Submission: Integrity of the National Disability Insurance Scheme

Prosperity Institute, Mark Humphery-Jenner

About Prosperity Institute: Prosperity Institute is dedicated to developing policy that 'grows the pie', leading to a more prosperous, higher growth, society.

Author: Mark Humphery-Jenner, PhD is an Associate Professor of Finance, and the founder and CEO of Otso Capital. He is also the founder of the Prosperity Institute. He has published more than 40 peer reviewed articles in leading journals, especially on governance, law and finance.

1 Key recommendations

This submission recommends that Australia significantly reduce NDIS costs to below the growth rate of the economy (specifically the growth in non-government GDP). Key recommendations to achieve this include:

1. NDIS spending is increasing faster than GDP, and especially faster than non-government GDP. This is unsustainable and NDIS cost increases must be reduced.
2. The government should impose a hard cap on NDIS growth to be the rate of growth of non-government GDP. This is essential because the NDIS relies on tax revenue. If it grows faster than the rate of non-government GDP, then tax revenue will tautologically be insufficient. This will result in NDIS service rationing. But, it will reduce the growth rate to be below the rate of GDP growth.

3. Reduce the number of conditions the NDIS covers. This can include reducing the severity levels that qualify for coverage.
4. Audit NDIS plan administrators in a randomized manner to monitor for profligate and wasteful spending, akin to how transport security spot-checks bags for threats. The risk of random audits, and penalties for profligate spending, can incentivize plan administrators to reduce spending. Do similarly for NDIS service providers.
5. Provide incentives for NDIS plan administrators who reduce spending, subject to the services being provided (i.e., as certified by a recipient). This gives the administrator an incentive to cost control.
6. Significantly greater scrutiny of 'overservicing' is required. As this submission outlines, specific regions have supernormal numbers of NDIS providers, which cannot be explained by demographic factors. The government should scrutinize billings where they appear to be 'abnormal' so as to reduce potential overspending.

In this Submission, Section 2 outlines the issues with NDIS spending and highlights that the NDIS is not financially sustainable. Section 3 contains several recommendations to reduce NDIS spending growth. Section 4 highlights that there is abnormal spending in specific regions and that regulators should focus attention on whether this has created networks of overservicing that require additional attention. The analysis contained in this submission draws upon my working paper in relation to the NDIS (see Humphery-Jenner, 2026).

2 The NDIS is not financially sustainable

Social service programs cost tax payers significant amounts of money. Health programs must be sustainable in order to be viable over the long term and to maintain their social license. This is important because unsustainable programs will ultimately become underfunded, putting pressure on budgets and rendering them vulnerable to economic headwinds (see e.g., Cylus et al., 2026).

The NDIS is simply not sustainable. The NDIS costs at least AUD 45 billion per year (Australian Government: Department of Health, Disability and Ageing, 2025) whereas Australia's GDP is around AUD 1.9 trillion, meaning that the NDIS accounts for approximately 2.2% of GDP. The purpose of such programs can be to alleviate the significant ancillary costs associated with managing disabilities (Desborough et al., 2025). Expenditure is growing at around 7.8% pa (Commonwealth of Australia, 2025, tbl. 5.3.1), which is faster than GDP. Therefore, the government, and taxpayer, should want value for money. Some cost-constraint efforts center around consumer cost-sharing and incentive-linked mechanisms (Glied, 2026; Remmerswaal et al., 2019).

The corollary of the foregoing is clear: If a program's cost grows faster than non-government GDP, money will run out. The focus is on non-government GDP growth because this is where tax revenue comes from (by contrast, GDP growth due to government spending tautologically involves using tax revenue). It is impossible to increase taxes to solve this: higher taxes will reduce non-government GDP growth. And, even if GDP growth remained unchanged, once tax rates ratchet up, receipts will continue to grow at the pace of GDP, which means that the NDIS spending would continue to outpace tax receipts. In short, we cannot maintain a program that grows faster than the economy because spending will grow faster than income.

3 Recommendation reduce spending and coverage

It is initially necessary to significantly reduce NDIS spending growth. There are several key ways to approach this to begin with. All such approaches will help to reduce the size of the NDIS.

3.1 Recommendation: Hard cap on NDIS spending growth

The initial stages of cost control should involve a cap on NDIS spending growth. A hard cap on spending growth is the most immediate recommendation to control NDIS costs. This hard cap should be the rate of non-government GDP growth. The rationale is tautological: a government program is not viable if it grows faster than the rate of growth in the economy.

The hard cap on spending will have some consequences: it will result in service rationing. This is tautological: it is clear that more people want to avail themselves of government money than there is money available, and this increases faster than the increase in money. A cap tautologically means that some people will miss out. Initially, this might result in some 'deserving' people being rationed out of the system. This is why a follow-on step is necessary as outlined below.

3.2 Recommendation: reduce NDIS coverage

The second step, after NDIS rationing, should be to reduce NDIS coverage. The NDIS simply covers too many conditions. Currently, the NDIS covers more than 700,000 Australians (NDIS, 2026a). Given the scope of the cost blowouts, government should consider trimming the number of people covered by the NDIS by reducing the number, or severity of the conditions. One way to do this is to assess potential recipients based on the severity of their condition, and restrict NDIS coverage based on severity, thereby denying coverage to lower end issues.

3.3 Recommendation: copayments

At present, NDIS recipients largely receive coverage and treatments for free. From the recipients perspective, this creates perfectly inelastic demand: the recipient will use as much of the service as possible because they do not pay the bill. This creates overuse and creates insensitivity to prices. For example, when a recipient does not pay, they do not need to find a cheaper service provider. One solution to this is to make demand more elastic by requiring a percentage copayment. Even a “small” copayment creates a price signal. Government can calibrate the desired percentage. However, even if that percentage is in the single digits, it creates a price signal ‘nudge’, which helps to inject elasticity into demand, thereby helping to somewhat reduce NDIS usage.

3.4 Recommendation: random audits, monitoring and/or incentives for frugality

The present NDIS situation creates a perverse incentive to spend more. This is because NDIS funding is typically administered for the ultimate recipient via a plan administrator. The administrator has no incentive to reduce costs. Indeed, they theoretically could have an incentive to maintain high coverage so as to generate management fees. But, because the plan administrator gains nothing from shopping around and finding low cost service providers, wastage can accrue. This can arise because of the aforementioned desire to grow the NDIS receipt pool (and fees) or rational inattention (i.e., because it is not worthwhile to scrutinize the ultimate service providers).

A solution to this is spot checks on NDIS plan administrators. The NDIS itself need not scrutinize every plan (or even a majority). However, the NDIS should randomly audit NDIS plan administrators for wasteful spending. Much like how security randomly checks bags at airports, random monitoring can be a low cost way to ensure compliance. This should not be so onerous or time consuming as to add cost, however.

The NDIS could also create incentives for driving down costs. These can include bonuses for *not* spending all of a recipient's theoretical maximum. These must be carefully calibrated so as to avoid gamesmanship. That is, it must be a bonus conditional on certification that the services were adequately provided.

4 Recommendation: scrutinize abnormal service provision

The government must also remove incentives to grow NDIS service provision. At present, it appears that there is a network of NDIS providers who have identified a lucrative revenue stream. This leads to a push to 'find' ways to extract government money. If the government scrutinizes service providers, then it reduces the incentive to establish a low quality service provider.

Concerns about unwarranted geographic variation arise from several sources. Enforcement actions in Australia (NDIS, 2026b) and the United States (White House, 2026) indicate that fraudulent provider activity does occur, though its prevalence is difficult to establish from enforcement data alone. Furthermore, given that misconduct tends to permeate among social networks (Dimmock et al., 2018), fears might arise about regional pockets of overservicing. Conversely, a separate and equally important concern is that some areas may be underserved, potentially entrenching access inequalities (Smith-Merry and Chang, 2025). Both concerns raise the same practical question: how can regulators use existing data to identify areas that warrant further investigation, whether for overprovision or for access gaps?

This section provides an approach to screen for, and identify, pockets of potential overservicing. The key recommendation from this section is to focus on reasons that appear to have abnormal service provision. We below identify that there are such regions of abnormal service levels and demonstrate ways to search for such regions.

4.1 Summary

Background: Governments face pressure to contain the cost of demand-driven health and social service schemes while ensuring adequate provision in under-served areas. Australia's National Disability Insurance Scheme (NDIS), which costs around AUD 45 billion annually (2.2% of GDP) and is growing faster than GDP, offers a setting to examine how regulators can identify geographic variation in provider supply.

Objective: To develop a replicable approach for identifying postal areas with higher- or lower-than-predicted provider numbers, so that scarce monitoring resources can be targeted efficiently.

Methods: We combine NDIS provider records (n ≈ 78,600 across 2,677 postal areas) with demographic, socio-economic, and health variables from the 2021 Australian Census. We apply chi-squared tests for geographic clustering and ordinary least squares regressions of log provider counts on demographic predictors, and use the residuals to identify outlier postal areas.

Results: Provider numbers are significantly clustered (χ^2 = 264,558, df = 2,676; p<0.01). Demographics explain approximately 80% of variation in provider counts. Provider numbers rise with population and proximity to GPs, and fall with median age, income, and proximity to hospitals. Areas with higher Indigenous populations have fewer providers. Residuals identify postal areas with provider counts materially above or below predicted values.

Conclusions: Regulators of demand-driven schemes can use routinely collected demographic data and provider registers to identify geographic outliers warranting review. We recommend publishing annual outlier lists and integrating residual-based screening into existing compliance workflows within 12 months, prioritizing review of the top 5% of positive-residual areas.

4.2 Background

This paper develops a practical approach that regulators can use to identify geographic pockets of potential overservicing and underservicing using routinely available data. The approach looks for clusters of provider frequency that cannot be explained by demographic characteristics, allowing regulators to focus scarce monitoring resources on areas where further investigation is most likely to be warranted. Concerns about fraud are one motivation for this kind of targeting, but the approach is equally useful for identifying access gaps and for broader market-stewardship functions.

We make several key insights. We first highlight a straightforward approach to determining whether social service provision clusters by region and identifying regions with the greatest amount of abnormal service provision (i.e., overservicing) and the most apparent scarcity (potential underservicing). We further document the demographic and socio-economic correlates of provider location, finding that roughly 80% of cross-sectional variation in provider counts is explained by a parsimonious set of population and demographic characteristics. The paper thus has implications for how regulators, and scrutineers, might focus their limited resources to improve service provision and investigate areas of potential overservicing.

4.3 Methods

The paper analyzes medical social service providers in Australia. These are within the NDIS scheme. The NDIS scheme involves the government funding private enterprises to perform health-adjacent services for people with disabilities, with the list of qualifying disabilities being broadly defined. The list of services is also broad, ranging from quasi-medical services through to administrative service in relation to people with disabilities.

We analyze the distribution, and drivers, of NDIS provider numbers. By way of context, Australia is divided into six states and territories, within which are postal areas. We focus on the number of NDIS providers within each postal area. This is because demographic data is also collected at the postal level. Thus, if we wished to obtain the number of NDIS providers per person, we would need to do this at the postal region level.

We collect NDIS provider data from the NDIS website (NDIS, 2026c). The NDIS provider data updates daily, meaning that the precise number of providers fluctuates. We collected data on 3 January 2026. The dataset is cross-sectional. We obtain this by downloading the underlying JSON file that contains the data. The NDIS provider information includes the address and head office for most providers; however, for some providers the precise address is kept confidential. The NDIS data also includes a Post code entry (denoted

Post_cd). We use this to assign each provider to a post code. We include providers across all registration groups. We then count the number of providers in each post code.

We next obtain demographic and statistical data for each post code region. We obtain this from the Australian Bureau of Statistics (ABS) 2021 Census. Here, we scrape the ABS 'QuickStats' pages for information on the location's population, age distribution, income, demographic data (including indigenous and overseas-born populations), education, reported health conditions, and employment status. Summary statistics for the variables are in Table 1.

We perform several types of statistical tests. We start with standard Chi-squared tests for clustering by post-code. The goal here is to see whether different postcodes have meaningfully different numbers of providers; and thus, whether further analysis is warranted. We next regress provider numbers onto various factors that might explain the number of providers.

We explore several regression specifications. Our preferred specification is to regress the natural logarithm of one plus the number of providers onto a set of factors that might explain that number, which we denote as ln(Providers). We prefer natural logs to raw counts because raw counts can be susceptible to skewness due to outliers. We prefer to look at the number of providers, and control for population counts, rather than look at the number of providers per capita. This is because the denominator in a per capital model (i.e., the population number) is plausibly mechanically endogenous with other population-level regressors. Our 'base' regression specification is ordinary least squares. We default to using robust standard errors. However, we also ensure the results are robust to clustering standard errors by state and to using state fixed effects.

We start with a parsimonious specification of baseline factors. These factors are designed to capture health and population data that might influence healthcare demand. The key variables include the number of people in the region, average children per family, median age, proportion of the population that are male, proportion with *no* long term health condition, proportion of the population that are indigenous, aboriginal, or Torres Strait islander, the proportion that require disability assistance, the percentage of the population under the age of 19, and the number of hospitals and GPs within 5km of the region. These characteristics are from the 2021 census; and thus, tautologically pre-date the provider data, which is from January 2026.

We also check that the results are robust to different regression specifications. These include tobit regressions, regressions where we require that the number of providers in the region be above the median, and regressions where we focus on the middle 50% of locations in terms of provider counts.

The third step is to then explore whether other extraneous factors influence provider numbers. These include the median weekly income, education level (i.e., proportion with tertiary education), proportion born in Australia, proportion that speak only English at home, and the proportion that are unemployed.

4.4 Results

4.4.1 Descriptive evidence of clustering

Figure 1 presents a heatmap of registered NDIS providers by postal area for the greater Sydney region. The map is descriptive and does not adjust for population or demographic composition, but it indicates substantial variation in provider counts across neighbouring postal areas.

The underlying distribution is heavily right-skewed. The postal area with the highest provider count in our data is 2170, with 795 providers. The mean number of providers across postal areas is 29.38, the median is 9, the standard deviation is 53.89, and the skewness coefficient is 5.3.

We test for clustering using two chi-squared specifications, each with 2,676 degrees of freedom. The first assumes that, under the null of no clustering, every postal area would have the mean number of providers (29.38). The second calculates expected provider counts as the national average providers-per-person multiplied by each postal area's population. The 1% critical value for this distribution is approximately 2,849. The test statistic is 264,558.8 in the first specification and 140,739.7 in the second. Both reject the null of uniform distribution at conventional levels.

4.4.2 Regression estimates of demographic drivers

Table 2 reports ordinary least squares regressions of the natural logarithm of one plus the number of providers on postal-area demographic characteristics. The parsimonious specification in Column 1 yields an adjusted R-squared of 0.807. Adding income, education, country of origin, language, and unemployment controls in Column 2 raises the adjusted R-squared only modestly. Column 3 adds state fixed effects and clusters standard errors by state.

Several coefficients are statistically significant at the 1% level across specifications. Population size enters positively. Median age enters negatively. Proximity to hospitals (within 5 km) enters negatively, while proximity to general practitioners enters positively. The share of the population identifying as Indigenous enters negatively in Column 1.

Among the extended controls in Column 2, log median income enters negatively and is significant at the 1% level. The share of the population that speaks only English at home enters negatively, as does the unemployment rate. Tertiary education, country of birth, and the share of the population requiring disability assistance are not statistically significant in the main specifications. The results are broadly consistent when we restrict the sample to New South Wales (Column 4) and Victoria (Column 5), the two largest states.

4.4.3 Top-quartile sub-sample

In the robustness appendix, we also analyze the regions with the greatest number of providers. Here, we undertake regressions restricted to postal areas in the top quartile of provider counts (those with at least 34 providers). Two coefficients change sign relative to the full sample. First, proximity to hospitals enters positively rather than negatively. Second, the share of the population requiring disability assistance enters negatively. This negative relationship holds whether we measure disability need as a share of the population or as an absolute count.

4.4.4 Robustness

We verify that the main results are robust to alternative specifications, including tobit regressions, OLS estimated on the sub-sample with provider counts above the median, and OLS estimated on the middle 50% of postal areas by provider count. Full results are reported in the Robustness Appendix. The signs, significance, and approximate magnitudes of the main coefficients are preserved across these specifications.

4.4.5 Identifying outlier postal areas

Having estimated the demographic drivers of provider counts, we use the regression residuals and predicted values to identify postal areas that deviate substantially from what demographics predict. For each postal area we compute the difference between actual and predicted provider counts, expressed in both absolute and proportional terms.

Table 3 reports the 20 postal areas with the highest raw provider counts, alongside their predicted values from the Column 3 regression in Table 2. A substantial number of high-count postal areas have actual provider counts materially above their predicted values. The rankings are stable across the regression specifications in Table 2.

4.5 Discussion

4.5.1 Principal findings

This study examined geographic variation in registered NDIS provider numbers across Australian postal areas and asked whether routinely available demographic data can help regulators identify areas warranting further scrutiny. Three findings stand out. First, provider numbers are highly clustered: a small number of postal areas account for a disproportionate share of registered providers, and chi-squared tests reject the null of uniform distribution at conventional levels whether the benchmark is equal counts per postcode or counts proportional to population. Second, a parsimonious set of demographic variables (population size, age structure, proximity to hospitals and general practitioners, and indicators of disability need) explains approximately 80% of the cross-sectional variation in provider counts, indicating that most of the observed variation is predictable from characteristics that regulators already observe. Third, after adjusting for these demographics, a non-trivial number of postal areas remain clear outliers in both directions, with provider counts materially above or below predicted values.

4.5.2 Interpretation

Several of the individual coefficients warrant comment. The negative relationship between median age and provider counts is consistent with the structure of the scheme itself: NDIS eligibility is capped at age 65, and a substantial share of participants are children with conditions such as autism and ADHD. Thus, regions with younger populations mechanically generate higher demand. The negative coefficient on proximity to hospitals, paired with the positive coefficient on proximity to general practitioners, is consistent with hospitals and NDIS providers acting as partial substitutes while general practitioners and NDIS providers act as complements, plausibly because GPs are central to the referral pathway for scheme access.

The negative relationship between median income and provider counts is more striking. One reading, consistent with established evidence on the income-health gradient, is that lower incomes are associated with worse health outcomes (Ettner, 1996; Hasager and Jorgensen, 2026; Thomson et al., 2022), which in a demand-driven scheme translates into higher realised demand and in turn attracts supply. A second, non-exclusive reading is that higher-income households substitute toward privately-funded services that sit outside the NDIS register altogether, mechanically reducing the count of registered providers we observe in high-income areas. Both readings point to the same caution: raw provider counts should not be read as a measure of service adequacy without adjusting for the private-market alternative.

The finding that postal areas with larger Indigenous populations have fewer providers per capita is particularly concerning from an equity standpoint. The most likely mechanism is geographic: Indigenous populations in Australia are disproportionately located in remote and very remote areas, and workforce supply to these areas is known to be constrained by factors including limited schooling and spousal employment opportunities, social distance from urban professional networks, and the relative compensation structure for remote practice. This is a long-standing challenge in Australian rural health policy and our results suggest it extends into the disability-services workforce as well.

The sign flip on the disability-assistance coefficient in the top-quartile sub-sample is the most puzzling result and deserves careful framing. In the full sample, areas with greater reported need for disability assistance have (weakly) more providers, as one would expect. Restricting to the top quartile of provider-dense areas, however, reverses this relationship: the most provider-dense areas have proportionally *fewer* residents reporting disability assistance needs. One possible interpretation is the emergence of provider "hubs" that serve catchments extending well beyond their home postal area, meaning the local population characteristics do not reflect the population being served. Another is that some high-density clusters reflect provider entry driven by factors other than local unmet need: a pattern that, while not direct evidence of waste, is consistent with the kind of supply-side behaviour that warrants regulatory attention. We cannot distinguish these interpretations with cross-sectional data, and we resist drawing stronger conclusions than the evidence supports.

4.5.3 Relation to prior literature

These findings connect to several established strands of research. The documentation of large, demographically-unexplained geographic variation in provision echoes the long tradition of small-area variation research in healthcare originating with Wennberg and Gittelsohn (1973), which has consistently found that clinical need explains only a portion of where care is delivered. More recent work on place effects in healthcare utilisation has used patient migration to decompose variation into demand-side and supply-side components. Finkelstein, Gentzkow, and Williams (2016) find that in the US Medicare population, 40 to 50% of geographic variation in utilisation is attributable to demand-side factors such as health and preferences, with the remainder driven by place-specific supply factors including provider behaviour and local practice norms. Our results are consistent with this broader pattern and extend it to a demand-driven disability-services context that has not previously been examined using administrative provider data.

The paper also speaks to the cost-containment literature reviewed by Stadhouders et al. (2019), which catalogues a wide range of policy levers including price controls, budget caps, and demand-side cost-sharing. Our contribution is complementary rather than substitutive: we do not propose a new containment instrument, but rather a targeting tool that allows whatever enforcement and market-stewardship resources a regulator already has to be directed where they are most likely to yield returns. In a scheme where total expenditure exceeds 2% of GDP and is growing faster than the economy, even modest improvements in targeting efficiency could translate into meaningful savings.

Finally, our results contribute to the emerging empirical literature on the NDIS specifically. Prior work has examined the scheme from institutional and equity perspectives (Salignac et al., 2024; Smith-Merry and Chang, 2025) but has not, to our knowledge, applied a systematic geographic-variation lens to the registered provider population. The approach we propose is deliberately replicable with data the scheme regulator already holds.

4.5.4 Policy implications

Three implications follow from these findings. First, regulators of demand-driven social service schemes should incorporate residual-based geographic screening into routine monitoring. The approach requires only a provider register, small-area demographic data, and a standard regression, capabilities that are well within the reach of most national scheme administrators. We would suggest annual publication of outlier lists and prioritised compliance review of the top 5% of positive-residual postal areas as a concrete operational target achievable within a 12-month horizon.

Second, the negative-residual tail deserves separate attention. Areas with provider counts well below demographic predictions, particularly those with larger Indigenous populations or high reported disability need, represent a different policy problem and call for different instruments, including market-stewardship interventions such as provider-of-last-resort arrangements, targeted recruitment incentives, or outreach funding. Treating positive and negative residuals symmetrically in a single "variation" frame risks conflating over-servicing concerns with access-gap concerns, which have opposing policy responses.

Third, our findings reinforce the broader point that transparency of provider-level administrative data has significant public value. Much of what we do in this paper could in principle be done by any researcher, journalist, or civil-society organisation with access to the provider register; continued public availability of these data supports accountability in a scheme that commands substantial public resources.

Although we focus on Australia’s NDIS, the approach applies broadly to demand-driven social and health service systems internationally. Examples include Medicaid-funded disability and home-care services in the United States, personal budget systems in the United Kingdom and the Netherlands, and long-term care insurance programs in Japan and Germany. These schemes share key characteristics: open provider entry, geographically heterogeneous demand, and administrative registers of providers. Residual-based geographic screening could therefore be implemented across multiple jurisdictions using routinely available data, enhancing regulatory targeting and improving equity of access.

4.5.5 Limitations

Several limitations should be noted. First, our analysis is cross-sectional. Provider numbers in 2026 are plausibly correlated with provider numbers in earlier years, meaning we cannot cleanly separate contemporaneous demographic drivers from historical patterns of entry. For the purposes of identifying current outliers this is not a serious problem (i.e., the regulator cares about where supply sits now, not why it got there) but it limits the causal claims we can make about the determinants of provider location. A related concern is reverse causation, since people with disabilities may migrate toward areas with better service availability, meaning provider location could itself shape the demographic characteristics we use as predictors. However, given the time-lag between the census data on which we base the population data, and the 2026 NDIS data, we argue that such reverse-causality is moderated in our study.

Second, we measure registered rather than active providers. The NDIS register includes entities that may be dormant or delivering minimal services, and our counts therefore overstate the true operational footprint in ways that may vary systematically by region. Linked data on actual billing activity would improve the precision of the outlier identification.

Third, our specification adjusts for a rich but not exhaustive set of demographic controls and does not model spatial autocorrelation explicitly. Provider location decisions are plausibly influenced by conditions in neighbouring postcodes, and a spatial-lag or spatial-error specification might refine the residual rankings. We verified that our substantive conclusions are unchanged across tobit, trimmed-sample, and fixed-effects specifications (see Robustness Appendix), but acknowledge that spatial econometric techniques represent a natural extension.

Fourth, provider counts alone are a coarse measure of scheme performance. They do not capture service quality, participant outcomes, or value-for-money, all of which a comprehensive regulatory framework would also need to assess. Our contribution is a targeting tool for one slice of the monitoring problem, not a complete assessment framework.

Finally, the approach is designed for demand-driven schemes with open provider entry and reasonably complete provider registers. Its applicability to schemes with different market structures (i.e., capitated systems, closed provider panels, or fee-for-service arrangements with strong gatekeeping) would require adaptation.

4.6 Conclusions

Regulators of demand-driven social service schemes face two simultaneous pressures: constraining expenditure in a context of rising outlays, and ensuring adequate provision in under-served areas. Enforcement and market-stewardship resources are scarce, and targeting those resources efficiently is itself a policy problem.

This paper has shown that a simple and replicable approach can help. Using routinely available data on registered providers and small-area demographics, a standard regression explains roughly 80% of the cross-sectional variation in NDIS provider counts across Australian postal areas. The residuals from that regression identify postal areas whose provider supply sits materially above or below what demographics would predict. Positive residuals indicate areas that warrant compliance review. Negative residuals, particularly in regions with high reported disability need or large Indigenous populations, indicate access gaps that call for targeted market-stewardship responses.

The approach requires no data that a scheme regulator does not already hold, and it can be implemented within existing monitoring workflows. While our application is to the Australian NDIS, the method generalizes to any demand-driven scheme in which provider registration is observable and small-area demographic data are available. In a program that accounts for more than 2% of Australian GDP and is growing faster than the economy, even modest gains in targeting efficiency would translate into meaningful returns to scarce public resources.

5 Bibliography

Australian Government: Department of Health, Disability and Ageing, 2025. Budget 2025–26: Strengthening the National Disability Insurance Scheme [WWW Document]. URL https://www.health.gov.au/resources/publications/budget-2025-26-strengthening-the-national-disability-insurance-scheme-html?language=en (accessed 1.30.26).

Commonwealth of Australia, 2025. Budget Strategy and Outlook: Budget Paper No 1.

Cylus, J., Thomson, S., Gregori, M.S., Martinez, M.G., Garcia-Ramirez, J.A., Evetovits, T., 2026. Health financing and population ageing: evidence on the links between financial sustainability and financial hardship from the PASH simulator. Health Policy 169, 105617. https://doi.org/10.1016/j.healthpol.2026.105617

Desborough, J., Maskell-Knight, C., Wang, S., Parkinson, A., Butler, D., Law, H.-D., Butler, K., Watts, L., Huynh, E., Hodson, F., Ibrahim, S., Veitch, J., Kingsford-Smith, J., Kidd, M., Donaldson, C., 2025. Lived experience of out-of-pocket costs of health care and medicines by people with chronic conditions and their families in Australia: a systematic review of the qualitative literature. Health Policy 158, 105359. https://doi.org/10.1016/j.healthpol.2025.105359

Dimmock, S.G., Gerken, W.C., Graham, N.P., 2018. Is Fraud Contagious? Coworker Influence on Misconduct by Financial Advisors. Journal of Finance 73, 1417–1450. https://doi.org/doi.org/10.1111/jofi.12613

Ettner, S.L., 1996. New evidence on the relationship between income and health. Journal of Health Economics 15, 67–85. https://doi.org/10.1016/0167-6296(95)00032-1

Finkelstein, A., Gentzkow, M., Williams, H., 2016. Sources of geographic variation in health care: Evidence from patient migration. Quarterly Journal of Economics 131, 1681–1726. https://doi.org/10.1093/qje/qjw023

Glied, S., 2026. Diminishing Returns—HSAs and Health Care Cost Control. JAMA Health Forum 7, e260270. https://doi.org/10.1001/jamahealthforum.2026.0270

Hasager, L., Jorgensen, M., 2026. Sick of your poor neighborhood? Quasi-experimental evidence on neighborhood effects on health. Journal of Public Economics 256, 105599. https://doi.org/10.1016/j.jpubeco.2026.105599

Humphery-Jenner, M., 2026. The geography of overservicing and underservicing: evidence from Australia's NDIS.

NDIS, 2026a. The NDIS in each state [WWW Document]. URL https://www.ndis.gov.au/understanding/ndis-each-state (accessed 4.16.26).

NDIS, 2026b. Sydney man charged with alleged $3.5 million NDIS fraud [WWW Document]. URL https://www.ndis.gov.au/news/11065-sydney-man-charged-alleged-35-million-ndis-fraud (accessed 1.21.26).

NDIS, 2026c. Provider Finder [WWW Document]. URL https://www.ndis.gov.au/participants/working-providers/find-registered-provider/provider-finder (accessed 1.3.26).

Remmerswaal, M., Boone, J., Bijlsma, M., Douben, R., 2019. Cost-sharing design matters: A comparison of the rebate and deductible in healthcare. Journal of Public Economics 170, 83–97. https://doi.org/10.1016/j.jpubeco.2019.01.008

Salignac, F., Barkemeyer, R., Franklin-Johnson, E., Dzhengiz, T., 2024. Understanding the evolution of competing institutional logics in the marketization of care: A stage model analysis of Australia's National Disability Insurance Scheme. Health Policy 149, 105173. https://doi.org/10.1016/j.healthpol.2024.105173

Smith-Merry, J., Chang, K., 2025. Equity first: mapping who gets what is essential to re-designing the NDIS. Medical Journal of Australia 222, 131–132. https://doi.org/10.5694/mja2.52587

Stadhouders, N., Kruse, F., Tanke, M., Koolman, X., Jeurissen, P., 2019. Effective healthcare cost-containment policies: A systematic review. Health Policy 123, 71–79. https://doi.org/10.1016/j.healthpol.2018.10.015

Thomson, R.M., Igelstrom, E., Purba, A.K., Shimonovich, M., Thomson, H., McCartney, G., Reeves, A., Leyland, A., Pearce, A., Katikireddi, S.V., 2022. How do income changes impact on mental health and wellbeing for working-age adults? A systematic review and meta-analysis. Lancet: Public Health 7, e515–e528.

Wennberg, J., Gittelsohn, A., 1973. Small area variations in health care delivery. Science 182, 1102–1108. https://doi.org/10.1126/science.182.4117.1102

White House, 2026. Fact Sheet: President Donald J. Trump Establishes New Department of Justice Division for National Fraud Enforcement [WWW Document]. URL https://www.whitehouse.gov/fact-sheets/2026/01/fact-sheet-president-donald-j-trump-establishes-new-department-of-justice-division-for-national-fraud-enforcement (accessed 1.30.26).

6 Tables

Table 1: Summary statistics

This table contains summary statistics for the variables in this paper. Variable definitions are in the Variable Definition appendix.

Variable	Mean	Median	Standard Deviation
Provider Count	29.38	9.00	53.90
Providers per Capita	0.01	0.00	0.11
Population Count	9805.92	3678.00	14033.98
Median Weekly Wage	1608.87	1494.00	528.40
Kids per Family (for families with kids)	1.84	1.80	0.21
Median Age	43.37	43.00	7.40
Hospitals in 5km	1.11	0.00	2.65
GPs in 5km	15.20	0.00	30.06
Male(%)	0.51	0.50	0.04
No long term condition (%)	0.57	0.57	0.07
Indigenous and ATSI (%)	0.04	0.02	0.08
Requires disability assistance (%)	0.13	0.13	0.03
Kids-to-Population (%)	0.23	0.23	0.05
Tertiary Education (%)	0.18	0.16	0.10
Born in Australia (%)	0.36	0.38	0.10
English only language at home (%)	0.80	0.86	0.15
Unemployed (%)	0.05	0.04	0.03

Prosperity Institute

Table 2: Factors that influence provider numbers

This table contains the results of an OLS regression that analyzes the factors that influence the number of providers in a postal area. The regression is cross-sectional. The dependent variable is the natural logarithm of the number of providers. The column title indicates the sample under analysis: the first three columns analyze all postal areas in Australia. Columns 4 and 5 restrict the sample to areas in NSW and Victoria, respectively. Column 3 also includes state fixed effects and clusters standard errors by state. Numbers in plain font are regression coefficients. P-values are in parentheses. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Dependent Variable			ln(Providers)		
Sample	Aus	Aus	Aus	NSW	Vic
Column	[1]	[2]	[3]	[4]	[5]
ln(People)	0.714***	0.720***	0.736***	0.900***	0.715***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Kids/Family)	0.465	-0.123	-0.126	0.993	-1.212**
	(0.273)	(0.732)	(0.764)	(0.221)	(0.047)
ln(Age)	-0.971***	-1.113***	-0.811***	-1.154***	-0.606*
	(0.000)	(0.000)	(0.010)	(0.002)	(0.060)
Male (%)	0.182	-0.647	-0.970	-1.169	-0.396
	(0.831)	(0.440)	(0.326)	(0.438)	(0.799)
No long term condition (%)	0.494*	1.538***	1.022	-2.438***	0.898
	(0.084)	(0.000)	(0.241)	(0.002)	(0.174)
ln(Hospitals in 5km)	-0.150***	-0.096***	-0.047	-0.327***	0.048
	(0.000)	(0.001)	(0.610)	(0.000)	(0.325)
ln(GPs in 5km)	0.094***	0.064***	0.039	0.157***	-0.019
	(0.000)	(0.001)	(0.215)	(0.000)	(0.558)
Indigenous and ATSI (%)	-0.038	-0.683**	-0.551	-0.553	-1.116**
	(0.856)	(0.013)	(0.213)	(0.274)	(0.013)
Requires disability assistance (%)	1.053	2.025***	0.709	2.026	1.675
	(0.110)	(0.003)	(0.343)	(0.266)	(0.160)
Kids-to-Population (%)	-3.072***	-2.050***	-1.305*	-1.012	-0.021
	(0.000)	(0.002)	(0.065)	(0.431)	(0.985)
ln(Income)		-0.612***	-0.533**	-0.271	-0.407***
		(0.000)	(0.015)	(0.129)	(0.007)
Tertiary Education (%)		-0.568*	-0.293	1.331*	-1.168**
		(0.071)	(0.539)	(0.066)	(0.031)
Born in Australia (%)		-0.209	-0.180	0.902	-1.350*
		(0.528)	(0.757)	(0.220)	(0.084)
English only language at home (%)		-0.848***	-0.961**	-1.694***	-0.668
		(0.000)	(0.037)	(0.000)	(0.156)
Unemployed (%)		-1.540**	-1.343	-4.255**	-0.303
		(0.044)	(0.370)	(0.034)	(0.806)
Fixed Effects	No	No	State	No	No
Observations	2565	2565	2565	627	682
Adj R-Squared	0.807	0.820	0.835	0.861	0.873

Prosperity Institute

Table 3: Actual vs Predicted Provider Numbers

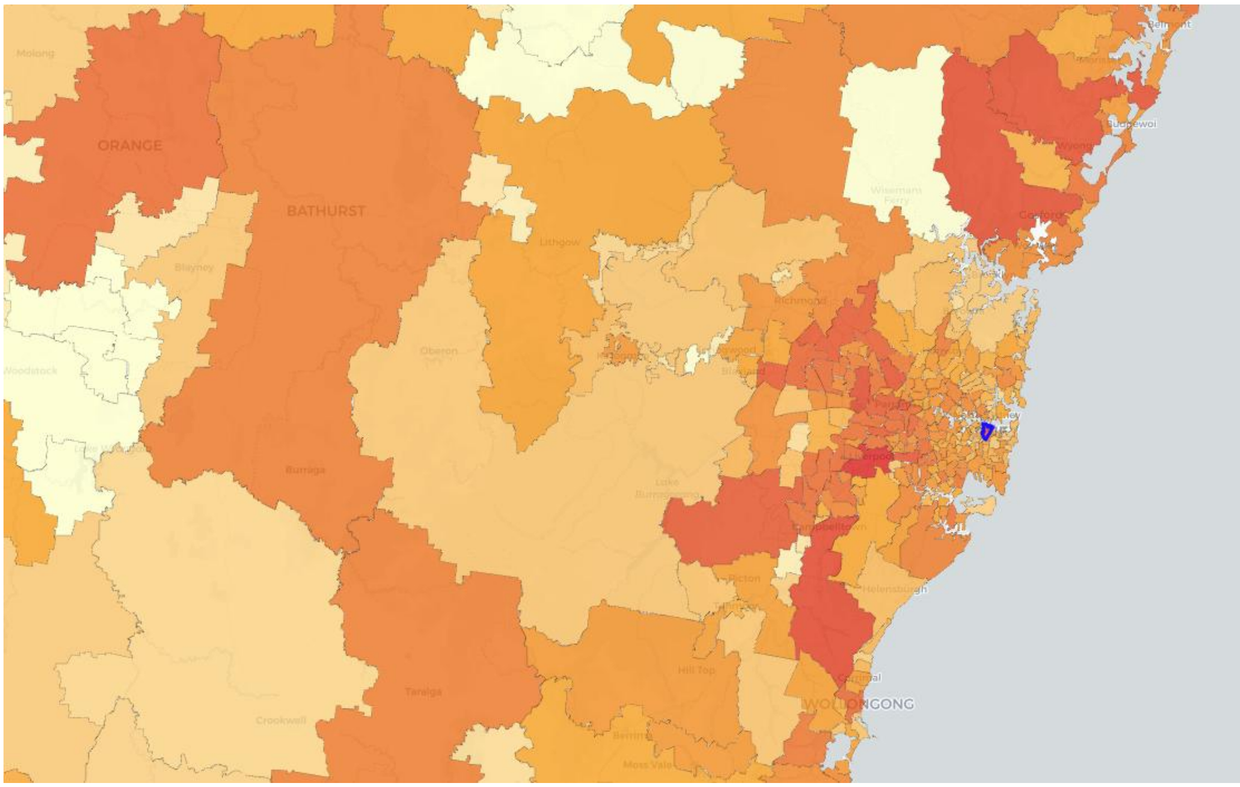
This table contains the actual provider account for the top 20 locations. The provider count is the raw number of providers. The predicted provider count (in Column 2) is the predicted value from Column 3 in Table 2.

Post Code	Provider Count [1]	Predicted Provider Numbers [2]	Difference [3]
2170	795	308	487
3029	737	320	417
3064	652	299	353
3977	578	217	361
3030	550	236	314
2560	424	144	280
4350	400	165	235
3978	381	124	257
2148	370	179	191
2148	370	179	191
2250	367	100	267
4870	360	124	236
2259	344	86	258
2200	316	201	115
2153	308	118	190
2150	306	148	158
6112	291	135	156
3175	287	193	94
2570	278	97	181
2765	270	101	169

Prosperity Institute

7 Figures

Figure 1: NDIS provider number heat map for greater Sydney (blue circle is Sydney CBD)



Prosperity Institute

8 Appendix: Variable Definitions

Variable	Definition
ln(Providers)	The natural log of one plus the number of NDIS providers in the location. Data is from the NDIS provider finder (https://www.ndis.gov.au/participants/working-providers/find-registered-provider/provider-finder) . Underlying JSON file retrieved on 3 January 2026.
ln(People)	The natural log of one plus the number of people in the location, per the 2021 census data.
ln(Kids/Family)	The natural log of the number of children per family (for families with children). From the 2021 census.
ln(Age)	The natural log of the median age in the location. From the 2021 census.
Male (%)	The proportion of the population in the location that is male. From the 2021 census.
No long term condition (%)	The proportion of the population that has *no* self-reported long term medical condition. From the 2021 census.
85 years and older (%)	The proportion of the population that is more than 85 years old. From the 2021 census.
ln(Income)	The natural log of one plus the median weekly household income. From the 2021 census.
Tertiary Education (%)	The proportion of the population that has completed tertiary education. From the 2021 census.
Born in Australia (%)	The proportion of the population that was born in Australia. From the 2021 census.
Both parents born in Australia (%)	The proportion of the population for whom both parents were born in Australia. From the 2021 census.
English only language at home (%)	The proportion of the population that only speaks English at home. From the 2021 census.
Unemployed (%)	The proportion of the population that is unemployed. From the 2021 census.
Indigenous and ATSI (%)	The proportion of the population that identifies as being of Aboriginal or Torres Strait Islander descent. From the 2021 census.
Requires disability assistance (%)	The proportion of the population that requires disability assistance, as reported in the 2021 census.
Kids-to-Population (%)	The proportion of the population that is 19 years or younger. From the 2021 census.
ln(Hospitals in 5km)	The natural log of one plus the number of hospitals within 5km of the region. This is from the national HealthDirect database: https://services.ga.gov.au/gis/rest/services/National_HealthDirect_Health_Facilities/MapServer
ln(GPs in 5km)	The natural log of one plus the number of general practices within 5km of the region. This is from the national HealthDirect database: https://services.ga.gov.au/gis/rest/services/National_HealthDirect_Health_Facilities/MapServer

9 Appendix: Robustness Tests

This appendix contains the results of alternative regression specifications.

Table 4: Sample restricted to areas with at least 10 providers

This table contains OLS regression results in which we restrict the sample to only those areas with at least 10 providers (the median number of providers is 9). Plain-font numbers are regression coefficients, parentheses contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The regressions use robust standard errors. Column 3 also clusters standard errors by state and includes state fixed effects.

Dependent Variable	ln(Providers)				
Sample	Aus	Aus	Aus	NSW	Vic
Column	[1]	[2]	[3]	[4]	[5]
ln(People)	0.689***	0.684***	0.702***	0.822***	0.723***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Kids/Family)	1.158	0.201	0.292	0.592	-0.507
	(0.186)	(0.776)	(0.666)	(0.506)	(0.612)
ln(Age)	-1.120***	-0.850***	-0.714**	-1.221***	-1.359***
	(0.000)	(0.000)	(0.049)	(0.009)	(0.002)
Male (%)	4.504***	4.191***	3.946	0.561	2.341
	(0.001)	(0.002)	(0.105)	(0.796)	(0.436)
No long term condition (%)	-0.535	0.129	0.050	-3.215**	0.485
	(0.143)	(0.838)	(0.968)	(0.024)	(0.716)
ln(Hospitals in 5km)	-0.049	0.019	0.018	-0.191***	0.104**
	(0.114)	(0.499)	(0.813)	(0.001)	(0.031)
ln(GPs in 5km)	0.029*	0.006	0.005	0.082***	-0.053*
	(0.089)	(0.774)	(0.822)	(0.009)	(0.080)
Indigenous and ATSI (%)	-0.023	0.010	-0.141	-1.872*	-1.241***
	(0.917)	(0.980)	(0.764)	(0.082)	(0.000)
Requires disability assistance (%)	-0.157	0.255	-1.550	-2.098	-2.832
	(0.892)	(0.822)	(0.330)	(0.428)	(0.191)
Kids-to-Population (%)	-2.075**	1.352	1.618*	1.368	2.172
	(0.013)	(0.157)	(0.074)	(0.475)	(0.175)
ln(Income)		-0.979***	-0.951***	-0.545**	-0.691**
		(0.000)	(0.005)	(0.031)	(0.020)
Tertiary Education (%)		0.771**	0.820	1.563	-1.424**
		(0.048)	(0.335)	(0.102)	(0.048)
Born in Australia (%)		-0.488	-0.532	1.106	-3.231**
		(0.250)	(0.401)	(0.209)	(0.029)
English only language at home (%)		-0.653***	-0.470	-1.431***	0.993
		(0.006)	(0.322)	(0.006)	(0.232)
Unemployed (%)		-5.719***	-4.642**	-6.145**	-1.134
		(0.000)	(0.022)	(0.016)	(0.688)
Fixed Effects	NA	NA	State	NA	NA
Observations	1308	1308	1308	365	333
Adj R-Squared	0.636	0.688	0.700	0.746	0.778

Prosperity Institute

Table 5: Tobit regressions

This table contains tobit regressions in which we impose a lower bound of zero on the dependent variable. Plain-font numbers are regression coefficients, parentheses contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Dependent Variable			ln(Providers)		
Sample	Aus	Aus	Aus	NSW	Vic
Column	[1]	[2]	[3]	[4]	[5]
ln(People)	0.743***	0.748***	0.702***	0.980***	0.730***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Kids/Family)	0.506	-0.088	-0.279	1.920**	-1.288**
	(0.130)	(0.787)	(0.337)	(0.032)	(0.029)
ln(Age)	-0.953***	-1.126***	-0.906***	-0.968**	-0.651**
	(0.000)	(0.000)	(0.000)	(0.017)	(0.032)
Male (%)	0.128	-0.683	-0.207	-2.624	-0.748
	(0.835)	(0.285)	(0.726)	(0.144)	(0.512)
No long term condition (%)	0.578**	1.656***	1.271***	-3.240***	1.159*
	(0.038)	(0.000)	(0.000)	(0.000)	(0.061)
ln(Hospitals in 5km)	-0.150***	-0.096***	-0.045	-0.309***	0.045
	(0.000)	(0.006)	(0.136)	(0.000)	(0.424)
ln(GPs in 5km)	0.088***	0.061***	0.035**	0.143***	-0.019
	(0.000)	(0.003)	(0.047)	(0.001)	(0.565)
Indigenous and ATSI (%)	-0.018	-0.640***	-0.655***	-0.508	-1.079*
	(0.922)	(0.004)	(0.002)	(0.438)	(0.097)
Requires disability assistance (%)	1.082	2.115***	0.905	1.627	1.995*
	(0.100)	(0.002)	(0.183)	(0.415)	(0.088)
Kids-to-Population (%)	-3.232***	-2.261***	-1.025*	-0.554	-0.230
	(0.000)	(0.000)	(0.060)	(0.703)	(0.827)
ln(Income)		-0.621***	-0.627***	-0.244	-0.461***
		(0.000)	(0.000)	(0.221)	(0.001)
Tertiary Education (%)		-0.627**	-0.308	2.159***	-1.314***
		(0.024)	(0.230)	(0.001)	(0.005)
Born in Australia (%)		-0.248	-0.131	0.573	-1.464**
		(0.431)	(0.640)	(0.536)	(0.037)
English only language at home (%)		-0.798***	-0.950***	-1.581***	-0.583
		(0.000)	(0.000)	(0.002)	(0.169)
Unemployed (%)		-1.653**	-1.470**	-4.339**	-0.601
		(0.021)	(0.027)	(0.043)	(0.639)
Fixed Effects	NA	NA	State	NA	NA
Observations	2565	2565	2380	627	682
Pseudo R-squared	0.434	0.452	0.519	0.517	0.566

Table 6: Locations with providers in the middle 50%

This table contains OLS regression results in which we restrict the sample to only those areas with between two and 34 providers, inclusive, reflecting the middle half of the distribution (the median number of providers is 9). Plain-font numbers are regression coefficients, parentheses contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The regressions use robust standard errors. Column 3 also clusters standard errors by state and includes state fixed effects.

Dependent Variable			ln(Providers)		
Sample	Aus	Aus	Aus	NSW	Vic
Column	[1]	[2]	[3]	[4]	[5]
ln(People)	0.442***	0.455***	0.471***	0.585***	0.508***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Kids/Family)	0.107	-0.197	-0.290	-1.091	-1.400**
	(0.812)	(0.651)	(0.538)	(0.401)	(0.026)
ln(Age)	-0.309*	-0.387**	-0.204	-0.592	0.349
	(0.070)	(0.045)	(0.444)	(0.141)	(0.321)
Male (%)	-0.142	-0.180	-0.515	1.092	-0.700
	(0.859)	(0.831)	(0.749)	(0.582)	(0.567)
No long term condition (%)	0.313	0.923***	0.487	-1.995*	0.348
	(0.249)	(0.009)	(0.365)	(0.076)	(0.579)
ln(Hospitals in 5km)	-0.086***	-0.082**	-0.047	-0.255***	0.086
	(0.010)	(0.010)	(0.475)	(0.000)	(0.125)
ln(GPs in 5km)	0.074***	0.075***	0.052*	0.129***	-0.004
	(0.000)	(0.000)	(0.052)	(0.005)	(0.904)
Indigenous and ATSI (%)	0.570***	0.286	0.506	0.402	0.342
	(0.005)	(0.289)	(0.241)	(0.462)	(0.444)
Requires disability assistance (%)	0.677	1.431**	0.191	4.483**	-0.016
	(0.257)	(0.025)	(0.833)	(0.044)	(0.990)
Kids-to-Population (%)	-1.603***	-0.678	-0.328	1.844	0.292
	(0.009)	(0.336)	(0.736)	(0.272)	(0.789)
ln(Income)		-0.420***	-0.304**	-0.212	-0.070
		(0.000)	(0.038)	(0.314)	(0.584)
Tertiary Education (%)		-0.104	0.073	1.276	-0.344
		(0.744)	(0.832)	(0.138)	(0.508)
Born in Australia (%)		-0.227	-0.212	-0.354	-0.045
		(0.504)	(0.523)	(0.739)	(0.951)
English only language at home (%)		-0.632***	-0.656**	-0.888	-0.702
		(0.007)	(0.026)	(0.172)	(0.144)
Unemployed (%)		-2.662***	-2.251	-5.046**	-1.931
		(0.000)	(0.114)	(0.038)	(0.204)
Fixed Effects	NA	NA	State	NA	NA
Observations	1466	1466	1466	306	398
Adj R-Squared	0.632	0.648	0.675	0.609	0.739

Prosperity Institute

Table 7: Locations with top quartile provider numbers

This table contains OLS regression results in which we restrict the sample to only those areas with at least 34 providers (i.e., the top quartile of the sample). Plain-font numbers are regression coefficients, parentheses contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The regressions use robust standard errors. Column 3 also clusters standard errors by state and includes state fixed effects.

Dependent Variable			ln(Providers)		
Sample	Aus	Aus	Aus	NSW	Vic
Column	[1]	[2]	[3]	[4]	[5]
ln(People)	0.612***	0.619***	0.642***	0.808***	0.748***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(Kids/Family)	1.524*	0.514	0.768	0.820	1.312
	(0.075)	(0.549)	(0.494)	(0.439)	(0.235)
ln(Age)	-0.794***	-0.730***	-0.432	-1.766***	-0.793
	(0.000)	(0.008)	(0.329)	(0.002)	(0.154)
Male (%)	3.181*	3.267*	3.371*	-1.875	2.248
	(0.075)	(0.062)	(0.059)	(0.484)	(0.451)
No long term condition (%)	-0.649	-0.177	-0.260	-3.009*	0.340
	(0.142)	(0.852)	(0.826)	(0.061)	(0.849)
ln(Hospitals in 5km)	0.048	0.087***	0.076	-0.034	0.166***
	(0.155)	(0.007)	(0.134)	(0.586)	(0.003)
ln(GPs in 5km)	-0.003	-0.021	-0.012	0.036	-0.050
	(0.858)	(0.315)	(0.499)	(0.296)	(0.161)
Indigenous and ATSI (%)	-0.638***	0.017	-0.212	-2.475	-0.963
	(0.001)	(0.975)	(0.625)	(0.141)	(0.848)
Requires disability assistance (%)	-3.632***	-2.743*	-5.369*	-4.653	-7.302**
	(0.009)	(0.057)	(0.054)	(0.110)	(0.013)
Kids-to-Population (%)	-0.637	1.567	1.953**	0.041	3.571
	(0.495)	(0.178)	(0.016)	(0.986)	(0.109)
ln(Income)		-0.746***	-0.707***	-0.121	-0.812**
		(0.000)	(0.006)	(0.688)	(0.039)
Tertiary Education (%)		0.365	0.482	-0.157	-0.910
		(0.427)	(0.398)	(0.883)	(0.373)
Born in Australia (%)		-0.796	-0.834	-0.193	-5.138**
		(0.174)	(0.212)	(0.818)	(0.012)
English only language at home (%)		-0.178	0.080	0.031	2.307**
		(0.506)	(0.809)	(0.957)	(0.041)
Unemployed (%)		-4.575**	-3.043*	2.735	-1.737
		(0.016)	(0.050)	(0.474)	(0.574)
Fixed Effects	NA	NA	State	NA	NA
Observations	675	675	675	202	179
Adj R-Squared	0.504	0.543	0.555	0.645	0.695