who do not screen positive for cognitive impairment or those who do not attend their specialist visit return to the eligible population and may seek an assessment again in the future, but a small proportion decide not to seek subsequent testing.

Dementia specialists evaluate patients to determine their stage of cognitive impairment (mild cognitive impairment, mild dementia, moderate dementia, severe dementia) and whether their presentation is consistent with Alzheimer's etiology. This assessment is individualized, but for most patients will include a detailed medical history, tests to rule out other causes of cognitive impairment, such as B₁₂ deficiency or hypothyroidism, and structural brain imaging. In cases with an atypical presentation, such as deficits in language, visuospatial cognition, or reasoning, a longer battery of neuropsychological tests may be necessary (Petersen et al., 2018). If, after assessment, a specialist believes that a patient may be eligible for treatment with Alzheimer's disease-modifying therapies, then they may refer the patient to biomarker testing to confirm the presence of amyloid plaques. Most often this is an amyloid PET scan, but CSF testing also meets CMS criteria. If the biomarker test is positive, then the specialist and patient will meet to decide

whether to initiate treatment. For Medicare to pay for a patient's treatment, this physician must participate in a qualifying registry (Centers for Medicare and Medicaid Services, 2023).

Treatment with lecanemab consists of intravenous infusions every other week. Donanemab requires infusions only once every four weeks. Side effects are common, including infusion reactions within a few hours of a dose and amyloid-related imaging abnormalities (ARIA), which usually develop over the first four months of treatment. Patients are observed for between 3 hours and 30 minutes after each dose to identify infusion reactions. Post-treatment monitoring for ARIAs consists of obtaining additional MRI scans, usually after the 5th, 7th, 14th, and 26th infusions, and in response to ARIA symptoms, such as headaches and dizziness (Cummings, Apostolova, et al., 2023). In this simulation, the treatment continues for 18 months (as in the clinical trial), or until the patient has an ARIA (modeled as a random chance in the first month of treatment), their dementia progresses beyond the mild stage, their age progresses beyond 90, or they die. Once treatment concludes or is discontinued, the patient exits the clinical pathway, though their health states are still tracked until death or the end of the simulation.

Clinical pathway inputs

Population estimates by state, sex, and single year of age from the 2020-Decennial Census (US Census Bureau, 2020) and extrapolated into future years using the growth rates from the 2017-2060 national population projection tables (US Census Bureau, 2017). Monthly estimates were linearly interpolated from annual data. Initially, the prevalent population aged 50-90 enters the clinical pathway, and each month thereafter the incident age 50 population is added.

Health care system capacity is estimated using the same methods as recent prior work (Liu et al., 2024). Health system capacities in 2021 are estimated using the 2021-2022 AHRF, which includes state-level data on the health care workforce (Health Resources and Services Administration, 2023a). These capacities are extrapolated using growth rates from the Health Resources and Services Administration (HRSA) health workforce projections from 2020 to 2035, assuming that the 2035 growth rate applies to subsequent years (Health Resources and Services Administration, 2023b). Monthly estimates were linearly interpolated from annual data.

PCPs were defined as the combined total of primary care physicians, the 61.6 % of nurse practitioners who work in primary care, and the 23.1 % of physician assistants who work in primary care (American Association of Nurse Practitioners, 2022; National Commission on Certification of Physician Assistants, 2020). Based on data from the National Hospital Ambulatory Medical Care Survey, PCPs were assumed to conduct 2,051 visits per year on average, of which up to 5% could include a brief cognitive assessment (Santo & Kang, 2023).

Dementia specialist capacity was defined as the sum of neurologists, geriatricians, and geriatric psychiatrists. The AHRF does not separately report geriatricians or geriatric psychiatrists, these were assumed to represent 2.6% of all internal medicine and family medicine physicians and 2.9% of all psychiatrists, respectively (Association of American Medical Colleges, 2021; Beck et al., 2018). Each specialist was assumed to provide 1,576 visits per year and spend 5% of these visits on diagnosing Alzheimer's disease and managing disease-modifying therapies, on average (Santo & Kang, 2023).

State-level AHRF data only include PET scanners in hospital settings, so these capacities were scaled by the total number of PET scanners in all settings (Lam et al., 2021). Each PET scanner was assumed to complete up to 1,166 scans annually (OECD, 2023), of which 50% were assumed to be available for Alzheimer's disease assessments (Liu et al., 2017). Infusion capacity was defined based on the 20% of registered nurses and the 15.2% of licensed practical nurses who work in outpatient settings (Coffman et al., 2015; U.S. Bureau of Labor Statistics, 2022), with each nurse able to administer 1,440 infusions per year, of which up to 20% could be used for administering disease-modifying therapies on average (Santo & Kang, 2023).

Details on patient demand and decision parameters, including in the low uptake scenario, are given in Table A3.1.

Table A3.1: Patient demand parameters

Patient Demand Variable	Baseline Demand	Low Demand
Proportion of patients who are willing to get a cognitive assessment	70%	30%
Proportion of those willing to get a cognitive assessment, who are over age 65 and have cognitive impairment who screen each year	30%	5%
Proportion of those willing to get a cognitive assessment, who are over age 65 and have normal cognition who screen each year	6%	1%
Proportion of those willing to get a cognitive assessment, who are age 50-64 and have cognitive impairment who screen each year	5%	0%
Proportion of those willing to get a cognitive assessment, who are age 50-64 and have normal cognition who screen each year	0%	0%
Proportion with a positive cognitive assessment who attend their specialist visit	70%	70%
Proportion of those with a negative cognitive assessment who exit clinical pathway	10%	10%
Proportion who exit the clinical pathway after specialist evaluation	20%	20%
Proportion who exit the clinical pathway after biomarker review	20%	20%

Each clinical test has a set of positive states and a corresponding sensitivity and specificity. The sensitivity of a cognitive assessment conducted in primary care in the general population was set to 0.84 and the specificity to 0.79, based on using the MoCA to differentiate the cognitively normal population from patients with mild cognitive impairment (Abd Razak et al., 2019; Roalf et al., 2013). Specialists are assumed to be very accurate at differentiating cognitive impairment and dementia from cognitively healthy patients, with a sensitivity and specificity of 0.97, but unable to conclusively differentiate Alzheimer's disease pathology from other dementias. Based on concordance with Consortium to Establish a Registry for Alzheimer's Disease (CERAD) criteria, PET scans are assumed to detect amyloid pathology with a sensitivity of 0.92 and a specificity of 0.88 (Salloway et al., 2017). Test parameters are shown in Table A3.2.

Table A3.2: Clinical test parameters

Test	Sensitivity	Specificity	Positive States	Source
Cognitive Assessment	0.84	0.79	Any cognitive impairment (mild cognitive impairment or dementia)	Roalf (2013), Abd Razak (2019)
Blood Biomarker	0.89	0.69	Any amyloid positivity (including cognitively normal)	Nakamura (2018)
Specialist Evaluation	0.97	0.97	Any cognitive impairment (mild cognitive impairment or dementia)	Assumption
PET Scan	0.92	0.88	Any amyloid positivity (including cognitively normal)	Salloway (2017)

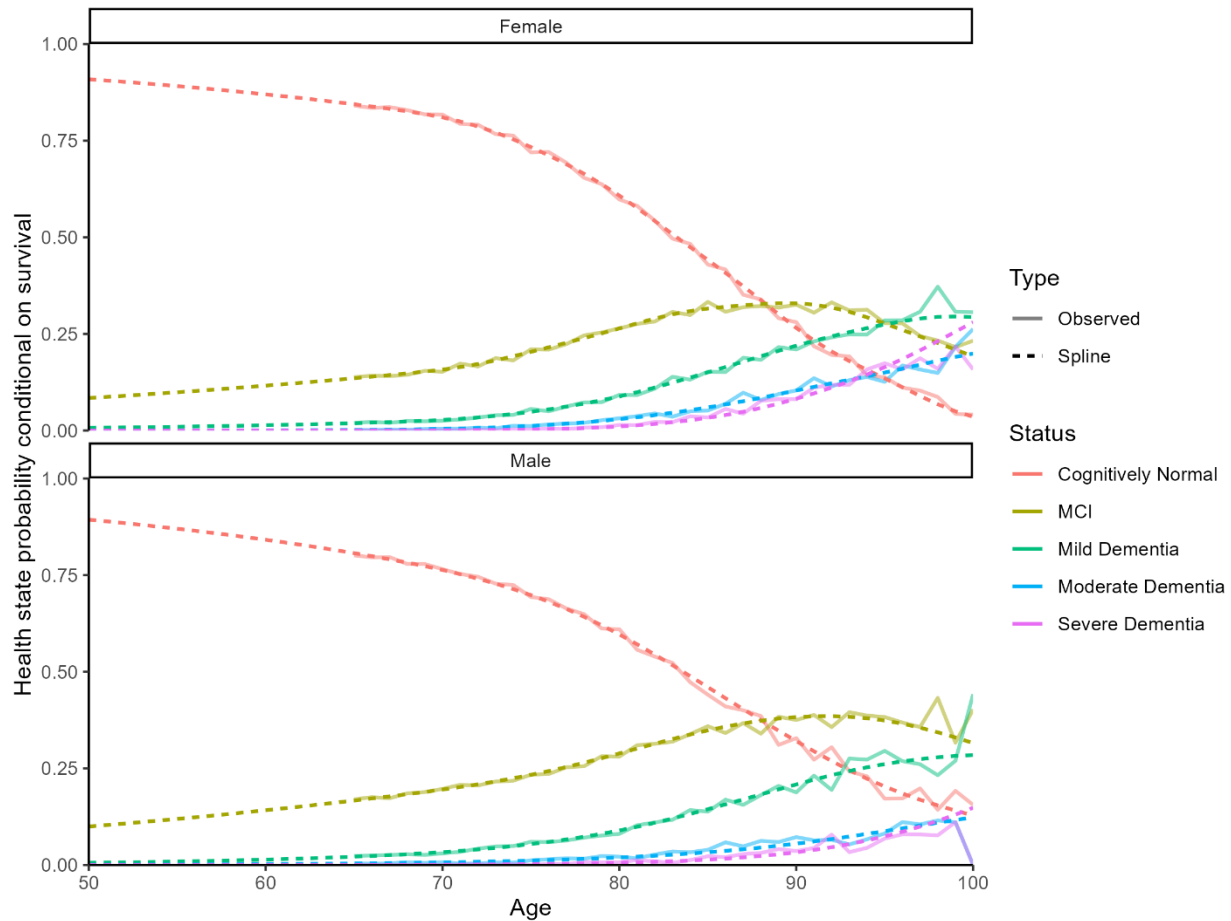
Data for lecanemab are taken from the Clarity AD phase III clinical trial and the appropriate use recommendations (Cummings, Apostolova, et al., 2023; van Dyck et al., 2023). Patients receive lecanemab for 18 months via 36 infusions every other week. There is a 6.9% chance that a patient will have an adverse event that causes discontinuation of the treatment and this is assumed to, on average, occur after one full month of treatment. About 2.7% of patients have an adverse event leading to hospitalization, including additional costs and disutility (Arbanas et al., 2023). Based on lecanemab clinical trial data, it is unclear whether the treatment effect persists after treatment concludes. However, the trial for donanemab, showed that the amyloid clearance and the protective effect of treatment remained transitioning treated individuals to a placebo arm (Sims et al., 2023). Amyloid may slowly reaccumulate in the brain, with a secondary analysis of an earlier trial estimating it would take approximately 4 years for patients to become amyloid-positive again (Shcherbinin et al., 2022). Treatment effects in the model persist on average for 4 years, or until a patient develops moderate dementia.

Health transition inputs

Health-state population prevalences by age were calculated using HRS data for individuals aged 65-100, which has categories equivalent to normal cognition, mild cognitive impairment, and dementia. Continuous cognitive scores developed by RAND researchers were used to further subdivide the dementia category into mild, moderate, and severe stages (Hudomiet et al., 2022). First, the overall proportions of mild, moderate, and severe dementia were determined using the mean of rates observed in two studies (Davis et al., 2018; Yuan et al., 2021). Cognitive score thresholds that would reproduce these overall population proportions were identified and applied to individual cognitive scores to classify each person with dementia into mild, moderate, or severe categories.

Data were aggregated by age and sex to calculate the mean probability of being in each health state by age. These estimates were smoothed and extrapolated to ages 50-64 by fitting gamma splines with a log-link. Prevalence probabilities were used to generate population estimates for each health state in each US state. Plots of observed health state prevalence and fitted splines are shown by sex and age in Figure A3.1.

Figure A3.1: Observed and fitted health state prevalence by sex and age



NOTES: Solid lines are observed data, dashed lines are fitted splines. MCI: Mild cognitive impairment

National Vital Statistics lifetables were used to calculate the average probability of death by age and sex (Arias & Xu, 2022). Mortality hazard ratios by dementia stage (relative to being cognitively normal) were estimated using Cox-proportional hazard models (Crowell et al., 2023). The parameters for these models were chosen such that they had similar average hazard ratios to a registry study (Aye et al., 2024), the hazard ratio was 1 for mild cognitive impairment, increasing for more advanced dementia, and decreasing with age (Crowell et al., 2023). These hazard ratios were used to calculate death probabilities by age and health state. Death probability

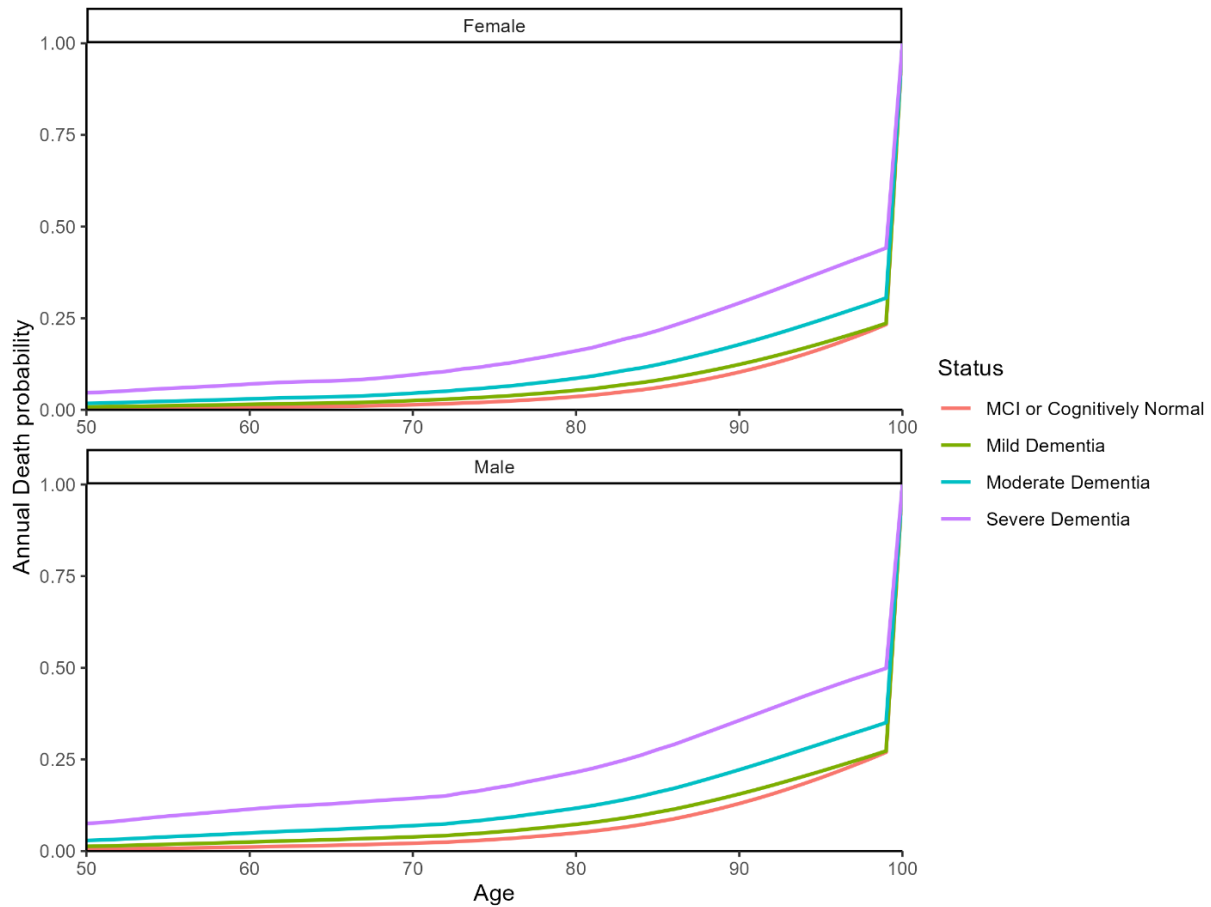
was set to 1 at age 100. Death probabilities by age and health state are shown in Figure A3.2 and the parameters used to calculate hazard ratios are shown in Table A3.3.

Table A3.3: Cox-proportional hazard model coefficients for mortality hazard ratios by age and health status.

Parameter	Coefficient
Main Effects	
Cognitively Normal	1
Mild cognitive impairment	1
Mild Alzheimer's disease	7.5
Moderate Alzheimer's disease	28
Severe Alzheimer's disease	125
Interaction Term	
Cognitively Normal x Age	1
Mild cognitive impairment x Age	1
Mild Alzheimer's disease x Age	0.98
Moderate Alzheimer's disease x Age	0.97
Severe Alzheimer's disease x Age	0.96

The hazard ratio for health state h , age a , health state main effect β , and health state age interaction γ is given by: $HR_{h,a} = \beta_h \times \gamma_h^a$. For instance, a 99-year-old with severe dementia has: $HR_{severe,99} = 125 * 0.96^{99} = 2.2$

Figure A3.2: Annual mortality probabilities by age and health status



NOTES: Probability of death assumed to be 1 at age 100. MCI: Mild cognitive impairment

Age-specific health state transition probabilities were initialized using matrices reported in a prior study National Alzheimer's Coordinating Center (NACC) Uniform Data Set and then modified such that they were consistent with prevalence data (Davis et al., 2018). Transition probabilities were chosen for ages 65 and 99, linearly interpolated for ages 65-99, and assumed to be constant for ages 50-65. The steady-state prevalence was calculated by multiplying the state prevalence vector at age 50 by each age transition matrix, producing state prevalence estimates for each age. The values for ages 65 and 99 were then modified until the calculated prevalence implied by the transition matrices matched the prevalence data estimated from the HRS shown in Table A3.1. These matrices are reported in Table A3.4.

Table A3.4: Annual transition probabilities for men ages 65 and 99

Age	Initial State	Cognitively Normal	Cognitively Normal (amyloid)	MCI	Mild Dementia	Moderate Dementia	Severe Dementia	Other CI	Treated MCI	Treated Mild Dementia	Death
65	Cognitively Normal	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
65	Cognitively Normal (amyloid)	0.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02
65	MCI	0.00	0.00	0.93	0.06	0.00	0.00	0.00	0.00	0.00	0.02
65	Mild Dementia	0.00	0.00	0.00	0.89	0.08	0.00	0.00	0.00	0.00	0.03
65	Moderate Dementia	0.00	0.00	0.00	0.14	0.75	0.05	0.00	0.00	0.00	0.06
65	Severe Dementia	0.00	0.00	0.00	0.00	0.07	0.80	0.00	0.00	0.00	0.13
65	Other CI	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.00	0.00	0.06
65	Treated MCI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.04	0.02
65	Treated Mild Dementia	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.91	0.03
65	Death	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
99	Cognitively Normal	0.62	0.00	0.06	0.00	0.00	0.00	0.06	0.00	0.00	0.27
99	Cognitively Normal (amyloid)	0.00	0.62	0.06	0.00	0.00	0.00	0.06	0.00	0.00	0.27
99	MCI	0.00	0.00	0.50	0.23	0.00	0.00	0.00	0.00	0.00	0.27
99	Mild Dementia	0.00	0.00	0.00	0.55	0.18	0.00	0.00	0.00	0.00	0.27
99	Moderate Dementia	0.00	0.00	0.00	0.03	0.36	0.25	0.00	0.00	0.00	0.35
99	Severe Dementia	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.50
99	Other CI	0.00	0.00	0.05	0.00	0.00	0.00	0.60	0.00	0.00	0.35
99	Treated MCI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.16	0.27
99	Treated Mild Dementia	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.60	0.27
99	Death	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

NOTES: CI: Cognitive impairment; MCI: Mild cognitive impairment

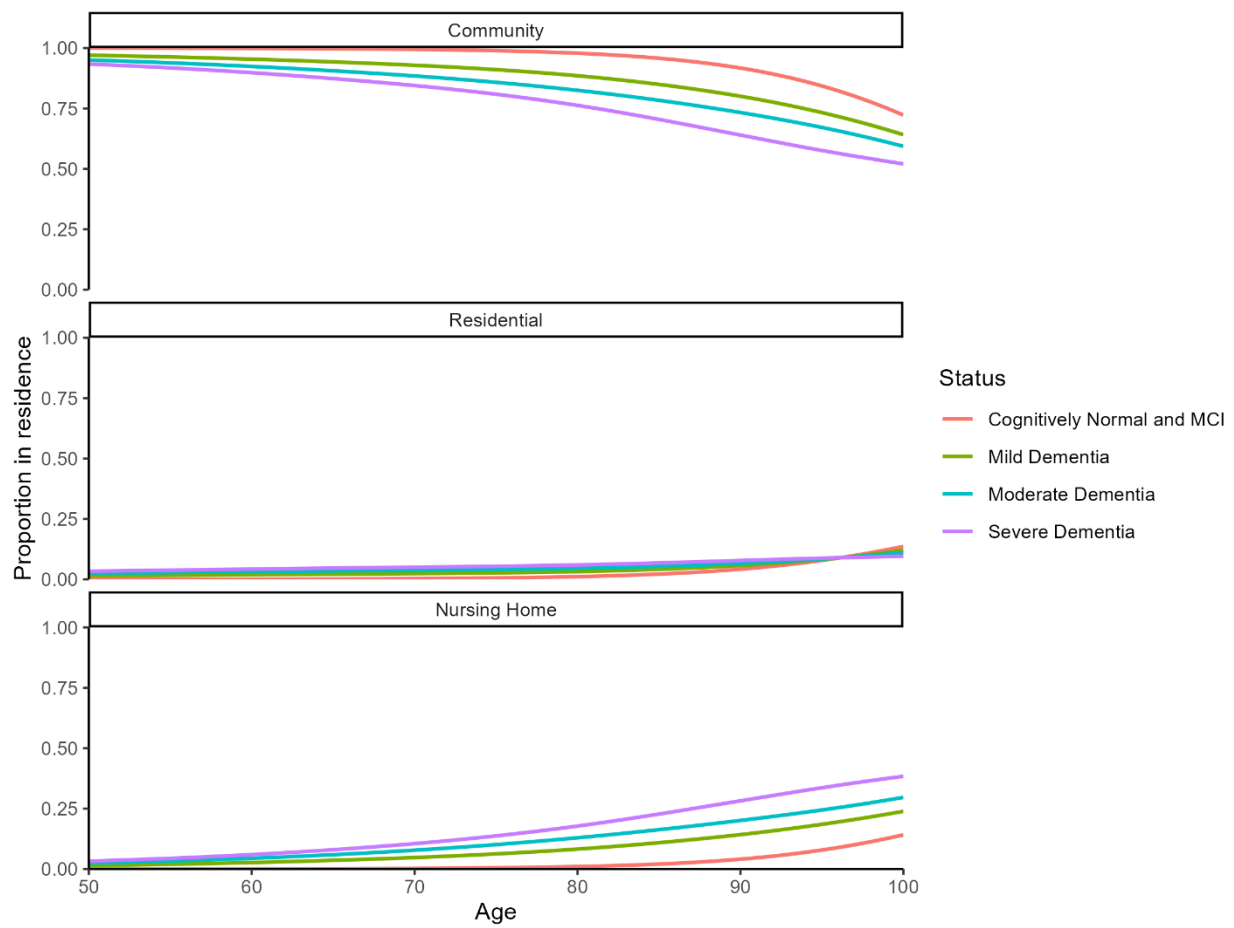
Residence transition inputs

Data from the National Health and Aging Trends Study (NHATS) were used to estimate prevalence and transition probabilities for residence type (NHATS, 2023). The NHATS includes data on residence type, 5-year age group, and cognitive scores. A previously validated methodology was used to impute dementia status (probable dementia or cognitively normal) using cognitive scores from three domains (Kasper et al., 2013). Data from NHATS waves 1-11, was used to estimate prevalence and transition probabilities.

The prevalence of each residence type was estimated as the survey-weighted mean for each 5-year age group and scaled such that it matched US totals from the National Post-acute and Long-term Care Study (National Post-acute and Long-term Care Study, 2023). Similarly, transition probabilities between each residence type were estimated as the survey-weighted mean of transitioning across any two consecutive waves (censoring individuals who were not observed across consecutive waves).

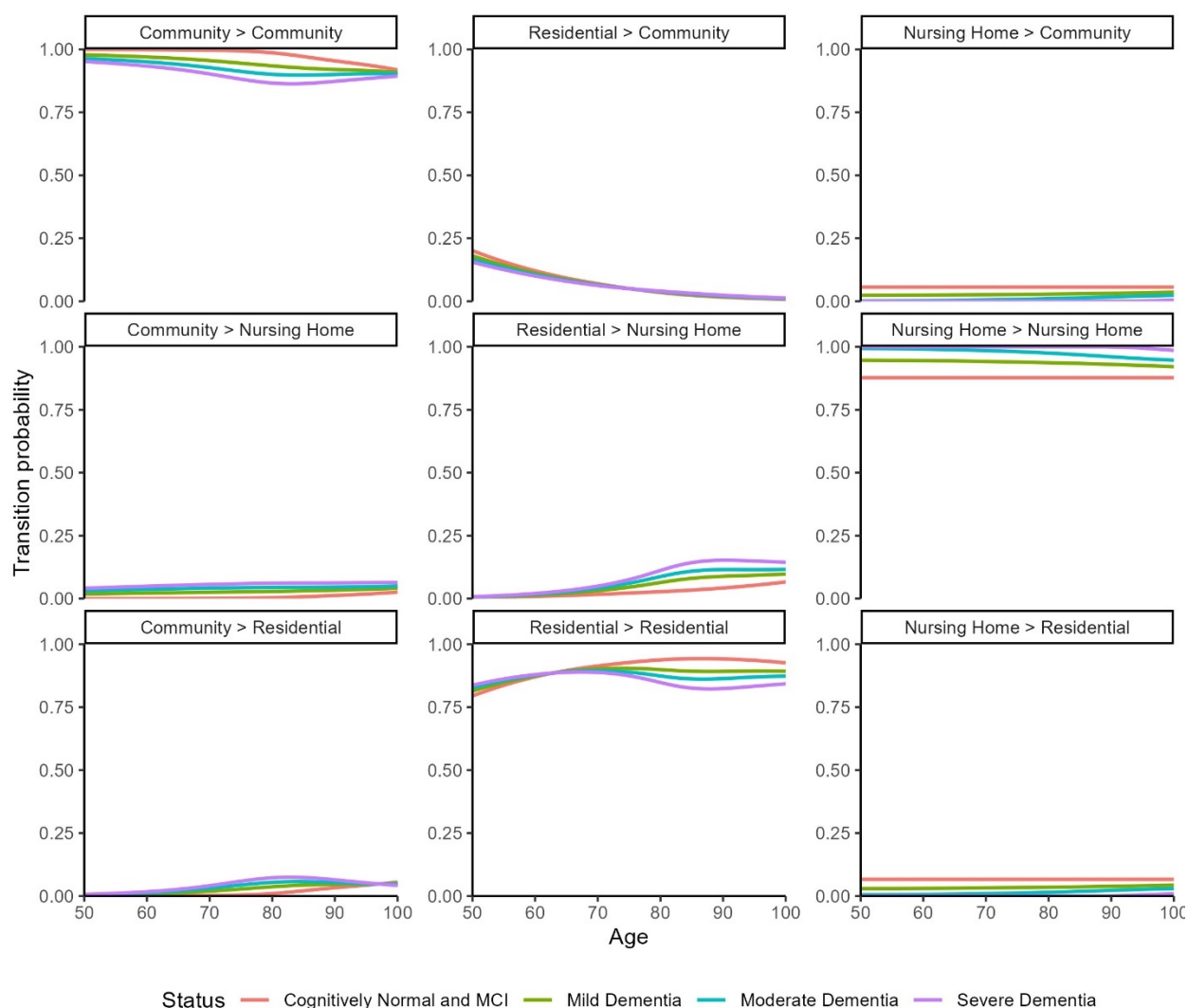
5-year age group estimates from age 65-95 were extrapolated to age 50-100 and interpolated to single-year age groups by fitting gamma splines with a log link using generalized additive models. Patients with mild cognitive impairment were assumed to have the same prevalence and transition probabilities as cognitively normal patients. There was too little data to estimate age-specific probabilities of transitions out of nursing homes, these were assumed to be constant with age. Prevalence and probabilities were split between mild, moderate, and severe dementia states such that the probability of transitioning to a nursing home is 4 times higher in moderate and severe states relative to mild, matching observational data (Spackman et al., 2012). Plots of residence type by age and health status are shown in Figure A3.3. Corresponding transition probabilities are shown in Figure A3.4.

Figure A3.3: Residence state prevalence by health state and age



NOTES: MCI: Mild cognitive impairment

Figure A3.4: Residence state annual transition probabilities by health state and age



NOTES: Probability of nursing home transition is assumed to be constant with age. MCI: Mild cognitive impairment

Cost model inputs

Medicare unit costs for specialist visits, MRI scans, PET scans, infusions, and ARIA hospitalization are obtained from a prior study of lecanemab costs (Arbanas et al., 2023). The list price of \$26,500 was used for the cost annual of the lecanemab. Annual wellness visit cost was estimated to be \$165, based on Medicare data (Centers for Medicare and Medicaid Services, 2024a), and the brief cognitive assessment was assumed to take 40% of the visit, leading to a unit cost of \$65. Medicare covers a separate visit for a more detailed cognitive assessment using CPT code 99483, and this was not considered.

Patient indirect medical costs, caregiver time costs, and home care costs attributable to Alzheimer's Disease and related dementias were obtained from a recent study of HRS patients (Nandi et al., 2024), and split into mild, moderate, and severe dementia using prevalence-weighted ratios from a survey of health care use among dementia patients (Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023). These costs were assumed to be zero among patients with normal cognition, and half the value of mild dementia for mild cognitive impairment. Residential home and nursing home costs were taken from the national Genworth 2023 cost of care survey and assumed to be the same for all health states, conditional on being in that residence (Genworth, 2023). Caregiver time costs and disutility were reduced to 44% of their original value for patients in residential or nursing home care (DiBenedetti et al., 2020; Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023). All costs were inflated to 2024 dollars using an index of health care expenditures (U.S. Bureau of Economic Analysis, 1947). Service costs are shown in Table A3.5 and health state costs are shown in Table A3.6

Table A3.5: Health service costs

Service	Cost Type	Cost	Source
PCP Visit	Physician	\$65	(Arbanas et al., 2023) (Centers for Medicare and Medicaid Services, 2024a)
Specialist Visit	Physician	\$164	(Arbanas et al., 2023)
MRI	Outpatient	\$468	(Arbanas et al., 2023)
PET Scan	Outpatient	\$1,646	(Arbanas et al., 2023)
Monthly Drug Cost	Drug	\$2,208	(Arbanas et al., 2023)
Monthly Infusion	Outpatient	\$281	(Arbanas et al., 2023)
ARIA Hospitalization Cost	Inpatient	\$15,466	(Arbanas et al., 2023)

NOTES: Monthly drug cost is based on the annual manufacturer list price divided by twelve. ARIA: Amyloid related imaging abnormality MRI: Magnetic resonance imaging; PCP: Primary care provider; PET: Position emission tomography

Table A3.6: Health state costs

Health State	Medical Costs	Home Care Costs	Residential Care Costs	Nursing Home Costs	Caregiver Time Cost (community residence)	Caregiver Time Cost (Residential or Nursing Home)
Cognitively Normal	\$0	\$0	\$66,169	\$113,799	\$0	\$0
Mild cognitive impairment	\$1,196	\$2989	\$66,169	\$113,799	\$0	\$0
Mild Dementia	\$2,391	\$5978	\$66,169	\$113,799	\$13,589	\$5,979
Moderate Dementia	\$3,183	\$9,522	\$66,169	\$113,799	\$20,079	\$8,835
Severe Dementia	\$3,657	\$15,967	\$66,169	\$113,799	\$33,612	\$14,789

NOTES: Residential care costs are conditional on residence in these settings. The difference in residential cost between health states occurs because different proportions of patients are in each residence type.

Quality of life (QoL) estimates for each health state were based on proxy-reported averages from a systematic review (Landeiro et al., 2020). Cognitively normal individuals were assumed to have a QoL of 0.85 (Lin et al., 2023). Caregiver and side effect disutility were based on estimates from previous studies (Tahami Monfared, Ye, Sardesai, Folse, Chavan, Kang, et al., 2023). Parameter values for QoL are given in Table A3.7.

Table A3.7: Health state utilities

Health State	Patient QoL	Caregiver Disutility	Severe Side Effect Disutility
Cognitively Normal	0.85	0	0.0137
mild cognitive impairment	0.8	0	0.0137
Mild Dementia	0.74	0.036	0.0137
Moderate Dementia	0.59	0.07	0.0137
Severe Dementia	0.36	0.086	0.0137

NOTES: QoL: Quality of life.

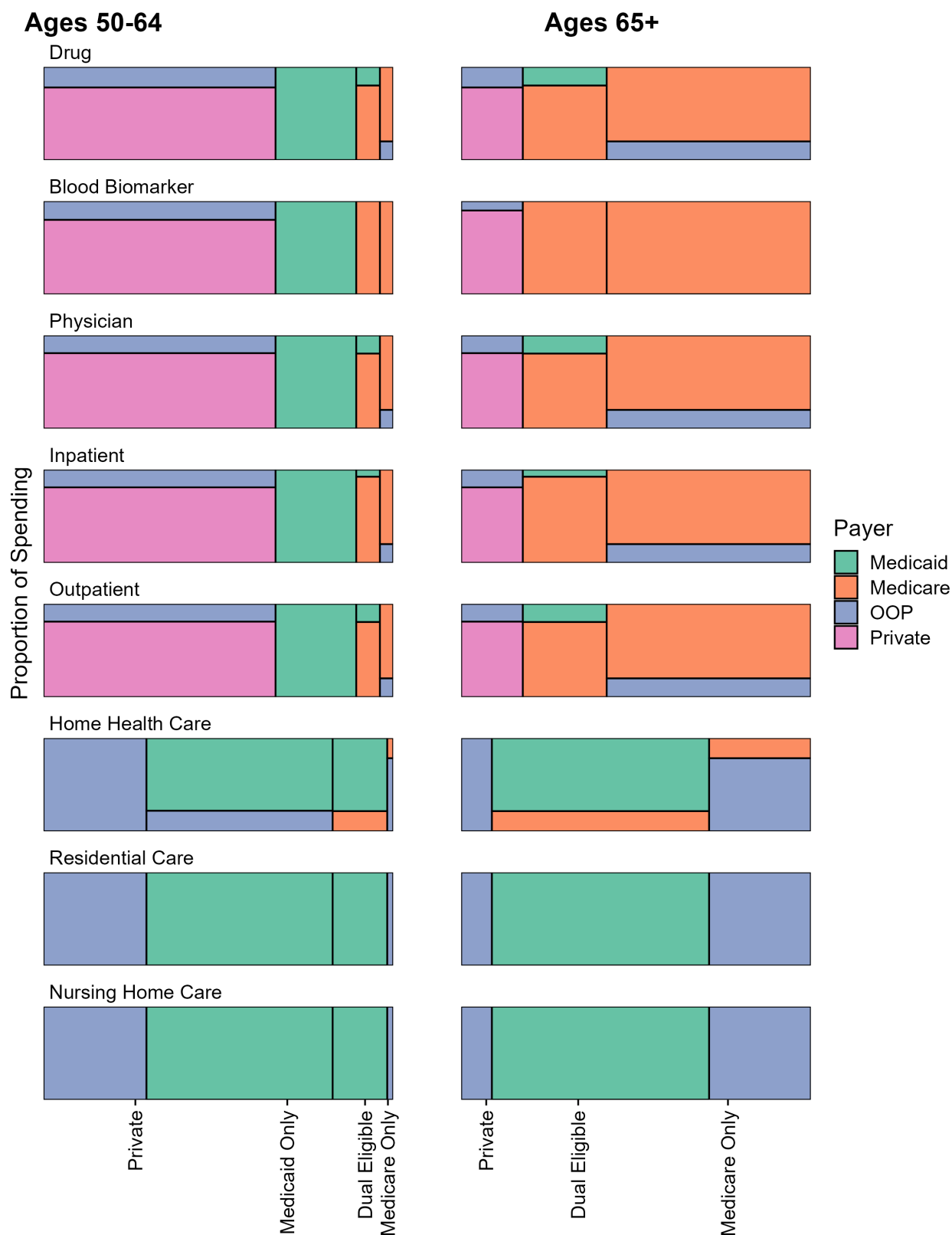
Insurance coverage prevalences for over-65s and 45-64-year-olds were based on National Center for Health Statistics data (Cha & Cohen, 2022). These values were corrected to assign over-65s with small group coverage to Medicare since Medicare usually pays first for these individuals (US Census Bureau, 2023a; US Government Accountability Office, 2022).

Patients with Alzheimer's disease are 2.4 times more likely than the general population to have Medicaid coverage than the general population (Alzheimer's Association, 2023). In addition, patients with Medicaid are more likely to use nursing homes, 62% of nursing home patients have Medicaid coverage (KFF, 2017) so the proportion of individuals with Medicaid coverage in these settings was inflated to match these figures.

It is assumed that Alzheimer's disease-modifying therapies are covered by Medicare, which pays 80% of drug, inpatient, outpatient, biomarker, and physician costs, with the remaining 20% being paid OOP or by Medicaid for dual eligibles (MACPAC, 2013) Lecanemab is administered via infusion, so is treated as a Part B, rather than Part D expense for Medicare beneficiaries. Clinical lab tests are assumed to be entirely covered by Medicare. Likewise, private plans are assumed to cover lecanemab and blood biomarker tests, paying for 80% of these costs on average with the remaining 20% paid out of pocket by enrollees.

Based on data from dual eligibles, Medicare is assumed to pay for 22% of home health care costs and the remaining 78% is paid for either out of pocket or by Medicaid (MedPAC & MACPAC, 2024). All residential care costs are paid by Medicaid for enrollees and are paid out of pocket otherwise. Insurance populations and coinsurance rates are shown in Figure A3.5.

Figure A3.5: Insurance populations and coinsurance rates by age group and cost type



NOTES: OOP: Out-of-pocket.

Payers may pay different prices for the same services, and these differences can be large, especially for outpatient services. The cost model applies average payment ratios identified in a literature review to price private inpatient, outpatient, and physician care relative to Medicare (Congressional Budget Office, 2022). The model also includes the relative price of Medicare to Medicaid for physician, outpatient, and inpatient costs (American Hospital Association, 2018; Kaiser Family Foundation, 2019). On average, Medicaid pays 65% of private payers for nursing home care (MACPAC, 2023), and this ratio was also applied to residential care. All payers were assumed to face the same prices for drugs, blood biomarkers, and home care. A list of relative prices is given in Table A3.8, all relative prices not given in the table are assumed to be 1.

Table A3.8: Relative prices by payer

Payer	Relative to	Cost Type	Multiplier
Medicaid	Medicare	Inpatient	1.01
Medicaid	Medicare	Outpatient	1.01
Medicaid	Medicare	Physician	0.72
Medicaid	Private	Nursing Home Care	0.65
Medicaid	Private	Residential Care	0.65
Private	Medicare	Inpatient	1.82
Private	Medicare	Outpatient	2.40
Private	Medicare	Physician	1.29

Donanemab Inputs

The modeling of donanemab as a treatment option was based on inputs from the Trailblazer-Alz 2 phase III clinical trial (Sims et al., 2023). For patients with mild cognitive impairment or mild dementia, donanemab treatment reduced progression to more severe dementia stages by 29% compared to untreated patients. Treatment effects were measured using CDR-SB scores rather than Integrated Alzheimer's Disease Rating Scale (iADRS) scores to maintain consistency in effectiveness measures between lecanemab and donanemab. Donanemab showed an 8.8% discontinuation rate due to side effects, higher than lecanemab, but a lower rate of severe side effects causing hospitalization at 1.6%.

Donanemab's trial design incorporated amyloid monitoring at 24-week intervals. Patients achieving amyloid clearance were switched to a placebo and maintained outcomes equivalent to those continuing treatment. Approximately half of the patients transitioned to placebo within 12

months. The model assumed an average treatment duration of 15 months, equivalent to half of patients being treated for 12 months and half for 18 months. The reduced treatment duration decreased treatment and infusion costs but required more PET scans compared to lecanemab due to the additional monitoring requirements. Donanemab has half the infusion frequency of lecanemab. The model assumes patients receive 50% more PET scans and 50% fewer infusions in donanemab scenarios compared to lecanemab scenarios. The model incorporated donanemab's higher annual list price of \$32,000

Outcomes

Wait times are tracked by observing when each group enters and exits a health system resource. The wait time for that unit is calculated as the population-weighted average of all wait times begun within a specified period (e.g., by year). Overall wait times are calculated as the sum of waits across all health system resources. This produces a wait time estimate for the entire clinical pathway, even though many patients will only progress part way before testing negative and may be tested multiple times. Wait times are only known upon exiting a queue and so are right-censored. To avoid this biasing our results, 5 additional years (until the end of 2049) are simulated so that wait times can be estimated for anyone who has not yet left a queue in 2044. For any patients remaining after these additional years, their remaining wait times are estimated based on extrapolating health resource capacity, queue position, and death rates.

Patients are counted as treated if they receive clinical benefit from treatment. These are patients who receive the treatment while having mild cognitive impairment or mild dementia attributable to Alzheimer's disease and do not have side effects that cause discontinuation in the first month. Patients who do not receive clinical benefit are not counted, otherwise, this outcome could be maximized by treating all patients, regardless of health status.

Costs are estimated using the cost model and differenced with the status quo scenario by payer and type. QALYs are estimated similarly; once per year, the number of individuals in each health state is counted and multiplied by the corresponding QoL values for patients, caregivers, and disutility from side effects. Costs and QALYs are not extrapolated beyond the end of the simulation.

Validation

Model outputs in 2025 were compared against projections from other studies for the number of people with Alzheimer's disease (both male and female), the resident population of nursing homes, the resident population of assisted living facilities, and total health care spending attributable to Alzheimer's disease for out-of-pocket costs, Medicare, and Medicaid. These comparisons are shown in Table A3.9

Table A3.9: Validation targets and errors for 2025

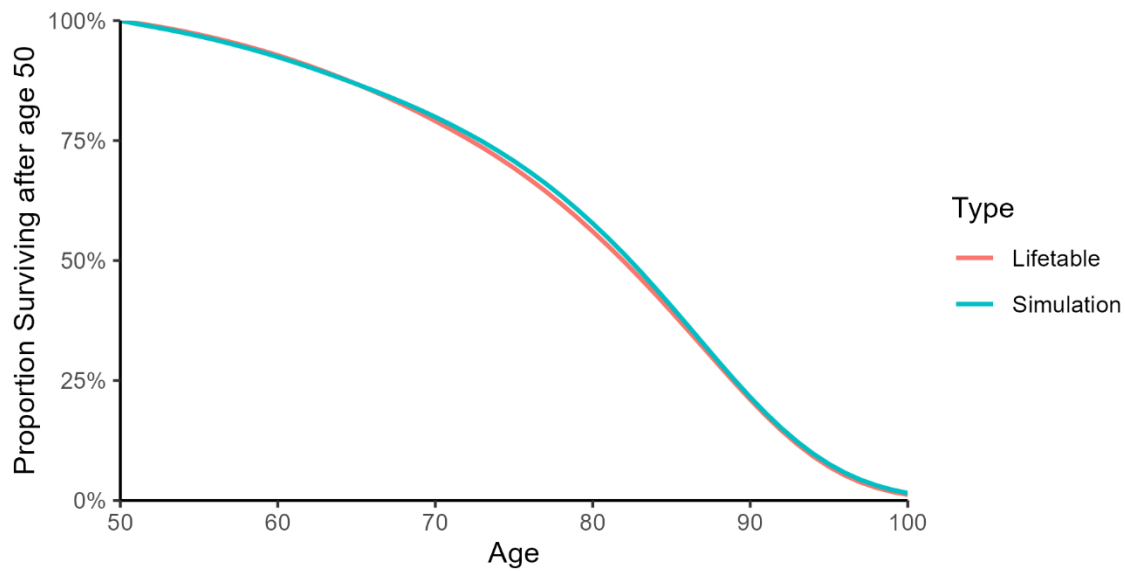
Variable	Model	Target	Percentage difference	Source
Number of men with Alzheimer's disease	3,680,000	4,100,000	-10.2%	(Matthews et al., 2019)
Number of women with Alzheimer's disease	2,300,000	2,520,000	-8.7%	(Matthews et al., 2019)
Residential care residents	790,000	818,000	-3.4%	(National Post-acute and Long-term Care Study, 2023)
Nursing home residents	1,220,000	1,290,000	-5.4%	(National Post-acute and Long-term Care Study, 2023)
OOP costs attributable to Alzheimer's disease (billions USD)	212	213	-0.3%	(Nandi et al., 2024)
Medicaid costs attributable to Alzheimer's disease (billions USD)	130	141	-8.0%	(Nandi et al., 2024)
Medicare costs attributable to Alzheimer's disease (billions USD)	40	39	2.3%	(Nandi et al., 2024)

NOTES: OOP: Out-of-pocket; USD: United States Dollar

The model reproduces external studies reasonably accurately. It underestimates the number of individuals with Alzheimer's disease, which may contribute to the underestimate of nursing home residents. The model may underestimate dementia prevalence because it does not include some covariates that are associated with dementia prevalence, such as race, education, and income.

The simulation's mortality rates were validated against lifetables (Arias & Xu, 2022). The validation process involved multiplying the incident population's vector of health states by yearly transition matrices for ages 50-100, separately by sex. Figure A3.6 compares the fraction of individuals surviving after age 50 between the simulation and lifetable data.

Figure A3.6: Validation survival curve comparison



Policy Implications

This dissertation looks at how changes in three different health policies affect access to care. Each essay has different policy implications.

Chapter 1 examined COVID-19 vaccination equity across racial and ethnic groups, finding that Black individuals were less likely to be vaccinated than the general population. The analysis demonstrated the importance of controlling for vaccine eligibility when interpreting vaccination rates. While early pandemic narratives suggested Hispanic communities were hesitant to receive their first vaccine dose compared to White communities (Reitsma et al., 2021), the data showed the opposite: eligible Hispanic individuals consistently had higher vaccination rates than eligible White individuals. The key barrier to vaccination in Hispanic communities was not hesitancy but eligibility, specifically the slower rate at which vaccines were made available to younger age groups. This pattern differed for booster shots, where eligible Hispanic individuals showed lower uptake rates than all other groups, suggesting that targeted outreach for boosters could improve health outcomes.

CDC faced significant challenges in determining vaccine priorities during the pandemic. While they prioritized groups with the highest mortality risk - primarily the elderly and those with comorbidities (CDC, 2021) - this age-based approach had unintended consequences. Because the White population is, on average, older than other racial and ethnic groups, the age-based criteria effectively gave them priority access, even though other racial groups faced higher overall mortality risks. However, it is unclear what a better policy would have been because age is a better predictor of COVID-19 outcomes than race (Gold, 2020). In addition, explicitly prioritizing racial groups would have been politically and legally fraught. One option would be to incorporate additional risk factors that drove racial disparities in mortality, such as occupations with high mortality rates (rather than only those deemed essential), additional comorbidities, and population density. A distribution strategy based on these factors might have achieved both more efficient vaccine distribution and more equitable uptake across racial groups.

The political polarization surrounding the COVID-19 public health response poses challenges for managing future pandemics. Notably, some of the populations with the lowest vaccination and were in relatively affluent, privileged communities with strong anti-vaccine sentiments. This pattern mirrors the historically low childhood vaccination rates observed in certain wealthy neighborhoods (Berezin & Eads, 2016). The vaccination data in Chapter 1 supported this trend, showing that White populations were less likely to receive initial vaccinations and experienced higher mortality rates than Hispanic and Asian populations by mid-2022. These findings present a unique challenge for policymakers, as they contradict traditional public health narratives about health disparities. In addition, it is important to recognize that future pandemics will likely have different mortality and transmission patterns than COVID-19. Policymakers must develop flexible approaches to prioritization and equity instead of extrapolating COVID-19-era policies.

Chapter 2 estimated how managed care payment reform impacted access to Medicaid dental services. The analysis found that emergency department visits for non-traumatic dental conditions increased immediately after managed care implementation, suggesting that children who previously received care from dentists began seeking treatment in emergency departments instead. This immediacy of the policy impact suggests that the transition itself was disruptive, potentially because of restrictions on dental provider choice under managed care. Other research has documented similar disruption during Indiana's managed care transition (Nasseh & Bowblis, 2022).

Seventeen states still administer Medicaid dental services primarily through fee-for-service payment. As these states consider transitioning to managed care, they can design their programs to minimize disruption to patients. One potential strategy is to ensure patients can maintain relationships with their current dentists through default plan and provider assignments. States

could also explore alternative payment structures that control costs without requiring restrictive provider networks. For example, Medicare's accountable care organization system uses retrospective assignment based on utilization patterns and creates cost-reduction incentives without disrupting existing patient-provider relationships. Minimizing disruption is particularly important for Medicaid beneficiaries, who often face multiple demands on their time and may have limited resources to navigate complex health care choices.

Before implementing any statewide changes, states should thoroughly evaluate their proposed modifications through pilot programs with appropriate control groups.

Chapter 3 assessed how expanding biomarker testing in primary care settings could affect access to new Alzheimer's disease-modifying therapies. Introducing blood biomarkers could significantly reduce specialist wait times, though at a substantial cost. Since Medicare is the primary payer for both clinical laboratory services and pharmaceuticals for older adults, these costs would largely fall on the federal program. While CMS maintains considerable authority over blood biomarker payment decisions, it is unclear how they should balance the competing priorities of treatment access and health care spending.

CMS has several tools available if it approves blood-based biomarkers for Alzheimer's disease testing. Through coverage with evidence determination, CMS could impose specific conditions on blood biomarker usage, such as requiring concurrent PET scans to gather evidence in support of their replacement with blood tests. CMS could also leverage its market power and role as a price-setter to manage costs through two mechanisms. First, by negotiating drug prices through the pharmaceutical negotiation program (S. D. Sullivan, 2023), and second, by strategically setting clinical laboratory test prices. Prices for new laboratory tests are typically based on similar existing tests and there is considerable ambiguity in determining which tests are the closest equivalent. For blood biomarkers, CMS could either compare them to routine blood protein tests, resulting in lower prices, or to Alzheimer's disease CSF tests, leading to higher prices. For 2025, CMS has delegated price setting to Medicare Administrative Contractors, who have chosen a price comparable to CSF tests (Centers for Medicare and Medicaid Services, 2024).

CMS must weigh the long-term implications of its pricing decisions for blood biomarkers. Setting prices too low could discourage innovation in Alzheimer's disease therapies and might lead to inadequate test availability. Furthermore, investing in screening and diagnostic infrastructure could accelerate progress toward widespread effective Alzheimer's disease treatment. This consideration is particularly relevant given the growing emphasis from

pharmaceutical companies on treating preclinical Alzheimer's disease (Jack Jr. et al., 2024), where blood biomarkers would serve as a crucial tool for early identification and diagnosis.

CMS faces a complex balancing act: they must first determine whether to cover blood-based biomarkers and then, if covered, set prices that are both fiscally responsible and encourage continued innovation.

Further research to inform CMS coverage policy decisions should address several key areas. Studies should examine how blood biomarker testing affects treatment equity across different populations. Research could also identify which patient subgroups would derive the greatest benefit from blood biomarker testing and evaluate whether testing should be limited to these populations. A randomized controlled trial of blood biomarker testing in primary care settings could determine how testing impacts patient outcomes and identify how testing changes which patients are treated.

This dissertation demonstrates how policymakers face complex tradeoffs between access, cost, equity, and efficiency across a broad range of health care contexts. These case studies show that even well-intentioned policies can have unexpected consequences, particularly for vulnerable populations. To achieve better outcomes, policymakers must carefully design health policies with advance planning, evaluate pilot programs before widespread implementation, and remain willing to revise policies that fail to deliver their intended results.