Exploratory Report: Annual Business Survey Ownership Diversity and Its Association with Patenting and Venture Capital Success

by

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CES 24-62 **October 2024**

Abstract

The Annual Business Survey (ABS) as the replacement for the Survey of Business Owners (SBO) serves as the principal data source for investigating business ownership of minorities, women, and immigrants. As a combination of SBO, the innovation questions formerly collected in the Business R&D and Innovation Survey (BRDIS), and an R&D module for microbusinesses with fewer than 10 employees, ABS opens new research opportunities investigating how ownership demographics are associated with innovation. One critical issue that ABS is uniquely able to investigate is the role that diversity among ownership teams plays in facilitating innovation or intermediate innovation outcomes in R&D-performing microbusinesses. Earlier research using ABS identified both demographic and disciplinary diversity as strong correlates to new-to-market innovation. This research investigates the extent to which the various forms of diversity also impact tangible innovation related intermediate outcomes such as the awarding of patents or securing venture capital financing for R&D. The other major difference with the earlier work is the focus on R&D-performing microbusinesses that are an essential input to radical innovation through the division of innovative labor. Evidence that disciplinary and/or demographic diversity affect the likelihood of receiving a patent or securing venture capital financing by small, high-tech start-ups may have implications for higher education, affirmative action, and immigration policy.

Keyword: Split-sample, false discovery, self-reported innovation, women and minority owned business, hypothesis testing

JEL Classification: O3, J15, J16, C12

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Acknowledgement: This work was supported in part by the National Science Foundation (NSF), National Center for Science and Engineering Statistics (NCSES), and by the Oak Ridge Institute for Science and Education (ORISE) for the Department of Energy (DOE). ORISE is managed by Oak Ridge Associated Universities (ORAU) under DOE contract number DE-SC0014664. All opinions expressed in this paper are the author's and do not necessarily reflect the policies and views of NSF, DOE, ORAU, or ORISE.
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Introduction

Wojan and Lambert (under review) provide comprehensive and transparent evidence that diversity in education specialization and diversity in life experiences mediated by race, ethnicity, or country of birth among ownership teams are strongly associated with the generation of novelty in the form of new-to-market innovation. One critique of the analysis is that the positive innovation measure from the Annual Business Survey does not differentiate between impactful innovations and innovations that are unsuccessful (Gault 2018). Substantive change and introduction in the market are the only criteria for reporting innovation. Accordingly, the evidence cannot differentiate between the competing hypotheses that ownership diversity increases business dynamism through increased innovation versus ownership diversity increases the likelihood of launching mediocre or poor innovations in the market. Possible mechanisms supporting these alternative hypotheses are 1) diversity contributing to cognitive conflict where a divergence of ideas owing to different experiences may resolve as performance-enhancing synthesis, and 2) diversity contributing to affective conflict where the attitudes or emotions of one group are incompatible with others that may be more reliant on market verdicts to settle disputes over the quality of an innovation (Brixy, et al. 2020).

This analysis uses other data collected in the Annual Business Survey on intermediate innovation outcomes that are mediated by a third party—patents awarded and venture/angel capital for R&D secured. These intermediate outputs are not a guarantee of eventual market success. But evidence that diversity is positively associated with either output would refute the affective conflict interpretation of the earlier findings that a higher probability of reporting new-to-market innovation results from less ability to internally assess innovation quality. The analysis is limited to R&D-performing microbusinesses (fewer than 10 employees) given the rarity of both patenting and venture/angel capital financing. Limiting the sample to R&D performers serves the dual purpose of ensuring the dependent variables are relevant measures of novelty generation given that most firms never apply for a patent or seek venture/angel capital funding as well as focusing on the tip of the spear of the innovation economy of small high-tech start-ups where the potential impacts of immigration or the diversify of STEM education may have important implications for policy.

Given that the economic value of diversity and its connection to innovation is a contentious topic, the split sample/dual method protocol developed by Wojan and Lambert (under review) to increase transparency and reduce the likelihood of false discovery is followed. As recommended by Anderson and Magruder (2017), a 35%/65% split into exploratory and confirmatory samples, respectively, is applied to the 2018 ABS that is used for the patent analysis. For the venture/angel capital analysis two separate years of data are used with 2021 ABS comprising the exploratory sample and 2022 ABS designated as the holdout sample for confirmatory analysis. This first paper presents the findings from the exploratory analysis that uses frequentist methods to identify models to pass through for hypothesis testing in the second confirmatory stage. The specification testing used in this exploratory stage will be used to construct a pre-analysis plan, specifying the exact models for *de novo* frequentist and Bayesian estimation using the holdout sample. The axiomatic approach to diversity measurement from Wojan and Lambert (under review) is also followed to decrease researcher degrees of freedom by identifying the single diversity measure that satisfies all requisite axioms (Sen 1976). The full set of exploratory results are available in the Appendix to eliminate the possibility of cherry-picking results. Any debate over the adequacy of the axiomatically selected diversity measure as a valid representation of the phenomenon is also fully transparent.

The paper begins with a discussion of how patenting and venture/angel capital success may be valid indicators of the quality of novelty generation in R&D-performing microbusinesses. The role of diversity or homophily in novelty generation and how it might be related to patenting and venture/angel capital success is then discussed. Discrimination provides an alternative explanation for the failure of high-quality innovative ideas that is also investigated. Gender diversity in venture capital funding has received the most attention in the literature with other dimensions of diversity, or the role of diversity in patenting, receiving much less attention. The axiomatic derivation of the ownership fractionalization measure used in the analysis is followed by a discussion of the data used in the analysis and specification of an empirical model. Exploratory findings emphasize the models passed through for hypothesis testing in the confirmatory stage that form the basis for a pre-analysis plan. The paper concludes with a discussion of how exploratory findings from the intermediate innovation outcome regressions differ from the earlier findings on new-to-market innovation.

Literature Review

The first issue that needs to be addressed is whether intermediate innovation outcomes like patents or venture/angel capital funding plausibly provide an indicator of innovation quality that is not necessarily captured in the ABS innovation self-reports. Patents have long been a proxy for innovation (Acs, et al. 2002). However, patented inventions are neither necessary (i.e., many innovations are not patentable) nor sufficient (i.e., many inventions are never launched in a market as an innovation), suggesting that patents are only weakly associated with impactful innovation (Argente, et al. 2020; Clancy 2024). These limitations of patents as a proxy for impactful innovation are arguably much less relevant for R&D-performing microbusinesses used in this analysis as these firms overwhelmingly come from patent-intensive industries (NAICS 54, 51, and 33) where inventions are likely to be patentable. Perhaps most importantly, many R&D-performing microbusinesses operate in the “market of ideas” where the objective is to demonstrate the feasibility of an invention to incumbents that may acquire the start-up or license the technology (Jankowski, et al. 2023; Baumol 2010; Arora, et al. 2017). Firms operating in the market of ideas may not meet the criteria for reporting an innovation that requires that it be launched on a market. The intellectual property protection afforded by a patent can be critically important for a small start-up negotiating with a large incumbent in order to reap the economic value of the invention through acquisition or licensing (Baumol 2010). For this reason, patents by start-ups are also highly valued by venture capital firms and are strongly associated with funding success (Mann and Sager 2007).

A patent provides protection for a venture capital firm that the intellectual property they are investing in will not be appropriated by a third party, as well as an independent source of information on the potential value of an invention. However, the decision to invest goes beyond the nonobviousness and utility of an invention considered by a patent examiner to assessing the likelihood that a new idea or invention will create value either from the launch of a product, licensing to other businesses, or acquisition of the firm by an incumbent. Venture or angel capital funding of R&D can thus be seen as a third-party evaluation of potentially impactful innovation by principals knowledgeable of what are often emerging markets. The failure rate of venture investing is high with roughly 75% of VC-backed start-ups not providing a return to investors (Gompers and Mukharlyamov 2022). The development of cloud computing that drastically reduced the information technology (IT) costs of start-ups by replacing a large, fixed investment with a pay-as-you-go service may increase this failure rate as venture capital firms shift to a “spray and pray” strategy to fund more ventures at lower levels and with less vetting to better identify the very small number of highly lucrative investments (Ewens et al. 2017). Accordingly, receiving venture capital funds of itself is not an indicator of an impactful innovation. However, it does indicate an innovative idea with more promise than the even larger set of ideas that do not receive funding. The empirical question posed is whether diversity in ownership teams increases or decreases the likelihood of innovative ideas of promise as judged by venture investors.

A critical difference between assessment by a patent examiner and assessment by venture investors is the degree of personal interaction with the ownership team. In contrast to the arm’s length interaction expected in a patent examination, close personal interaction between owners and the principals in a venture capital firm is expected and may extend to mentoring or coaching. The decision to fund a firm may be influenced by subconscious biases that may have little to do with objective assessments of potential value of the investment that are instead governed by affective assessments. Diversity has been associated with lower levels of trust and social capital (Putnam 2007) that may disadvantage ownership teams that differ from the male majority composition of most venture capital firms (Gompers and Wang 2017). Most attention in the literature has been focused on the role of gender diversity given the difficulty that female founders have in securing venture capital (Kanze et al. 2018). The current analysis will allow extending the potential problems of heterophily and venture investment to other diversity dimensions. Comparing the role of diversity in patenting relative to venture/angel capital financing may provide insight on how personal interaction influences the relative benefits of diversity and homophily.

Diversity may affect innovativeness independent of the interaction between R&D-performing start-ups and patent examiners or venture capital firms. The argument that homophily within an ownership team may produce advantages similar to homophily between funders and founders due to high levels of trust and social capital does not appear to apply to creativity and innovation as summarized by Putnam (2007). Stronger evidence of homophily facilitating innovation comes from the management literature demonstrating a freer flow of information among partners from similar groups (Darr and Kurtzberg 2000; Luo and Deng 2009). These findings reinforce the hypothesis that affective conflict among diverse teams may inhibit coming to consensus that is the conjecture that could explain the higher rates of self-reported information in Wojan and Lambert (under review) but that would adversely affect patenting or venture capital success.

The cognitive conflict hypothesis of diversity facilitating meaningful innovation has broader support in the literature. Diversity supports a combinatorial conception of innovation that is based on the bringing together of seemingly unrelated ideas (Hong and Page 2001; Johnson 2010). Business owners coming from different academic specializations to combine ideas from different domains provide noncontentious examples of this. More controversial is whether business owners coming from different life experiences mediated by race, gender, or place of birth are also more likely to generate more novel ideas (Lee 2015). However, evidence that places characterized by greater diversity are also more innovative is the dominant paradigm in the literature compared to the counterclaim that regional homophily induces innovation (Ottaviano and Peri 2006; Niebuhr 2010; Audretsch et al 2010).

Diversity Measurement to Avoid False Discovery

The study of diversity is particularly susceptible to false discovery as the very large number of researcher degrees of freedom make conventional hypothesis testing criteria of $p < 0.05$ or $p < 0.01$ largely irrelevant. At least 20 different diversity measures have been used in the literature and the combinatorial possibilities of even a small number of diversity dimensions explodes the number of candidate measures (Nijkamp and Poot 2015). The current analysis uses seven attributes of owners in ABS to differentiate homophilic ownership teams from diverse ownership teams: age, educational level, sex, ethnicity, education specialization, race, and foreign-born status (see Table 1). The seven attributes can be combined in 127 unique ways. To limit the multiple comparison problem to 127 from a possible 2540 (127 X 20), we select a single diversity measure on the basis of its ability to satisfy four axioms (Sen 1976). Explicit consideration of these four axioms does not guarantee the ideal diversity measure but it does make the arguments for selection transparent. Addressing the multiple comparison problem of 127 possible measures will be addressed in the confirmatory analysis using false discovery rate (FDR) and family-wise error rate (FWER) corrections.

The four axioms the diversity measure must satisfy are:

1. HOMOPHILY AXIOM: All owners belonging to the same group must result in the lowest diversity measure value.
2. FRACTIONALIZATION AXIOM: Increasing the number of groups must increase the diversity measure value.
3. TEAM SIZE AXIOM: Larger ownership teams not demonstrating homophily must increase the diversity measure value relative to smaller ownership teams.
4. CONCENTRATION OF OWNERSHIP AXIOM: Ownership concentrated in one team member must reduce the diversity measure value relative to ownership that is more equally distributed among team members.

The first two axioms are straightforward, requiring that an absence of diversity results in the lowest possible value for the measure and that increasing the number of groups in an ownership team representing greater diversity is also manifest in the measure. The third team size axiom runs counter to that of nearly all diversity measures that are designed to be invariant to population size, allowing comparison across countries or regions of varying size. However, measuring diversity in small teams of 4 members or less—where interaction among team members is guaranteed—changes the underlying mechanism governing diversity from that of being the probability of interacting with someone from another group to the absolute number of interactions with members from another group. A four-person ownership team split between 2 different groups would have twice the number of interactions with someone from another group than a 2-person/2-group team. The fourth concentration of ownership axiom also differs from conventional diversity measures, which recognizes that the influence of any ownership team member may vary considerably based on their ownership share. An ownership share approaching 1 for any owner approaches a single owner firm that is homophilic by definition.

Table 1. Unique Groups per Diversity Dimension and Group Descriptions.

Dimension	Unique Groups	Group Descriptions
Age	6	Under 25 25-34 35-44 45-54 55-64 65 or over
Educational level	9	Less than high school High school graduate Technical or trade school Some college Associate degree Bachelor’s degree Master’s degree Doctorate degree Professional degree
Ethnicity	5	Not Hispanic Mexican Puerto Rican Cuba Other Hispanic
Sex	2	Male Female
Education specialization	17	Biological/agriculture/environmental life sciences Chemistry, except biochemistry Computer/mathematical/technology sciences Earth/atmospheric/ocean sciences Economics/political/psychology/sociology and other social sciences Engineering Health Physics/Astronomy Science/mathematics teacher education Other science/engineering related fields, not listed above Art and humanities fields Education other than science/mathematics Management and administration fields Sales and marketing fields Social service and related fields Other non-science/non-engineering related fields not listed above No 4-year degree or higher
Race	14	White Black or African American American Indian or Alaska Native Asian Indian Chinese Filipino Japanese Korean Vietnamese Other Asian Native Hawaiian Guamanian or Chamorro Samoan Other Pacific Islander
Foreign-born Status	2	Born in the U.S. Not born in the U.S.

Source: 2018 Annual Business Survey

A simple modification to the widely used ethnolinguistic fractionalization measure satisfied all four axioms and is named the ownership fractionalization (*OF*) measure:

$$OF = 1 - \sum_{i=1}^{o} p_i^n \tag{1}$$

where p = ownership share, raised to the power of n = the number of unique groups, summed over o = the number of owners, produces a number between 0 (homophily) and near 1 (maximally diverse) for diversity on a single dimension.

An unweighted composite ownership fractionalization (*COF*) index defined by:

$$COF = \frac{\left(D - \sum_{i=1}^{D} \sum_{j=1}^{o} p_{ij}^{ni}\right)}{D} \tag{2}$$

where D = the number of diversity dimensions produces a diversity measure for the 120 unique combinations of the seven dimensions. Normalizing by D ensures that estimates and odds ratios are comparable across measures.

Wojan and Lambert (under review) provide a much more detailed discussion of the mathematical properties of the *OF* measure that includes a direct comparison with the widely used ethnolinguistic fractionalization measure that includes the correlation between the two measures in the ABS data (Alesina, et al. 2003). The measures are highly correlated and produce qualitatively similar results in regressions of ownership diversity on self-reported innovation. However, the network effects present in the *OF* measure produce estimates of considerably larger magnitude.

Data

The data used in the analysis come from different years of the ABS due to the modular nature of noncore sections of the survey that change from year to year. Detailed data on patents applied for and patents owned are available in the inaugural 2018 ABS (reference year 2017). Given the large size of ABS in Economic Census years (drawn from a sample of roughly 850,000 firms), splitting the dataset and using 35% for this exploratory analysis is feasible even when analyzing the small share of R&D-performing microbusinesses. A split sample strategy is less feasible in years when the Economic Census is not collected when a sample of 300,000 firms is used. The venture/angel capital questions were included in consecutive years for 2021 and 2022, allowing use of the 2021 ABS as for the exploratory analysis and 2022 ABS for the eventual confirmatory sample, separated by a single year.

R&D-performing microbusinesses in the 2018 ABS are defined in the data as businesses with fewer than 10 employees in the 2016 Business Register that was used as the sample frame that reported R&D expenses of at least $50,000 in 2017 (Kindlon 2020). For the 2021 ABS, R&D-performing microbusinesses were defined by fewer than 10 self-reported employees and R&D expenses of at least $50,000 in 2020. There are fewer than 20,000 R&D-performing microbusinesses in the U.S. in either 2017 or 2020. The usable 35% sample from the 2018 ABS for this analysis is roughly 1,800 and the 2021 usable sample of R&D performing microbusinesses is roughly 3,100.

Empirical Model

A parsimonious specification is indicated given the interest in reducing researcher degrees of freedom. The central purpose of the logistic regression model is to control for confounding factors that might otherwise bias the diversity measure estimates. Variables that might reasonably be expected to be correlated with both the diversity measure and the dependent variable of interest are prime candidates for inclusion.

Industry fixed effects are commonly used in patenting and venture capital studies as both patent intensity and the attractiveness for early-stage investment vary substantially by sector (Dushnitsky and Lennox 2006). The difficulty of applying industry fixed effects in the current analysis is that many industries have very few R&D-performing microbusinesses that may produce unstable estimates. An alternative is to use an indicator variable for Professional and Technical Services (NAICS 54) that makes up a majority of observations in the 2018 ABS data and a plurality in the 2021 ABS data. That approach is used in the current analysis. An alternative to provide an indicator variable for patent/R&D intensive sectors (NAICS 325, 334, 336, 3391, 51, and 54, from Shackelford 2013) will be tested before specifying the regression equations for the confirmatory analysis.

Firm size is often included as a control variable in studies of innovation or patenting as larger firms are more likely to innovate or invent (Wojan and Lambert under review). Within R&D-performing microbusinesses we do not observe a correlation between firm size and patenting or VC funding. Not including firm size in the model specification avoids the problems that might be caused by a plausibly endogenous explanatory variable.

ABS includes information on whether the firm is a family business or owned jointly by domestic partners. Family businesses have been associated with lower rates of innovation (Jankowski, et al. 2023) and are also more likely to have diverse ownership on the dimension of sex and age. An indicator variable of whether the firm is a family business or jointly owned is included in the specification to control for possible confounding effects. Firm age is also included as a control variable that may be helpful in differentiating long-lived R&D-performing microbusinesses from the high-tech start-ups that can be assumed to have different objectives regarding patenting and VC funding.

A logistic regression is used to provide an estimate of the log odds that diversity increases or decreases the likelihood of a firm reporting patents pending, patents owned, or venture/angel capital funding R&D, controlling for the firm characteristics discussed above:

$$\Pr(y = 1) = \operatorname{logit}(\beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \beta_4 \cdot x_4) \qquad (3)$$

where:

y = patent pending, patent owner, or venture/angel capital funding (0/1);

x_1 = OF or COF index;

x_2 = NAICS 54 indicator (0/1);

x_3 = family/joint ownership indicator (0/1);

x_4 = firm age;

logit = the logistic link function.

The advantage of logistic regression relative to other limited dependent variable models is that the estimated log odds can be easily interpreted as odds ratios when exponentiated. An odds ratio is interpreted as the change in likelihood of an event given a unit change in the independent variable. It is important to note that none of the *OF* measures represent a unit change going from homophily to maximal diversity with the minimum range being 0.75 for binary dimensions such as sex or foreign-born status, approaching 1 for dimensions characterized by a large number of groups such as race or education specialization. Ranges for all the *OF* measures and for the seven-dimension *COF* are provided in the descriptive statistics below.

Exploratory Findings

Table 2 presents descriptive statistics for both the 35% 2018 ABS and the 2021 ABS samples used in the analysis. The mean provides some clues on the rarity of ethnic, racial, and place-of-birth diversity that are all close to zero resulting from the great majority of firms being homophilic along these dimensions. Diversity along the dimensions of sex, age, educational level, and education specialization is more common across firms. The range statistic for the diversity measures is critical for assessing the implications of the odds ratios from the logistic regression results to follow. Since an odds ratio is interpreted as the change in the likelihood of an event (i.e., patent pending, patent owned, or venture/agnel capital funding) associated with a unit change in the independent variable, all ranges being less than one require the odds ratios used for comparing a maximally diverse team to a homophilic team be discounted accordingly. For example, the change in likelihood associated with sex diversity would be 75% of the reported odds ratio.

The means of the dependent variables are also provided in Table 2 indicating that patenting and venture/angel capital funding are reported by a small minority of R&D-performing microbusinesses. However, these phenomena are much more common for this group of microbusinesses than is true of the population of all businesses.

Table 2. Descriptive Statistics

	2018 ABS 35% Sample R&D-Performing Microbusinesses		2021 ABS R&D-Performing Microbusinesses	
Variable	Mean	Range	Mean	Range
Age Diversity (A)	0.2675	0.9837	0.2729	0.9837
Educational Level Diversity (E)	0.2939	0.9844	0.2929	0.9844
Sex Diversity (G)	0.2898	0.75	0.2485	0.75
Ethnic Diversity (H)	0.0297	0.75	0.03038	0.75
Education Specialization Diversity (M)	0.1886	0.9844	0.3102	0.9844
Race Diversity (R)	0.05444	0.9375	0.06994	0.9375
Foreign-born Status Diversity (U)	0.08683	0.75	0.1129	0.75
Composite Diversity (AEGHMRU)	0.1729	0.83	0.2119	0.83
NAICS 54 (0/1)	0.322		0.4926	
Family/Jointly Owned (0/1)	0.5486		0.3458	
Firm Age	8.866		10.38	
Patent Owned (0/1)	0.09009			
Patent Pending (0/1)	0.1041			
Venture/Angel Capital (0/1)			0.06994	

Sources: 2018 ABS 35% exploratory sample and full 2021 ABS.

Before estimating the models, the criteria used for passing models onto the confirmatory analysis using the holdout sample was established. The criteria used in the earlier Wojan and Lambert (under review) analysis included both significance at the 0.05 level as well as sufficient magnitude of the coefficient estimate corresponding to Cohen's d of ≥ 0.2 or an odds ratio ≥ 1.44 (or < 0.6945) (Borenstein et al. 2021). The magnitude criterion was added to guard against estimating statistically significant results that are nonetheless very close to zero due to a very large sample size but of little or no economic significance (McCloskey and Ziliak 1996). Sample size in the current analysis is roughly two orders of magnitude smaller than the earlier analysis making the magnitude criterion unnecessary. The only criterion used in the current analysis is a significance level of 0.05 or less for the diversity measure.

All regression results for each of the 3 dependent variables are presented in Appendix Tables A1 (patent pending), A2 (patent owned), and A3 (venture/angel funding), in ranked order according to the size of the log odds of the diversity measure coefficient estimate. Presentation and discussion in the body of the paper is limited to the top and bottom few rows of the Appendix Tables.

Table 3 includes estimates from the patent pending logistic regression. The top row of the table provides estimates of composite ownership fractionalization measure including all 7 diversity dimensions (AEGHMRU). The magnitude of the log odds is very large, indicating that a maximally diverse ownership team on these dimensions would be roughly 34 times (0.83 [AEGHMRU range] x 41.7 [odds ratio]) more likely to report a patent pending relative to a homophilic ownership team. Diversity measures in the top half of the table all include ethnicity (H), race (R) and foreign-born status (U), with age (A) and education specialization (M) included in 4 of the 5 diversity measures. In contrast, diversity measures in the bottom half of the table with the lowest log odds values include sex (G), ethnicity (H), and foreign-born status (U). The only negative and significant log odds translating into a decreased likelihood of reporting a patent pending is for the ownership fractionalization measure pertaining to sex diversity. This finding is somewhat consistent with other research suggests that women are less likely to apply for a patent than men (Cook and Kongcharoen 2010). However, it is important to recognize that sex diversity represents the presence of both male and female owners of the business. The findings in Table 3 are still unable to distinguish between the affective conflict and cognitive conflicts explanations for why diversity might increase innovation self-reports as patent pending still lacks a verdict from a patent examiner regarding the utility, novelty, and nonobviousness of the patent application.

Table 3. Logistic regression of patent pending as a function of ownership diversity and firm controls

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AEGHMRU	3.731	0.2087	41.7	0.784	-0.7086	-0.0564
AEHMRU	3.707	0.1891	40.73	0.7414	-0.5471	-0.0546
EHMRU	3.678	0.1965	39.58	0.7388	-0.5653	-0.0536
AHMRU	3.666	0.1922	39.08	0.7283	-0.5264	-0.055
AEHRU	3.663	0.1948	38.98	0.7989	-0.5459	-0.0565
GU	1.006	0.171	2.734	0.9534	-0.7771	-0.0613
H	0.6822	0.206	1.978	0.9583	-0.6752	-0.0619
GH	-0.2673	0.2233	0.765	0.9622	-0.6398	-0.0624
G	-0.4249	0.1304	0.654	0.9516	-0.5656	-0.0622

Notes: A = age, E = educational level, G = sex, H = ethnicity, M = education specialization, R = race, U = foreign-born status. Shaded estimates not passed through. Total of 126 of 127 equations passed through for confirmation.

Source: 2018 ABS 35% exploratory sample.

Table 4 does provide this harder test of diversity being associated with potentially impactful innovation as patents are only granted to inventions that do meet the criteria of utility, originality, and nonobviousness. Magnitudes of the odds ratios in the top half of the table are lower than in Table 3 but are still quite large. Maximally diverse ownership teams along the dimensions of educational level (E), ethnicity (H), education specialization (M), race (R), and foreign-born status (U) would be more than 20 times as likely to own a patent relative to a homophilic team. A diverse set of disciplinary and life experiences appears to be associated with higher levels of inventiveness and innovation, supporting the cognitive conflict hypothesis. Sex diversity is again a common attribute of the measures in the bottom half of the table, being negative and statistically significant for two measures. An ownership team maximally diverse with respect to sex and ethnicity would be roughly four times less likely to own a patent relative to an ownership team of the same sex and ethnicity.

As noted earlier, patents are only weakly associated with impactful innovation as some innovations are never patented and some patented inventions are never launched on the market. Venture/angel capital funding provides another means of examining the diversity/innovation nexus as the innovation pitched to investors is being evaluated on likely market impact either in the form of an initial public offering or acquisition by an incumbent firm. In contrast to patenting where the patent examiner evaluating an invention is not assuming any risk, venture investing is placing a bet on the potential value of an innovation and thus might be regarded as a more stringent test. Alternatively, evidence that smaller venture investments in a larger number of projects—a practice termed "spray and pray" (Ewens et al. 2018)—may be a better strategy for identifying investments with the highest return suggests that early-stage investing may be funding projects with little chance of success. The magnitude of the largest odds ratio in Table 5 (AHR) is less than half that of the largest odds ratio in Table 4 (EHMRU). However, this odd ratio value of 10.02 is significantly larger than the largest odds ratio estimated with respect to self-reported innovation of 6.58 (HMRU) in Wojan and Lambert (under review). The populations of the two studies are very different but the findings suggest that diversity does engender cognitive conflict supporting high quality innovation in a segment of the business population most likely to be engaged in radical innovation. One notable difference between the venture/angel capital results and the patenting results is the prevalence of age diversity and the disappearance of education specialization in the top half of the table.

Sex diversity is included in all the measures on the bottom half of the table where two of the estimates are negative and statistically significant. This is somewhat consistent with research examining venture capital funding of women owned firms (Gompers et al. 2022). It is important to reiterate that the diversity finding relates to R&D-performing microbusinesses that are owned by both men and women, after controlling for family business which can be expected to be associated with sex diversity and lower rates of innovation (Jankowski et al. 2023). The most surprising result from the bottom half of the table is the common occurrence of education specialization in these diversity measures. The combination of seemingly unrelated ideas from different domains is thought to be a critical source of innovation that should be supported by having owners with training in different disciplines (Johnson 2010). Education specialization in diversity measures in the top half of the patenting tables (Table 3 and 4) supports this hypothesis. A plausible explanation for the seemingly contradictory result for venture/angel capital funding harkens back to the multiple comparison problem and false discovery—that these results are anomalies owing to the luck of the draw. The confirmatory analysis using the holdout sample will provide a self-replication to test that possibility. However, in this exploratory analysis we can assess whether education specialization is consistently associated with a lower probability of receiving venture/angel capital funding across all 127 measures using a regression decomposition model discussed next.

Table 4. Logistic regression of patent owned as a function of ownership diversity and firm controls

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
EHMRU	3.288	0.2073	26.79	0.6391	-0.6149	0.0294
AEHMRU	3.241	0.1993	25.57	0.6402	-0.6005	0.0285
EHMR	3.216	0.2015	24.92	0.6434	-0.6398	0.0284
AEHMR	3.116	0.1917	22.56	0.6483	-0.6184	0.0275
AHMRU	3.094	0.2034	22.07	0.6368	-0.5841	0.0274
GU	-0.00089	0.1905	0.999	0.8604	-0.6959	0.0189
GR	-0.1061	0.2099	0.899	0.8618	-0.685	0.0188
GHR	-0.1268	0.2826	0.881	0.862	-0.687	0.0188
G	-1.137	0.1436	0.321	0.8367	-0.3989	0.0199
GH	-1.719	0.2529	0.179	0.8482	-0.4684	0.019

Notes: A = age, E = educational level, G = sex, H = ethnicity, M = education specialization, R = race, U = foreign-born status. Shaded estimates not passed through. Total of 122 of 127 equations passed through for confirmation.

Source: 2018 ABS 35% exploratory sample.

Table 5. Logistic regression of venture/angel capital funding as a function of ownership diversity and firm controls

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AHR	2.305	0.1765	10.02	0.191	-0.5474	-0.1343
AHRU	2.116	0.174	8.301	0.2053	-0.5481	-0.135
AH	2.014	0.1504	7.493	0.2082	-0.6014	-0.1367
AHU	2.012	0.1603	7.482	0.2172	-0.5775	-0.1364
AGHRU	1.877	0.1987	6.536	0.2056	-0.6659	-0.1376
EGM	-0.2468	0.143	0.781	0.2355	-0.6243	-0.1396
GMR	-0.287	0.1546	0.751	0.2381	-0.6316	-0.1398
GHM	-0.3109	0.1646	0.733	0.2359	-0.6249	-0.1395
GM	-0.4759	0.1137	0.621	0.2285	-0.6001	-0.139
G	-0.4937	0.1206	0.61	0.2547	-0.5222	-0.1382

Notes: A = age, E = educational level, G = sex, H = ethnicity, M = education specialization, R = race, U = foreign-born status. Shaded estimates not passed through. Total of 107 of 127 equations passed through for confirmation.

Source: 2021 ABS.

Regressing the log odds for each diversity measure from the logistic regression against the diversity dimensions included in the measure will provide an estimate of the average effect of each dimension across all measures:

$$y_{aeghmru} = \beta_0 + \beta_a \cdot a + \beta_e \cdot e + \beta_g \cdot g + \beta_h \cdot h + \beta_m \cdot m + \beta_r \cdot r + \beta_u \cdot u \qquad (4)$$

where $y_{aeghmru}$ = the diversity log odds estimate for any of the 127 logistic regressions;

a = 1 when age is included in the diversity measure, 0 otherwise;

e = 1 when educational level is included in the diversity measure, 0 otherwise;

g = 1 when sex is included in the diversity measure, 0 otherwise;

h = 1 when ethnicity is included in the diversity measure, 0 otherwise;

m = 1 when education specialization is included in the diversity measure, 0 otherwise;

r = 1 when race is included in the diversity measure, 0 otherwise;

u = 1 when foreign-born status is included in the diversity measure, 0 otherwise.

A separate regression decomposition was done for each of the dependent variables and the results are presented in Table 6. In the patent pending equations racial diversity has the largest average effect on the log odds of the diversity measure in which it is included. With the exception of sex diversity, which is negative and statistically significant at the 0.05 level, the average effect of the remaining diversity dimensions is fairly similar at between 0.46 and 0.59. The negative effect of sex diversity in the patent pending equations is relatively small when compared to the effect of sex diversity in the patent owned equations. To the extent that the patent pending variable provides a more contemporaneous view of current patenting activity than the patent owned variable, this finding suggests that the female patenting gap may be narrowing. However, findings that women are less likely to resubmit revised patent applications suggest the importance of revisiting the patents owned analysis on a regular basis (Aneja et al. 2024).

Disciplinary diversity as represented by the education specialization dimension has the largest effect on the log odds of the diversity measure where it is included in the patent owned equations. This finding is consistent with the top rows of Table 4 and reinforces the notion that exploration of the adjacent possible essential to invention is aided by the combination of ideas from seemingly disparate or unrelated domains (Johnson 2010). This makes the large negative effect of education specialization in the venture/angel capital funding equations more surprising. Particularly since an awarded patent may be the only legal protection of intellectual property available to an early-stage investor. A much less surprising finding is the negative effect of sex diversity on the log odds of the diversity measure in the venture/angel capital equations given research that has identified a gender venture capital gap (Gompers et al. 2022). The age diversity coefficient estimate is nominally and statistically the largest in the venture/angel capital funding regression decomposition suggesting that investors value both experience of older founders along with cutting edge skills of younger founders on the same ownership team.

Table 6. Regression Decomposition of Estimated Log Odds of Diversity Measure on Diversity Dimensions

	Patent Pending		Patent Owned		Venture/Angel Capital Funding	
Diversity Dimension	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Age	0.5356	0.0552	0.4875	0.06482	***0.7126***	0.03437
Educational Level	0.4625	0.0552	0.6601	0.06482	0.04	0.03437
Sex	-0.1401	0.0552	***-0.5885***	0.06482	***-0.3389***	0.03437
Ethnicity	0.5902	0.0552	0.3391	0.06482	0.5044	0.03437
Education Specialization	0.4933	0.0552	***0.8541***	0.06482	***-0.4923***	0.03437
Race	***0.8539***	0.0552	0.6315	0.06482	0.2861	0.03437
Foreign-born Status	0.5451	0.0552	0.4404	0.06482	0.2729	0.03437
Intercept	0.9116	0.08152	0.556	0.09572	0.4031	0.05076

Notes: All coefficient estimates significant at <0.0001 level except for Sex in Patent Pending equation (0.05 level) and Educational Level in Venture Capital equation (not significant).

Sources: 2018 ABS 35% exploratory sample, and full 2021 ABS.

Pre-analysis Plan for Confirmatory Analysis

Frequentist estimation of all 127 ownership fractionalization diversity measures using the 35% 2018 ABS sample for patenting and the full 2021 ABS sample venture/angle capital funding provides valuable information on the equations to pass through for confirmation using the remaining 65% 2018 ABS and full 2022 ABS holdout samples. All the equations to be passed through for *de novo* estimation are those in Appendix Tables A1-A3 that are not shaded, indicating a p-value on the ownership fractionalization measure coefficient estimate of less than 0.05.

The specification in the confirmatory analysis will differ slightly from the one used here based on a suggestion for an alternative specification that replaces the NAICS 54 indicator variable with an indicator variable for patent intensive industries (NAICS 325, 334, 336, 3391, 51, and 54). The NAICS 54 indicator was chosen as a feasible alternative to industry fixed effects that produced unreliable estimates given the small number of R&D-performing microbusinesses in some 2-digit NAICS categories. One possible explanation for the negative effect of sex diversity on patents owned is that women are underrepresented in ownership teams in patent intensive industries. NAICS 54 (Professional and technical services) is identified as a patent and R&D intensive industry but misses the high probability of patenting in some manufacturing industries. Testing the alternative specification with the exploratory sample confirms that part of the negative effect of sex diversity may be explained by lower levels of sex diversity in these manufacturing industries.

The specification that will be applied to 126 of the patent pending equation, 122 of the patent owned equations and 107 of the venture/angel capital funding equations is:

$$\Pr(y = 1) = \operatorname{logit}(\beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \beta_3 \cdot x_3 + \beta_4 \cdot x_4) \tag{5}$$

where:

y = patent pending, patent owner, or venture/angel capital funding (0/1);

x_1 = OF or COF index;

x_2 = Patent intensive industry indicator (0/1);

x_3 = family/joint ownership indicator (0/1);

x_4 = firm age;

logit = the logistic link function.

Bayesian estimation will be used in addition to a frequentist specification that will allow including information from this exploratory analysis as weakly informative priors (Wojan and Lambert under review). Bayesian procedures use simulation methods to generate posterior distribution conditional on prior information. The priors for the intercept, β_0 is the normal distribution centered on zero with a standard deviation of 10. The standard deviation of 10 corresponds with a prior variance of 100. Setting the variance to this value means the prior distribution is centered over the parameter value from the exploratory findings but with very wide, symmetric tails. The wide tails associated with a standard deviation of 10 ensure a more extensive search space around the prior learned from the exploratory step, allowing the sampling procedure to explore the posterior distribution more fully. The priors for the parameters on patent intensive industry, family business and firm age (β_2 - β_4) are also normal but centered on zero, with a standard deviation of 10. The priors for OF and COF (β_1) are centered on the estimates for these variables from the exploratory results (Tables A1-A3), with a standard deviation of 10.

Increasing statistical power in the confirmatory stage by leveraging information produced in the exploratory stage is critical given the very stringent *p*-values imposed by false discovery rate (FDR) and family-wise error rates (FWER) corrections. For example, a significance level of 0.000397 (0.05/126) will be required for statistical significance in the patent pending equations after applying the FWER correction. The other advantage of Bayesian estimation is that the Pr(effect of diversity | sample) for the posterior distribution is available in place of the Pr(sample | no effect of diversity) provided by frequentist estimation, allowing for much richer inference.

Discussion

The value of diversity in a liberal democracy is currently a highly contentious topic requiring analysis which is both comprehensive and fully transparent. A protocol to reduce false discovery that was earlier applied to self-reported innovation data was applied to the arguably harder test of whether diversity increases or decreases the probability of intermediate innovation outcomes such as patents awarded or receiving venture/angel capital funding. The evaluation of the innovative idea implicit in either outcome allows testing two competing explanations for why diversity increases the probability of self-reported innovation. The affective conflict explanation argues that diverse teams may have more difficulty coming to consensus regarding the value of an innovation and thus are more likely to launch new products that are poor or mediocre. The cognitive conflict explanation argues that the different attitudes or experiences in diverse teams increase the combination of seemingly incongruent ideas, leading to better, more novel innovation.

The very strong positive association between different types of disciplinary and demographic diversity and intermediate innovation outcomes provides strong initial support for the cognitive conflict explanation. In addition to mirroring the positive association found in the earlier self-reported innovation analysis, magnitudes of the estimates in intermediate outcome regressions are substantially larger. The main qualitative difference with respect to the earlier analysis is that sex diversity appears to be negatively associated with patenting and venture/angel capital funding—a finding that is consistent with other research examining gender gaps in these intermediate innovation outcomes.

The much smaller size of the sample used in this analysis, limited to R&D-performing microbusiness, relative to the earlier analysis using the entire population of businesses does make the confirmatory analysis more important. As a replication of the current analysis, confirmatory analysis can address concerns regarding Type I errors and Type M errors (magnitude). The potential Type I error of most concern is whether the seemingly opposite effect of education specialization on patenting (+) and venture/angel capital funding (-) is due to the luck of the draw. If the relatively small samples selected for the exploratory analysis include a disproportionate number of firms highly active in patenting but either uninterested or unable to raise venture capital funds, the finding may be an anomaly. Type M errors may also result from small draws being less likely to be representative of the underlying population. The log odds for some of the diversity measures in the current analysis are 3 to 5 times larger than the effects estimated in the earlier self-reported innovation analysis. Replicating the analysis with another draw will provide information on the generalizability of the finding. If the much larger magnitude of diversity on intermediate innovation outcomes is confirmed, this would suggest that diversity may be more important for small start-ups that are more likely to be engaged in radical innovation.

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Appendix

Table A1. Logistic Regression Estimates of Patent Pending on Ownership Diversity and Control Variables

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AEGHMRU	3.731	0.2087	41.7	0.784	-0.7086	-0.0564
AEHMRU	3.707	0.1891	40.73	0.7414	-0.5471	-0.0546
EHMRU	3.678	0.1965	39.58	0.7388	-0.5653	-0.0536
AHMRU	3.666	0.1922	39.08	0.7283	-0.5264	-0.055
AEHRU	3.663	0.1948	38.98	0.7989	-0.5459	-0.0565
AGHMRU	3.649	0.2159	38.45	0.7825	-0.7137	-0.0571
EGHMRU	3.596	0.2188	36.44	0.7966	-0.7467	-0.0561
AEGHRU	3.587	0.2159	36.14	0.8446	-0.7296	-0.0582
AHRU	3.57	0.1992	35.52	0.7958	-0.5192	-0.0574
AEGHMR	3.524	0.2051	33.91	0.8035	-0.7465	-0.0574
EHMR	3.501	0.1925	33.15	0.7505	-0.5959	-0.0548
AEHMR	3.496	0.1825	32.98	0.7559	-0.5706	-0.0557
AHR	3.492	0.2018	32.84	0.8205	-0.5365	-0.0589
AHMR	3.489	0.1874	32.76	0.738	-0.5463	-0.0562
EHRU	3.482	0.202	32.53	0.8133	-0.5705	-0.0559
AEHR	3.454	0.1899	31.63	0.8255	-0.5737	-0.0577
AGHMR	3.449	0.2156	31.46	0.8026	-0.7577	-0.0583
HMRU	3.434	0.1982	31.02	0.737	-0.5518	-0.0541
AGHRU	3.391	0.2257	29.71	0.8543	-0.7347	-0.0593
EGHMR	3.368	0.2187	29.03	0.8195	-0.7955	-0.0572
AEGHR	3.328	0.2138	27.89	0.8754	-0.7754	-0.0593
EHR	3.316	0.2034	27.54	0.8437	-0.6082	-0.0573
AEGMRU	3.313	0.1846	27.46	0.7842	-0.7082	-0.0564
HMR	3.278	0.1979	26.52	0.7429	-0.5795	-0.0554
GHMRU	3.254	0.2259	25.9	0.8106	-0.7528	-0.057
EGHRU	3.225	0.2263	25.15	0.8731	-0.7686	-0.0582
AEMRU	3.219	0.1631	25.03	0.7399	-0.5393	-0.0546
AEGHMU	3.206	0.1943	24.68	0.8141	-0.744	-0.0576
AGMRU	3.169	0.1867	23.78	0.7827	-0.7131	-0.0571
EGMRU	3.161	0.1907	23.6	0.7955	-0.7491	-0.0559
AEHMU	3.16	0.1718	23.57	0.7713	-0.587	-0.0559
EMRU	3.145	0.1655	23.23	0.7337	-0.5552	-0.0534
AEGRU	3.135	0.1875	22.99	0.8466	-0.7303	-0.0583
AGHR	3.113	0.2314	22.5	0.8902	-0.787	-0.0606
AERU	3.111	0.1636	22.45	0.7987	-0.5345	-0.0565
AMRU	3.086	0.1604	21.89	0.7255	-0.5152	-0.0549

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AHMU	3.079	0.1748	21.74	0.7567	-0.5708	-0.0565
EHMU	3.073	0.1782	21.61	0.7745	-0.6129	-0.0549
AGHMU	3.071	0.2023	21.56	0.8142	-0.7539	-0.0585
AEHU	3.029	0.1754	20.68	0.8378	-0.5942	-0.0579
AEGMR	3.025	0.1765	20.59	0.8052	-0.747	-0.0575
EGHMU	2.993	0.2042	19.95	0.8333	-0.7862	-0.0573
AEGHU	2.968	0.2001	19.45	0.881	-0.7688	-0.0595
GHMR	2.936	0.2312	18.84	0.8389	-0.8037	-0.0584
HRU	2.913	0.2009	18.41	0.835	-0.5598	-0.0572
ERU	2.909	0.1643	18.35	0.8092	-0.5542	-0.0557
AHU	2.905	0.1816	18.26	0.8349	-0.5731	-0.0592
ARU	2.902	0.1591	18.22	0.7938	-0.5006	-0.0574
AEMR	2.901	0.1513	18.19	0.7559	-0.5643	-0.0558
AGRU	2.873	0.1902	17.69	0.8569	-0.7354	-0.0593
AGMR	2.852	0.1794	17.31	0.8048	-0.7579	-0.0583
EGHR	2.848	0.2297	17.25	0.9117	-0.8204	-0.0595
AEGHM	2.831	0.1851	16.96	0.841	-0.7797	-0.0588
EGMR	2.829	0.1837	16.94	0.8205	-0.8001	-0.0572
MRU	2.809	0.1589	16.61	0.7293	-0.5374	-0.0537
EMR	2.808	0.1531	16.57	0.7468	-0.5877	-0.0547
EGRU	2.784	0.1932	16.19	0.8751	-0.774	-0.0581
AEGMU	2.779	0.1678	16.11	0.8145	-0.7455	-0.0577
GMRU	2.772	0.1911	15.99	0.8101	-0.7561	-0.0568
AEGR	2.769	0.1785	15.94	0.8795	-0.7774	-0.0594
HMU	2.768	0.1804	15.93	0.7721	-0.6047	-0.0556
EHU	2.768	0.1824	15.92	0.8634	-0.6289	-0.0574
AEHM	2.762	0.1586	15.83	0.7954	-0.6171	-0.0574
AMR	2.739	0.1473	15.48	0.7368	-0.5363	-0.0562
AER	2.737	0.1501	15.44	0.8273	-0.5645	-0.0579
HR	2.676	0.2134	14.53	0.8712	-0.5898	-0.0589
AGHU	2.675	0.2128	14.51	0.8941	-0.7774	-0.0607
AEMU	2.652	0.143	14.18	0.7697	-0.5809	-0.056
AHM	2.621	0.1605	13.75	0.7808	-0.602	-0.0583
AGHM	2.617	0.1945	13.69	0.8456	-0.7934	-0.06
EHM	2.615	0.1647	13.67	0.8019	-0.654	-0.0567
AGMU	2.58	0.1695	13.2	0.8142	-0.7563	-0.0586
EGMU	2.552	0.1726	12.83	0.8327	-0.7926	-0.0573
AEH	2.532	0.1603	12.58	0.8764	-0.6323	-0.0595
GHMU	2.531	0.2126	12.57	0.8522	-0.7912	-0.0585
AR	2.529	0.1453	12.55	0.8205	-0.517	-0.059

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
EGHM	2.515	0.1966	12.37	0.8672	-0.8272	-0.0588
ER	2.514	0.1513	12.35	0.8421	-0.5945	-0.0572
EMU	2.509	0.1425	12.29	0.7683	-0.6056	-0.0548
AEGU	2.509	0.1684	12.29	0.8839	-0.7727	-0.0596
GHRU	2.484	0.2337	11.98	0.9039	-0.7623	-0.0596
AMU	2.466	0.1384	11.78	0.7522	-0.5611	-0.0565
EGHU	2.463	0.2111	11.74	0.917	-0.8054	-0.0596
AEGH	2.461	0.1898	11.72	0.918	-0.8065	-0.0608
AEU	2.449	0.1398	11.58	0.8379	-0.5851	-0.0581
AGR	2.44	0.1839	11.48	0.8958	-0.7888	-0.0607
MR	2.401	0.1434	11.03	0.7355	-0.566	-0.0551
AH	2.352	0.1703	10.5	0.88	-0.6125	-0.0615
AEGM	2.331	0.1534	10.28	0.8435	-0.7816	-0.059
GMR	2.32	0.185	10.18	0.8416	-0.8087	-0.0583
EGR	2.289	0.1858	9.865	0.9173	-0.8291	-0.0595
RU	2.265	0.1498	9.63	0.8286	-0.5349	-0.0568
AU	2.197	0.1337	9.001	0.8307	-0.5545	-0.0594
HM	2.174	0.1671	8.793	0.8033	-0.6498	-0.0579
EU	2.173	0.1374	8.786	0.8598	-0.6171	-0.0572
AGU	2.16	0.1717	8.671	0.8974	-0.7832	-0.061
AEM	2.151	0.1237	8.592	0.7961	-0.6131	-0.0576
EH	2.137	0.1695	8.476	0.9152	-0.6832	-0.0594
MU	2.107	0.1329	8.221	0.7585	-0.593	-0.0551
GMU	2.054	0.1722	7.8	0.8518	-0.7998	-0.0585
HU	2.041	0.1848	7.695	0.8907	-0.6239	-0.0591
EGU	2.032	0.1729	7.627	0.9211	-0.8172	-0.0596
GRU	2.026	0.1911	7.586	0.9077	-0.7679	-0.0596
AGM	2.023	0.1528	7.562	0.8489	-0.7953	-0.0602
EGM	1.98	0.1561	7.246	0.8699	-0.8341	-0.059
AGH	1.963	0.2073	7.12	0.938	-0.8086	-0.0622
AEG	1.913	0.1495	6.773	0.923	-0.8099	-0.061
EM	1.883	0.1177	6.575	0.7993	-0.6508	-0.0569
AM	1.839	0.1132	6.289	0.7799	-0.5954	-0.0586
GHM	1.797	0.2076	6.029	0.8971	-0.8158	-0.0603
AE	1.792	0.1135	6.001	0.8798	-0.6272	-0.06
R	1.709	0.1294	5.523	0.8645	-0.5562	-0.0584
GHR	1.69	0.2488	5.42	0.9476	-0.7846	-0.0612
EGH	1.682	0.2027	5.377	0.9582	-0.8244	-0.0611
U	1.443	0.1186	4.232	0.8779	-0.5978	-0.0585
GHU	1.408	0.2231	4.088	0.9483	-0.771	-0.0612

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AG	1.341	0.1489	3.822	0.9444	-0.81	-0.0625
A	1.325	0.0964	3.764	0.8809	-0.5987	-0.0622
E	1.283	0.0999	3.606	0.9199	-0.6826	-0.0598
M	1.238	0.0947	3.45	0.7939	-0.6445	-0.058
GM	1.232	0.1505	3.429	0.9023	-0.819	-0.0605
EG	1.175	0.1485	3.238	0.9648	-0.8308	-0.0613
GR	1.141	0.1861	3.131	0.9544	-0.7848	-0.0613
GU	1.006	0.171	2.734	0.9534	-0.7771	-0.0613
H	0.6822	0.206	1.978	0.9583	-0.6752	-0.0619
GH	-0.2673	0.2233	0.765	0.9622	-0.6398	-0.0624
G	-0.4249	0.1304	0.654	0.9516	-0.5656	-0.0622

Notes: A = age, E = educational level, G = sex, H = ethnicity, M = education specialization, R = race, U = foreign-born status. Shaded estimates not passed through. Total of 126 of 127 equations passed through for confirmation.

Source: 2018 ABS 35% exploratory sample.

Table A2. Logistic Regression Estimates of Patent Owned on Ownership Diversity and Control Variables

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
EHMRU	3.288	0.2073	26.79	0.6391	-0.6149	0.0294
AEHMRU	3.241	0.1993	25.57	0.6402	-0.6005	0.0285
EHMR	3.216	0.2015	24.92	0.6434	-0.6398	0.0284
AEHMR	3.116	0.1917	22.56	0.6483	-0.6184	0.0275
AHMRU	3.094	0.2034	22.07	0.6368	-0.5841	0.0274
AHMR	3.001	0.1975	20.11	0.6398	-0.5975	0.0263
AEGHMRU	2.962	0.2201	19.34	0.6952	-0.7381	0.0256
HMRU	2.955	0.2106	19.19	0.6482	-0.6041	0.0279
AEHRU	2.938	0.2051	18.87	0.7075	-0.6045	0.0264
HMR	2.909	0.2083	18.34	0.6466	-0.6248	0.0268
EMRU	2.902	0.1746	18.21	0.6268	-0.6012	0.0299
EHMU	2.888	0.1887	17.95	0.6636	-0.6554	0.0281
AEMRU	2.883	0.1719	17.86	0.6334	-0.5898	0.0287
AEHMU	2.854	0.1816	17.36	0.6622	-0.6327	0.0272
EGHMRU	2.834	0.2311	17.02	0.7124	-0.7685	0.0255
AEGHMR	2.817	0.2159	16.72	0.7092	-0.7673	0.0246
AEHR	2.801	0.1993	16.46	0.7261	-0.6237	0.0252
EHRU	2.789	0.2136	16.26	0.7285	-0.6242	0.0265
AEGMRU	2.699	0.1948	14.87	0.6908	-0.7382	0.0257
AGHMRU	2.693	0.2288	14.77	0.7069	-0.7368	0.0242
AMRU	2.687	0.1698	14.69	0.6273	-0.5691	0.0277
AHMU	2.687	0.1852	14.68	0.6561	-0.6185	0.0259
EHR	2.685	0.2128	14.66	0.7516	-0.6516	0.0253
EMR	2.682	0.1603	14.62	0.6305	-0.6275	0.0287
EGHMR	2.669	0.2298	14.42	0.7298	-0.8064	0.0244
AEMR	2.659	0.1591	14.29	0.6424	-0.6085	0.0275
AHRU	2.623	0.2117	13.78	0.7191	-0.5894	0.0247
AEGHMU	2.595	0.2054	13.39	0.718	-0.7667	0.0244
EHM	2.589	0.1733	13.31	0.6817	-0.6926	0.0264
EGMRU	2.581	0.2016	13.21	0.7056	-0.7725	0.0258
AEHM	2.572	0.1672	13.09	0.6795	-0.6572	0.0257
AERU	2.569	0.1721	13.05	0.7021	-0.5913	0.0265
MRU	2.531	0.1688	12.57	0.6307	-0.5847	0.0286
HMU	2.531	0.1923	12.67	0.669	-0.6467	0.0265
AHR	2.525	0.2132	12.49	0.7363	-0.6005	0.0233
AGHMR	2.52	0.228	12.43	0.7223	-0.767	0.023
AEGHRU	2.5	0.2285	12.18	0.7607	-0.7449	0.0235
AEHU	2.497	0.1853	12.14	0.7371	-0.6408	0.0249

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AEGMR	2.494	0.1861	12.11	0.7058	-0.7691	0.0246
AEMU	2.459	0.1512	11.69	0.6553	-0.6239	0.0273
AMR	2.451	0.1554	11.6	0.6306	-0.5822	0.0264
EMU	2.449	0.1511	11.581	0.6494	-0.6449	0.0286
ERU	2.431	0.1733	11.37	0.7184	-0.6063	0.0271
EGHMU	2.422	0.2163	11.26	0.7396	-0.8016	0.0242
AGMRU	2.419	0.1981	11.24	0.7014	-0.7371	0.0243
AHM	2.368	0.1694	10.68	0.6715	-0.6421	0.0241
EGMR	2.345	0.1935	10.43	0.7241	-0.8146	0.0245
AEGHM	2.324	0.1954	10.22	0.7385	-0.7954	0.0231
AEGMU	2.316	0.1775	10.13	0.7138	-0.7694	0.0244
EHU	2.315	0.1936	10.12	0.7659	-0.6691	0.025
AER	2.302	0.1574	9.999	0.7225	-0.6115	0.0252
GHMRU	2.293	0.2409	9.901	0.7412	-0.763	0.0236
AGHMU	2.279	0.2146	9.767	0.7312	-0.766	0.0228
MR	2.274	0.1511	9.723	0.6249	-0.6044	0.0274
AEGHR	2.273	0.2261	9.705	0.7829	-0.7728	0.0224
AEGRU	2.257	0.1985	9.555	0.7583	-0.7465	0.0236
AMU	2.232	0.1467	9.318	0.6442	-0.6048	0.026
ARU	2.224	0.1688	9.245	0.711	-0.5694	0.0248
AGMR	2.177	0.1902	8.822	0.718	-0.7695	0.023
HM	2.157	0.1758	8.642	0.6859	-0.6858	0.0242
ER	2.155	0.1573	8.631	0.7426	-0.6351	0.0257
EGMU	2.153	0.183	8.611	0.7332	-0.811	0.0244
AHU	2.143	0.1929	8.528	0.7487	-0.6272	0.0229
AEH	2.143	0.169	8.524	0.7671	-0.6689	0.0232
AEU	2.089	0.1475	8.074	0.7323	-0.63	0.0249
EGHRU	2.081	0.2414	8.015	0.794	-0.7672	0.0228
EGHM	2.075	0.2071	7.966	0.7661	-0.8357	0.0227
AEM	2.069	0.1305	7.919	0.6743	-0.65	0.0256
AEGHU	2.061	0.2124	7.85	0.7873	-0.7707	0.0222
GMRU	2.056	0.204	7.812	0.7337	-0.7684	0.0238
MU	2.049	0.142	7.761	0.6426	-0.6302	0.0273
HRU	2.014	0.2192	7.493	0.767	-0.6242	0.0238
AGMU	1.993	0.1799	7.338	0.7256	-0.77	0.0228
GHMR	1.987	0.2454	7.295	0.7653	-0.7934	0.0222
AEGM	1.984	0.162	7.269	0.7362	-0.7997	0.023
AEGR	1.971	0.1889	7.178	0.7824	-0.7768	0.0223
AGHRU	1.964	0.2426	7.131	0.7854	-0.7376	0.0218
EM	1.96	0.124	7.102	0.6693	-0.6868	0.0265

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AR	1.942	0.1535	6.973	0.7291	-0.5775	0.0232
AGHM	1.928	0.2058	6.876	0.7559	-0.7927	0.0214
EU	1.921	0.1455	6.828	0.7564	-0.6564	0.0256
EH	1.887	0.1786	6.599	0.8083	-0.7126	0.023
EGRU	1.886	0.206	6.596	0.7913	-0.7742	0.023
AEGU	1.809	0.1786	6.109	0.786	-0.7759	0.0222
GHMU	1.771	0.2275	5.875	0.7727	-0.7882	0.0221
AGRU	1.746	0.2045	5.734	0.7826	-0.7397	0.0217
AM	1.744	0.1196	5.723	0.6617	-0.6302	0.0238
EGM	1.731	0.1646	5.645	0.7626	-0.8492	0.0227
AH	1.707	0.1794	5.514	0.7827	-0.6534	0.0207
AU	1.706	0.1415	5.505	0.7384	-0.608	0.0229
EGHR	1.701	0.2442	5.482	0.8219	-0.7906	0.0215
RU	1.693	0.1631	5.434	0.7536	-0.5987	0.0245
GMR	1.692	0.1968	5.432	0.7596	-0.8039	0.0223
HR	1.684	0.2357	5.388	0.7994	-0.6475	0.022
AEGH	1.668	0.2015	5.304	0.8143	-0.7919	0.0209
AE	1.588	0.1196	4.893	0.7659	-0.6614	0.0229
AGHR	1.579	0.2489	4.848	0.8117	-0.7567	0.0205
AGM	1.574	0.1617	4.827	0.7528	-0.7986	0.0212
GMU	1.539	0.1841	4.66	0.7654	-0.8006	0.0222
EGHU	1.525	0.2258	4.594	0.8242	-0.7854	0.0214
EGR	1.467	0.1974	4.336	0.8221	-0.8026	0.0215
AGHU	1.399	0.2288	4.052	0.8145	-0.7546	0.0204
AEG	1.367	0.1585	3.924	0.8155	-0.7989	0.0207
M	1.359	0.1	3.895	0.6565	-0.676	0.0244
HU	1.359	0.2045	3.894	0.8087	-0.6677	0.0218
EGU	1.341	0.1843	3.823	0.8237	-0.799	0.0215
AGR	1.325	0.198	3.764	0.8112	-0.7616	0.0203
R	1.259	0.1426	3.522	0.7832	-0.6126	0.0227
E	1.242	0.1049	3.464	0.8075	-0.7122	0.023
AGU	1.201	0.184	3.322	0.8128	-0.7611	0.0203
GHM	1.178	0.2206	3.249	0.8091	-0.796	0.0204
U	1.1	0.1301	3.004	0.7902	-0.6435	0.0227
A	1.045	0.101	2.845	0.7768	-0.6367	0.0201
GHRU	0.9497	0.2603	2.585	0.8358	-0.7346	0.0203
GM	0.9153	0.1595	2.497	0.8061	-0.8108	0.0203
EGH	0.8839	0.2158	2.42	0.8519	-0.7792	0.0199
GRU	0.8493	0.213	2.338	0.8344	-0.7407	0.0203
AGH	0.7309	0.2226	2.077	0.8442	-0.7475	0.0192

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
EG	0.6953	0.1571	2.004	0.8546	-0.793	0.0198
AG	0.556	0.159	2.381	0.8451	-0.7536	0.019
H	0.00296	0.2465	1.003	0.8604	-0.696	0.0189
GHU	-0.00001	0.2515	1	0.8604	-0.6959	0.0189
GU	-0.00089	0.1905	0.999	0.8604	-0.6959	0.0189
GR	-0.1061	0.2099	0.899	0.8618	-0.685	0.0188
GHR	-0.1268	0.2826	0.881	0.862	-0.687	0.0188
G	-1.137	0.1436	0.321	0.8367	-0.3989	0.0199
GH	-1.719	0.2529	0.179	0.8482	-0.4684	0.019

Notes: A = age, E = educational level, G = sex, H = ethnicity, M = education specialization, R = race, U = foreign-born status. Shaded estimates not passed through. Total of 122 of 127 equations passed through for confirmation.

Source: 2018 ABS 35% exploratory sample.

Table A3. Logistic Regression Estimates of Venture/Angel Capital Funding on Ownership Diversity and Control Variables

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AHR	2.305	0.1765	10.02	0.191	-0.5474	-0.1343
AHRU	2.116	0.174	8.301	0.2053	-0.5481	-0.135
AH	2.014	0.1504	7.493	0.2082	-0.6014	-0.1367
AHU	2.012	0.1603	7.482	0.2172	-0.5775	-0.1364
AGHRU	1.877	0.1987	6.536	0.2056	-0.6659	-0.1376
AEHRU	1.856	0.1716	6.397	0.2232	-0.5871	-0.1365
AGHR	1.854	0.2013	6.388	0.1983	-0.6958	-0.1381
AEHR	1.811	0.1672	6.12	0.2196	-0.6014	-0.1365
AGHU	1.735	0.1885	5.667	0.2149	-0.704	-0.1389
HR	1.709	0.1961	5.527	0.2115	-0.56	-0.1367
AEGHRU	1.701	0.1923	5.479	0.2192	-0.6686	-0.1382
HRU	1.651	0.1863	5.214	0.2205	-0.5617	-0.1369
AHMRU	1.651	0.1903	5.214	0.2474	-0.5652	-0.1372
AEHU	1.649	0.1558	5.202	0.2339	-0.6132	-0.1377
AEGHR	1.599	0.19	4.948	0.2166	-0.6899	-0.1386
EHRU	1.59	0.1882	4.904	0.2334	-0.5958	-0.1377
HU	1.58	0.1769	4.857	0.235	-0.5895	-0.1385
AEHMRU	1.574	0.1869	4.828	0.25	-0.5888	-0.1377
AGH	1.552	0.1816	4.721	0.2113	-0.743	-0.1398
AEGHU	1.507	0.1794	4.513	0.2275	-0.6937	-0.1392
AHMR	1.501	0.187	4.484	0.2497	-0.5748	-0.1375
ARU	1.499	0.1383	4.477	0.2092	-0.5618	-0.1352
EHR	1.48	0.1891	4.395	0.2318	-0.6122	-0.138
AR	1.471	0.1288	4.355	0.1954	-0.5656	-0.1344
AEH	1.453	0.1415	4.275	0.2325	-0.6366	-0.1382
AEHMR	1.425	0.1821	4.158	0.2512	-0.6002	-0.138
AHMU	1.403	0.1738	4.069	0.2595	-0.5879	-0.1383
H	1.399	0.1678	4.051	0.2337	-0.6169	-0.1398
AERU	1.395	0.1435	4.035	0.2254	-0.5972	-0.1366
EHU	1.352	0.1722	3.867	0.2456	-0.6242	-0.1391
AEGHMRU	1.351	0.2025	3.861	0.243	-0.6491	-0.1389
AGRU	1.349	0.167	3.855	0.2105	-0.6693	-0.1379
AGHMRU	1.342	0.2065	3.826	0.2404	-0.6432	-0.1388
AEHMU	1.339	0.1711	3.814	0.2587	-0.6083	-0.1386
AU	1.299	0.117	3.664	0.2211	-0.5908	-0.1364
AEGH	1.295	0.1695	3.651	0.2266	-0.7156	-0.1398
AEGRU	1.289	0.1666	3.629	0.222	-0.6711	-0.1383
AER	1.265	0.1329	3.542	0.2223	-0.613	-0.1367

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
EGHRU	1.253	0.2126	3.501	0.2291	-0.6742	-0.1393
AGR	1.205	0.1611	3.336	0.2056	-0.6961	-0.1384
AEMRU	1.176	0.161	3.241	0.25	-0.5984	-0.1378
AEU	1.161	0.1237	3.192	0.2357	-0.6227	-0.1377
GHRU	1.159	0.2172	3.189	0.2229	-0.6704	-0.1393
AEGHMR	1.157	0.1983	3.181	0.2434	-0.6594	-0.1392
AMRU	1.155	0.1581	3.175	0.248	-0.5792	-0.1375
AGU	1.155	0.1514	3.174	0.2194	-0.7036	-0.1391
AEGR	1.129	0.1593	3.093	0.2204	-0.6899	-0.1388
AEGHMU	1.127	0.1889	3.088	0.249	-0.6632	-0.1396
AGHMR	1.103	0.2018	3.014	0.2413	-0.6546	-0.1392
EHMRU	1.097	0.2037	2.996	0.2552	-0.6034	-0.1388
AGHMU	1.094	0.1923	2.986	0.2477	-0.6599	-0.1396
AHM	1.092	0.1582	2.98	0.2616	-0.6045	-0.1389
AEHM	1.089	0.1582	2.973	0.2593	-0.6225	-0.139
AEGU	1.079	0.1506	2.943	0.2298	-0.6934	-0.1393
A	1.032	0.089	2.806	0.2122	-0.6224	-0.1364
ERU	1.03	0.1515	2.802	0.2356	-0.6084	-0.138
AEGMRU	0.9978	0.1786	2.712	0.2434	-0.6509	-0.139
EH	0.9931	0.1553	2.7	0.2457	-0.6499	-0.1398
AEMR	0.9824	0.1511	2.671	0.2509	-0.6101	-0.1382
EGHU	0.979	0.2007	2.662	0.2368	-0.6921	-0.1402
EGHR	0.9718	0.214	2.643	0.2298	-0.6864	-0.1398
AEMU	0.9385	0.1423	2.556	0.2575	-0.6164	-0.1387
AMR	0.9251	0.1461	2.522	0.2497	-0.5914	-0.1379
AGMRU	0.9226	0.1775	2.516	0.2414	-0.6458	-0.139
RU	0.9124	0.1376	2.49	0.2262	-0.5825	-0.1374
HMRU	0.8998	0.1985	2.459	0.2527	-0.5951	-0.1389
AE	0.8935	0.1016	2.444	0.2347	-0.6464	-0.1382
AMU	0.8915	0.1367	2.439	0.2581	-0.6004	-0.1385
AEGHM	0.8644	0.1781	2.374	0.2486	-0.6705	-0.1399
AG	0.8611	0.1331	2.366	0.2178	-0.734	-0.1399
GHU	0.8526	0.2119	2.346	0.2321	-0.6917	-0.1403
AEG	0.8278	0.1347	2.288	0.2296	-0.7101	-0.1398
EHMU	0.7825	0.1851	2.187	0.2595	-0.6222	-0.1396
ER	0.7822	0.1399	2.186	0.2351	-0.6259	-0.1384
AEGMR	0.7798	0.1703	2.181	0.2436	-0.6587	-0.1394
AEGMU	0.7779	0.1628	2.177	0.2482	-0.662	-0.1396
EGRU	0.7712	0.1801	2.162	0.2327	-0.6701	-0.1395
EHMR	0.7691	0.1972	2.158	0.2539	-0.6182	-0.1393

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
AGHM	0.7569	0.1781	2.132	0.2473	-0.6669	-0.14
EU	0.7488	0.1275	2.114	0.2462	-0.6342	-0.1392
EGHMRU	0.7487	0.2183	2.114	0.2462	-0.65	-0.1397
GHR	0.746	0.223	2.108	0.2265	-0.6791	-0.1399
AGMU	0.675	0.1596	1.964	0.2468	-0.6582	-0.1397
AEM	0.6721	0.1238	1.958	0.257	-0.6296	-0.1392
M	0.6613	0.0939	1.937	0.0972	-0.819	-0.1824
U	0.6606	0.111	1.936	0.2395	-0.6077	-0.1387
AGMR	0.6525	0.1667	1.92	0.242	-0.6537	-0.1394
EMRU	0.6496	0.1702	1.915	0.2523	-0.6159	-0.1391
R	0.6187	0.1214	1.857	0.2227	-0.5936	-0.1377
GRU	0.5638	0.1757	1.757	0.2304	-0.6633	-0.1396
AM	0.5509	0.1107	1.736	0.2578	-0.6174	-0.1391
HMU	0.5287	0.176	1.697	0.2556	-0.6182	-0.1397
EGH	0.5284	0.1893	1.696	0.2382	-0.6873	-0.1405
AEGM	0.5129	0.1475	1.67	0.2472	-0.6651	-0.1399
GHMRU	0.4959	0.2135	1.642	0.244	-0.645	-0.1398
EGU	0.4787	0.1627	1.614	0.2389	-0.6773	-0.1402
HMR	0.4482	0.184	1.565	0.2496	-0.6181	-0.1395
EGHMU	0.4454	0.2023	1.561	0.2474	-0.6542	-0.1401
EGR	0.4214	0.1726	1.524	0.2354	-0.6699	-0.1399
MRU	0.4016	0.1557	1.494	0.2489	-0.6158	-0.1393
EGHMR	0.3807	0.211	1.463	0.2445	-0.6506	-0.1399
EGMRU	0.3737	0.1883	1.453	0.2446	-0.6478	-0.1398
EMU	0.3538	0.1463	1.424	0.2528	-0.6316	-0.1397
EHM	0.3534	0.1636	1.424	0.2525	-0.6358	-0.1399
AGM	0.348	0.1385	1.416	0.2453	-0.6587	-0.14
E	0.3205	0.0906	1.378	0.2453	-0.6529	-0.1398
EMR	0.3026	0.1547	1.353	0.2485	-0.6308	-0.1396
GU	0.1852	0.1597	1.203	0.2388	-0.6591	-0.1401
GHMU	0.1438	0.1942	1.155	0.2433	-0.6453	-0.14
GMRU	0.1057	0.1766	1.112	0.2422	-0.6427	-0.1399
GH	0.0963	0.2012	1.101	0.2399	-0.6523	-0.1401
EGMU	0.0958	0.1685	1.1	0.2431	-0.6452	-0.14
MU	0.0803	0.1238	1.084	0.2448	-0.6366	-0.1399
GR	0.0423	0.1663	1.043	0.2403	-0.645	-0.1399
GHMR	0.0387	0.1994	1.039	0.2417	-0.6422	-0.1399
EGHM	0.0323	0.1837	1.033	0.2419	-0.6429	-0.1399
EG	0.0288	0.1388	1.029	0.2412	-0.6454	-0.14
EGMR	0.0163	0.1747	1.016	0.2416	-0.6419	-0.1399

Diversity Measure	Diversity Estimate	Diversity Standard Error	Diversity Odds Ratio	NAICS 54	Family Business	Firm Age
HM	0.00803	0.1383	1.008	0.2417	-0.641	-0.1399
EM	-0.00598	0.1146	0.994	0.2411	-0.6415	-0.1399
MR	-0.00692	0.1281	0.993	0.2412	-0.6418	-0.1399
GMU	-0.1907	0.1514	0.826	0.2378	-0.6335	-0.1398
EGM	-0.2468	0.143	0.781	0.2355	-0.6243	-0.1396
GMR	-0.287	0.1546	0.751	0.2381	-0.6316	-0.1398
GHM	-0.3109	0.1646	0.733	0.2359	-0.6249	-0.1395
GM	-0.4759	0.1137	0.621	0.2285	-0.6001	-0.139
G	-0.4937	0.1206	0.61	0.2547	-0.5222	-0.1382

Notes: A = age, E = educational level, G = sex, H = ethnicity, M = education specialization, R = race, U = foreign-born status. Shaded estimates not passed through. Total of 107 of 127 equations passed through for confirmation.

Source: 2021 ABS.