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DOCTORAL THESIS

Education and the Labour Market in Canada

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Declaration of Authorship

I, Xiaoxue Li, hereby declare that this thesis, titled “Education and Labour market in Canada”, is the result of my original research. Chapter one is research done by myself. Chapters two and three are co-authored with Dr. Pierre Brochu, with equal contributions from both of us. I would like to express my gratitude to Dr. Pierre Brochu for his invaluable collaboration and contributions to the research in these chapters.

I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: XIAOXUE LI

Date: Febuary, 2025

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In memory of my dearest grandfather and grandmother.*

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Abstract

The first chapter examines how COVID-19 affected post-secondary enrolment in Canada. Using Labour Force Survey data, I find that university enrolment increased during the pandemic for younger (17-24) and older (25-39) women. For men, the effect is only present in the younger age group and is more moderate. My results suggest that for older women, it is those that work full-time that key, and the COVID effect is larger for high-skilled and telework-susceptible occupations. For younger women, it is teenagers whose families are poorer and who live just outside the core of census metropolitan areas or census agglomerations with a university that drive my findings.

The second chapter examines how job stability has evolved since the Great Recession using the Canadian Labour Force Survey, a rich source of tenure data. We find that jobs have become more stable, particularly for women and low-tenure jobs. Rising educational attainment (but not ageing of the workforce) appears to play a role in explaining some of the new job stability patterns. Contrary to the findings for the U.S. labour market, job-to-job transitions are not key to our findings. Instead it is changes in the employment to non-employment transition, particularly to unemployment, that matters for low-tenure jobs and it is employer driven.

The third chapter explores the source of the job stability gender gap puzzle identified in the second chapter. It delves into the underlying reasons why women's job stability, as gauged by the female retention rate, did not simply converge towards the male rate but in fact caught up to it and then regularly eclipsed it since the mid- to late 2000s. To do so, we take advantage of the richness of the Labour Force Survey tenure data. Our cross-sectional and panel analysis both indicate that compositional differences, in particular education and industry composition, are at the core of the gender gap puzzle.

General Introduction

This dissertation contains three chapters in education and labour economics.

The first chapter analyzes the effect of COVID-19 on post-secondary enrolment in Canada. It utilizes the master files of the Labour Force Survey which is a rich and timely source of post-secondary enrolment data. The findings indicate that university enrolment increased during the pandemic, particularly for younger (17–24) and older (25–39) women. Among men, this effect is present only in the younger age group and is more moderate. For older women, working full-time appears to be a key factor, with the COVID effect being most pronounced in high-skilled and telework-compatible occupations. These findings are in line with the idea that in COVID-19 times (as a result of online schooling) going back to university and upgrading one's skills did not require sacrificing a career job. Among younger women, it also appears to be a cost of education story, but the channel through which it operates is different. It is a direct education cost channel: because one can now study from home it is now less costly to attend university. The fact that the increase in enrolment is driven by teenagers from lower-income families who reside just outside the core of census metropolitan areas or census agglomerations with a university supports this claim.

The second chapter investigates the evolution of job stability in Canada since the Great Recession, leveraging the Labour Force Survey's rich tenure data. The analysis reveals that job stability has increased, particularly for women and workers in low-tenure positions. These patterns are present for both cross-sectional and panel approaches. While rising educational attainment contributes to this trend, workforce aging does not appear to be a significant factor. Unlike in the U.S. labour market, job-to-job transitions do not drive these findings. Instead, changes in employment-to-non-employment transitions, particularly shifts to unemployment, play a crucial role in shaping job stability for low-tenure workers, with employer decisions being a key determinant. A secondary goal of this paper is to document job stability patterns of individuals of Indigenous identity living off-reserve, immigrants (i.e., vulnerable populations) which had yet to be examined in Canada because of previous data limitation. Individuals of Indigenous identity living off-reserve, as with other labour market outcomes, do poorly along the job stability dimension. For immigrants, the story is less dismal. Although they do not do as well the native-borns upon their arrival, they eventually catch-up and surpass them as they have a steeper assimilation pattern.

In this third and last chapter, we again rely on the richness of the Labour Force Survey tenure data, but this time to explore the gender retention rate gap puzzle documented in the second chapter. More precisely, this chapter explores why women's job stability, as measured by the female retention rate, did not simply converge towards the male rate, but caught up to it, and then systematically surpassed it since the mid- to late 2000s. In the

process, we also address the equally puzzling gender differences at the bottom of the tenure distribution, where female jobs are in fact relatively more stable. To examine the role of compositional differences we first rely on a cross-sectional approach which assign the other gender's socio-demographic characteristics. We find that education and most importantly industry are key to these findings. We complement this cross-sectional investigation by carrying-out regression analysis, taking advantage of the panel feature of the Labour Force Survey. Our regression results confirm our cross-sectional findings. By controlling for all factors at the same time, we can further conclude that as a group, age, education and industry can fully explain the gender gap puzzle, and the gender differences observed in new (low-tenure) jobs.

Chapter 1

Post-Secondary Enrolment in the Time of COVID

1.1 Introduction

COVID-19 dramatically affected the Canadian economy and the well-being of Canadians, whether it be through the employment and participation rates (Lemieux et al., 2020; Brochu, Cr chet and Deng, 2020), GDP (Green et al., 2021), or consumption, debt and savings (MacGee et al., 2022). In particular, the adoption of precautionary health measures that followed the advent of COVID-19 significantly affected the behaviour of Canadians, with changing work arrangements, i.e., working from home, receiving much press (Mehdi and Morissette, 2021; Lindzon, 2022). One aspect that has yet to receive much attention, at least from academics, is how it influenced post-secondary enrolment.

There are reasons to believe that post-secondary enrolment could have been affected, for reasons beyond the traditional business cycle explanation.¹ At the start of the pandemic, post-secondary institutions were forced to dramatically alter their provision of education, i.e., they had to switch to an online approach. Even when social distance restrictions were relaxed, many post-secondary institutions did not completely revert back to in-person teaching.² Within a human capital framework, such changes in the provision of education could affect the cost of education, and in turn influence enrolment decisions.³

¹In recessionary times and during subsequent recoveries, it is harder to find a job, and as such, the opportunity cost of going to school is lower, resulting in an increase in school attendance/enrolment.

²Even in the cases where universities offered in-person classes (typically for the smaller classes) there usually was an online option (i.e., hybrid learning).

³There are different ways through which the changes in the provision of education could affect the cost of education. It can, for some, reduce the direct cost of attending a post-secondary institution through lower food and lodging costs, as a person coming out of high school and going to college/university can now do it from home. On the other hand, the flexibility of online learning could make it possible for someone to better juggle work and schooling. As such, the opportunity cost of attending a post-secondary institution would be lower as an individual would not need to give up their career job to go to school. See

In this paper, I rely on the master files of the Labour Force Survey (LFS), a rich and timely source of post-secondary enrolment data, to examine how the advent of COVID-19 affected post-secondary enrolment in Canada, and explore the sources of change. Although international evidence is starting to emerge (U.S.: [Aucejo et al. \(2020\)](#), Germany: [Sandner et al. \(2023\)](#)), there is no Canadian evidence to date.⁴

I find that after controlling for confounding factors, university enrolment increased in COVID-19 times for both young (17-24) men and women, but in the case of men, the effect was more muted (men: 1.3 p.p.; women: 3.2 p.p.). For older (25-39) women, one saw a 1.2 p.p. rise in university enrolment. Given that only 5.1% of older women were attending university each September over the three years prior to COVID-19, this increase is economically sizeable. Interestingly, there was no associated increase in college enrolment for either age or gender group.

Cost of education appears to matter for both younger and older women, but the way through which it operates appears to differ across the two groups. The evidence suggests that for older women it is those who are attached to the workforce that are driving the results. This goes in line with the notion that in COVID-19 times (due to online schooling) one did not have to sacrifice a career job to go back to university and upgrade one's skills. The fact that the COVID effect is stronger for occupations that are more susceptible to telework and tend to be higher-skilled further supports this claim. Finally, the observation that a larger university enrolment effect for employed women that already possess a post-secondary certificate, diploma or degree reinforces the idea that they went back to school to upgrade their human capital.⁵ It is teenagers—a group that is at best only partially attached to the workforce—that are driving the findings for younger women. Two key pieces of evidence suggest that the direct education cost channel (i.e., it is now less costly to attend university because they can now study from home) may matter. First, the COVID effect gets larger when I focus on poorer families. More precisely, the effect increases by half (double) when I restrict my attention to the bottom 50th (25th) percentile of the family income distribution. Second, the effect is larger when, in addition to conditioning on family income, one starts to move away from the core of

section 1.5.2 for more details on possible channels.

⁴To date, the Canadian literature which has looked into school closures/online learning has tended to focus on outcomes of young children ([Haeck and Lefebvre, 2020](#)), or their parents ([Green et al., 2021](#); [Beauregard et al., 2022](#)). It should be noted that there has been some preliminary discussion of the potential impact of COVID-19 for post-secondary students ([Zeman and Frenette, 2021](#); [Mahboubi and Higazy, 2022](#)), but the evidence is still very preliminary. In particular, I am not aware of any study that has looked into the impact of COVID-19 on post-secondary enrolment in Canada, nor explored the source of change.

⁵Some evidence also aligns with the possibility that COVID-19 affected the perceived benefits of certain occupations. Workers in sectors more exposed to viral risk (e.g., health and education) may have sought to switch professions, thus requiring retraining (i.e., going back to school). It should also be noted that it is not unreasonable to surmise a complementarity with the cost of education channel, as having online classes would make it easier to retrain for a new profession while working full-time at one's current profession.

census metropolitan areas (CMAs) or census agglomerations (CAs) that have a university.

This paper contributes to two strands of literature. First, it adds to the large, and still growing, Canadian COVID-19 literature. The advent of COVID-19, and the precautionary health measures/behaviours that accompanied it, had far-reaching influences that went well beyond the poor economic outcomes typically associated with recessionary times.⁶ It affected mental health (Beland et al., 2022), energy use (Villeneuve et al., 2021), credit usage (Ho et al., 2022), and even religiosity (Lacasse and Cornelissen, 2022), to name just a few. This paper provides another avenue through which COVID-19 affected Canadians. It should be noted that the current increase in post-secondary enrolment will have long-term consequences, even if the enrolment behaviour of future cohorts reverts back to pre-COVID level once COVID concerns have subsided. Individuals that currently increased their schooling will, according to the human capital model, be able to command a higher wage in subsequent years (and well-after the pandemic is over), due to their increased productivity generated by more schooling.⁷

Second, this paper contributes to the education literature. Although a substantive part of this literature has looked at the impact of having more education, whether it be on wages (Lemieux and Card, 2001; Aakvik et al., 2010; Oreopoulos et al., 2012), job stability (Brochu, 2013), and lower unemployment incidence and better re-employment success (Riddell and Song, 2011), my paper contributes to the part of the literature that focuses on the enrolment/attendance decision (Foley et al., 2014; Foley, 2019; Kottelenberg and Lehrer, 2019). More precisely, my paper is closest to those that have looked at how the external environment, whether it be the business cycle, an oil boom or COVID-19, influences the decision to stay or continue schooling.⁸ This literature finds that the external environment matters. Papers that have looked at the business cycle effect find that an increase in the unemployment rate tends to reduce post-secondary enrolment (Alessandrini, 2018; Boffy-Ramirez, 2017). Interestingly, Alessandrini (2018) finds that for Canada the effect is only felt at the university level. The oil boom in Western Canada did affect the timing of schooling, i.e., it delayed, but did not reduce the total accumulation of human capital (Emery et al., 2012; Morissette et al., 2015). As for the COVID effect, there is still no consensus as the international evidence is still very preliminary. Bulman and Fairlie (2022) find that it led to a decrease in enrolment in California's community colleges, whereas Aucejo et al. (2020) see it delaying the graduation plans of University of Phoenix

⁶The COVID-19 recession was severe but short-lived. Having said that, it did take some time for the economy to fully recover to its pre-pandemic levels.

⁷Accounting for general equilibrium effects could dampen the pursuit of more skills. This holds true because the increase in supply of highly-skilled workers, combined with the fact that employers are having difficulties hiring low-skilled workers, will impact the relative wage of high-skilled workers. See Card and Lemieux (2001) for a discussion of general equilibrium effects in the presence of supply shocks.

⁸Although somewhat tangential, one also needs to mention papers that look at large labour supply shocks, such as the Ontario double cohort which resulted in important year-to-year changes in university enrolment/graduation rates (Morin, 2015a; Zhang, 2022).

students. Fiaschi and Tealdi (2022) who focus on the school-to-work transition in Italy, see evidence of young adults going back to school. Finally, Sandner et al. (2023) look at mental well-being as a possible channel of how COVID-19 could affect the enrolment decisions of German post-secondary students. They find those whose mental health was more affected by COVID-19 were more likely to want to delay their graduation and tended to show less interest in pursuing further studies.

The rest of the paper is as follows. Section 1.2 introduces the data, and section 1.3 presents summary statistics. In section 1.4, I discuss the econometric strategy and some results. Section 1.5 conducts a further exploration. Section 1.6 carries out robustness checks. Finally, section 1.7 concludes.

1.2 Data

For my main analysis, I rely on September data of the LFS master files for the 2017–2021 period.⁹ The LFS is the official source of labour market information of the working age population in Canada. This long-running monthly household survey has a rotating panel design where households are interviewed for six consecutive months, with one-sixth of the sample being replaced every month.

A lesser-known feature of the LFS, which is key to my analysis, is the richness of the enrolment data. As part of the regular questionnaire, the LFS asks a series of questions regarding current school enrolment/attendance (i.e., the school attendance block). More precisely, it asks “*Last week, was ... attending a school, college or university?*” If the response is yes, it continues with the question “*Was he/she enrolled as a full-time or part-time student?*” and “*What kind of school was this?*”. The answer to the last question allows me to identify whether the respondent is currently attending a post-secondary institution, and if so, the kind/type of post-secondary institution, i.e., college or university. In addition, the enrolment information is refreshed in subsequent interviews, unlike the socio-demographic information which is only asked at the birth interview and carried forward in subsequent interviews.¹⁰ Given that I am mainly interested in whether a person is enrolled in the month of September, having enrolment information refreshed in subsequent interviews is critical to my analysis. It means that I can use all six rotations.¹¹

Another critical feature of the LFS is its frequency and timeliness. It is a monthly survey, and the time between enumeration and the release of the data is less than a month.

⁹The LFS master files were accessed at the Ottawa-Outaouais Research Data Centre (ORDC).

¹⁰If, for example, a household first entered the survey in January 2020 and remained in the survey until June 2020, then the January interview is referred to as the birth interview, and the February through June interviews are subsequent interviews.

¹¹Irrespective of when a person initially entered the survey, there will be September enrolment information if the person answered the survey in September.

As such, I can credibly examine the effect of COVID-19 and do so in a timely manner. Finally, the large sample sizes (i.e., about 56,000 households are surveyed each month) are also important since much of the analysis is at the subgroup level, which in some cases is narrowly defined (e.g., women 17 to 24 years of age).

I require the master files of the LFS because much of the richness of the enrolment data is suppressed in the public-use files. More precisely, from January 2017 onwards, the information on the type of schooling is not made available in the public-use microdata. As such, one cannot separate out post-secondary from high school enrolment. Even in situations where one could possibly argue that the enrolment is probably post-secondary (e.g., an individual in her/his 30s), one cannot determine if it is university or college. Furthermore, I need to be able to identify foreign students (as to exclude them) but this information is also unavailable in the public-use files for my period of study.

My sample includes individuals that are 17 to 39 years of age who are born in Canada or are (or ever were) landed immigrants. The age restrictions reflect the fact that many individuals enrol at a post-secondary institution as early as 17 years of age, and if they decide to do graduate studies it will typically be done before the age of 40. I focus on the Canadian born and those who are (or ever were) landed immigrants as to exclude foreign students, as some foreign students could have decided to attend a Canadian university but study from home (i.e., in their home country) during the COVID-19 pandemic.¹² For my main analysis, I also restrict my sample to September data over the 2017 to 2021 period. September is the first month of the fall semester, which typically reflects the enrolment decisions for the school year.¹³ Finally, I rely on three pre-COVID years because post-secondary enrolment rates are stable over this period. Having stable pre-COVID enrolment rates is key for my identification strategy which I discuss in section 1.4.¹⁴

Finally, it should be noted that much of my analysis is carried out by age (17-24 versus 25-39) and gender subgroups. Teenagers and young adults are of the ages when they typically attends post-secondary, i.e., soon after high school. Furthermore, the socio-demographic characteristics and labour market characteristics of the older age group (25-39) are very different than for their younger counterparts (see section 1.3 for more details). As such, one can expect the factors that determine post-secondary enrolment to also vary across the two age groups.¹⁵

¹²Such an approach (to exclude foreign students) is necessary as there is no citizenship question in the LFS. This approach is also favoured by Brochu, Gross and Worswick (2020).

¹³My results are not sensitive to the choice of month. I get very similar results when relying on October data, and when including winter semester months.

¹⁴As a robustness check, I slightly increase and decrease the pre-COVID period to verify the sensitivity of my findings. In all cases, my results are essentially unchanged. See section 1.6 for more details.

¹⁵Alessandrini (2018) also favours such an age/gender breakdown.

1.3 Summary Statistics

Figure 1.1 shows post-secondary enrolment rates (by type) for 17 to 39 year olds over the 1976 to 2021 period, as of September of each year.¹⁶ One can observe a long-term secular increase in post-secondary enrolment. As of 1976, 9.5% of 17 to 39 year olds were enrolled in a post-secondary institution, whereas in 2019 (the year just prior the pandemic), it had reached 18.6%.¹⁷ This secular increase is present for both college and university enrolment in the early years, but by 2000 their patterns started to diverge, with university enrolment subsequently playing a more important role.¹⁸ One should also note the relative stability in enrolment rates in the years just prior the advent of COVID-19 for university and post-secondary overall. Finally, the business cycle also appears to matter; one can observe increases in enrolment rates during and immediately following recessions, and this is particularly true for the recent COVID-19 recession.¹⁹ I will attempt to address the source of this recent increase in the next few sections.²⁰

Figure 1.2 shows post-secondary enrolment rates, again for 17 to 39 year olds during the September 1976–September 2021 period, but by gender. Women’s enrolment rates started to surpass those of men in the early 1980s, with the gap becoming more prominent over time. In 2019, the gap stood at 4.6 p.p. Of interest to this paper, the magnitude of the increase in post-secondary enrolment rates of women observed during COVID-19 times is larger than men’s.²¹

¹⁶Foreign students are included in figure 1.1, and also in figures 1.2 and 1.3, as the questions on the country of birth and whether the person is (or ever was) a landed immigrant was only introduced as of January 2006. Only by going back to 1976 can one identify long-term secular trends, and most importantly, put the recent rates into perspective. It should be noted that if I restrict the sample to Canadian born and those who are (or ever were) landed immigrants, the figures for 2006 onwards would look very similar to those of figures 1.1 to 1.3, but the levels are a little lower.

¹⁷Although a substantial increase, the final number may nonetheless appear small because one is dealing with current post-secondary enrolment, and not highest educational attainment. That means, for example, that an older individual who has completed her/his university studies and is, say, presently attached to the workforce, will bring down the university enrolment rate as they are not currently enrolled despite having a university degree.

¹⁸It should be noted that the college series includes those living in Québec. Yet, Québec has a distinct post-secondary structure. Students that attend high school in the province of Québec who want to go to university must first attend college (i.e., CEGEP). CEGEP is typically two years in length. In the rest of Canada, high school students can go directly to university from high school. As such, colleges in the rest of Canada play a different role. However, if I compare the college enrolment rate for the whole country to those where I exclude Québec residents, I find the two college enrolment rates have the same trends and the only difference is that the one which excludes Québec is a little lower than the national one.

¹⁹There are five economic recessions since 1976: January 1980–June 1980, June 1981–October 1982, March 1990–April 1992, October 2008–May 2009 and February 2020–April 2020 (Cross and Bergevin, 2012; C.D. Howe Business Cycle Council, 2021). The latest recession was the shortest, but the most severe since the Great Depression.

²⁰It should be noted the recent enrolment patterns observed by education type (i.e., college and university) and by gender are also present in administrative data (Statistics Canada, 2022a). In order to get a clearer comparison, appendix figures A.1 to A.3 show the series from 2000 onwards.

²¹If one were to focus just on university enrolment rates, one still sees the gender imbalance, but one also observes a small increase for men.

Figure 1.3 breaks down post-secondary enrolment by age groups, i.e., 17-24 versus 25-39. The enrolment rates for the younger age group are significantly higher, and the differential has grown over time. Combined, these results indicate that if individuals go to post-secondary education, it is typically right (or soon) after high school. This clear age dichotomy is reflected in other socio-demographic characteristics, and also in labour market characteristics. For example, if one focuses on the year just prior the pandemic (i.e., 2019), the proportion of 25 to 39 year olds that are married (including common-law) stands at 60.4%, whereas it is only 10.4% for 17 to 24 year olds. Furthermore, the proportion who have a young child (under the age of six) at home is also very different (25-39: 29.6%; 17-24: 2.4%), and if one focuses on having a child 18 years or younger, the gap increases by another 10.0 p.p. Finally, the older age group is clearly more attached to the labour market. The employment rate for the older age group is 83.1% in 2019, but only 62.5% for the younger age group; the differential grows even large when focusing on full-time employment—a gap of 40.2 p.p.²²

1.4 Econometric Model and Results

1.4.1 Econometric Methodology

As previously discussed, the objective of the study is to better understand the decision to attend a post-secondary institution during COVID-19 times. I carry out regression analysis as to control for confounding factors. The basic econometric model takes the following form

$$Enrol_{ipt} = \beta_0 + \beta_1 COVID_t + X'_{ipt}\gamma + \psi UR_{pt} + \phi_p + \epsilon_{ipt} \quad (1.1)$$

where the dependent variable $Enrol_{ipt}$ is a binary measure of post-secondary enrolment for individual i living in province p in period t (see below for more details). The main explanatory variable $COVID_t$ is a dummy variable equal to one if the individual is in COVID-19 times as of the enrolment date. COVID-19 times is defined as of March 2020 onwards.²³ The vector X represents socio-demographic characteristics of the individual

²²Employment is considered full-time if the individual's usual hours at all jobs is 30 hours or more. If one were to go back to 1976 (as is done for the enrolment rates), one could see some long-term secular changes in these socio-demographic and labour-market characteristics, but the stark differences across age groups remain (see appendix figures A.4 to A.7).

²³Given that my main analysis relies on September enrolment data, the COVID variable will therefore equal one only in 2020 and 2021, as September 2020 and September 2021 are the only post-March 2020 months in my sample. As a robustness check, I also carry out regressions where COVID is defined as of the time of application deadlines. The main results remain unchanged. It should be noted that in the case where I use the previous January as the deadline month, the COVID variable will equal one only in 2021—as the decision to apply for September 2020 had to have been made in January 2020 which was prior to the advent of COVID-19. More details are provided in the robustness checks section (i.e., section 1.6).

(i.e., age and age squared, and binary variables for gender (female), marital status (married or common-law), and the presence of a child under the age of six). UR and ϕ_p indicate the provincial unemployment rate and province fixed effects, respectively.²⁴

Equation (1.1) is estimated using three different post-secondary enrolment measures: whether the individual is enrolled in a college, university or any post-secondary institution. Finally, the regression analysis is also carried out by subgroups (e.g., age and gender).

It should be noted that I must rely on a difference estimator, but not the more commonly used difference-in-difference estimator. I do so because there is no natural control group, i.e., all Canadians received the COVID treatment. The presence of pre-COVID trends in enrolment rates would not be fatal to this empirical strategy, but would nonetheless necessitate strong identification assumptions. When looking at all age groups combined (Figure 1.2), the enrolment rates by gender are fairly stable in the expansionary period that followed the Great Recession, and of particular interest to us is the three pre-COVID years. The analysis by age and gender group requires common (gender) enrolment trends in the pre-COVID for both the younger and older groups. As with the full age group, one sees fairly stable gender enrolment rates for the older age group (see Figure 1.4). For the younger (17-24) age group, however, one sees an upward trend for both men and women, with the trend being slightly steeper for women. As such, my COVID binary variable—a dummy that equals one in the last two years of my sample—will, in addition to the COVID-19 effect also capture the differential long-term trend between men and women. Having said this, over the post-Great-Recession period the gender difference in the long-term trend is small,²⁵ whereas the jump for (young women) in COVID-19 times is very large. As such, the COVID-19 variable should mainly capture the COVID effect.

1.4.2 Results

Table 1.1 shows the Linear Probability Model regression results of equation (1.1) when a post-secondary enrolment dummy is the dependent variable.²⁶ Column (1) shows the findings for the full sample, whereas columns (2) and (3) are for the male and female subsamples, respectively. The remaining six columns carry out the same breakdown but for 17-24 and 25-39 year olds, separately.

²⁴The unemployment rate (measured from zero to one) is defined as of the enrolment date. As with the COVID variable, I also carry out regressions where the unemployment rate is measured as of the application deadline. Again, the results are essentially the same. See the robustness checks section for more details.

²⁵This is contrast to the pre-Great-Recession period where one observed important differences in long-term trends across genders.

²⁶All regressions are weighted using official survey weights provided by the LFS. Heteroskedasticity-robust standard errors are shown in parenthesis. In the robustness checks section, I cluster the standard errors at province-year and province levels. In the latter case I also account for the small number of clusters. My main findings remain unchanged.

When focusing on the full sample (i.e., column (1)), one sees a 1.2 p.p. increase in post-secondary enrolment in COVID-19 times, after controlling for such confounding factors as the unemployment rate. This estimate is economically important (and also statistically significant at the 1% level), as the post-secondary enrolment rate is only 17.8% on average over the three years prior to the pandemic. When one looks at men and women separately, one sees that it is women that are driving the overall result; one observes a 2.0 p.p. increase for women, whereas the effect for men is both economically and statistically insignificant.

The results for the remaining columns confirm what was observed in the summary statistics, that the two age groups should be treated separately. When focusing on the younger age group (see columns (4) to (6)), the COVID coefficient estimates become larger, and this holds true for both genders. In the case of men, the effect now becomes economically significant. The COVID effect is, however, smaller in magnitude for the older age group (see columns (7) to (9)). Having said this, the size of the coefficient estimate for women must be put into perspective. Accounting for the fact that only 7.8% of women 25 to 39 were enrolled in a post-secondary institution in the three pre-COVID years, a 1.6 p.p. increase is quite substantive; it represents a 20.5% increase.

It is worth researching which kind of post-secondary education drives the post-secondary enrolment increase. Is it university, college or both? Table 1.2 shows similar regressions to that of table 1.1, but for a college binary dependent variable (i.e., a binary variable that equals one if individual i in period t is enrolled in a college and zero otherwise). Clearly, the COVID effect is not at the college level.²⁷ Across the board, whether it is by gender or age, the COVID effects are economically and statistically insignificant. These findings suggest that university enrolment, which has become the most prevalent form of post-secondary education in Canada, must be the driving force behind the post-secondary increase in COVID-19 times.

The results in table 1.3, when the dependent variable is a binary measure for university enrolment, confirm that university is the key. When looking at the full sample (i.e., column (1)), the COVID coefficient estimate is very similar to that of table 1.1 (1.1 p.p. versus 1.2 p.p.). The effect is also more substantive for young adults, a 2.2 p.p. increase in COVID-19 times. Again, the effect is stronger for women. One observes a 3.2 p.p. increase for young women, which is both economically and statistically significant, whereas for men the increase is only 1.3 p.p. and statistically insignificant. Finally, the economically (and statistically) significant effect observed for older women is still present.

²⁷I also carry-out regressions when excluding Québec, and it does not change any of my results.

1.5 Further Exploration

In this section, I try to better understand the results shown in the previous section. More precisely, I attempt to get at the causal link: what can explain the increase in university enrolment in COVID-19 times for the younger age group (17-24) and for older women (25-39). This section is divided into three parts. First, I briefly present the underlying theoretical framework. I then put forth theoretical predictions that could explain such findings. Finally, I provide evidence in support (or against) these predictions.

1.5.1 Theoretical Framework

The overarching framework I utilize when exploring the causal link is the human capital model. I rely on [Card \(2001\)](#)'s representation of the model as it is rich enough to account for various hypotheses that could account for the rise in post-secondary enrolment in COVID-19 times, while still remaining tractable. The model assumes a continuous time environment, where individuals are identical and infinitely lived. Human capital is accumulated through schooling and labour market experience. There are direct costs to go to school which take the form of tuition fees ($T(\cdot)$),²⁸ and a psychic cost of attending school ($\phi(\cdot)$) (relative to work) which increases with each additional year of schooling. Individuals make a once-for-all decision on when to leave school. Individuals can work part-time while in school but can only work full-time when they are done schooling. Part-time income ($p(\cdot)$) depends on years of schooling (S), whereas full-time income ($y(\cdot)$) depends on both years of schooling and labour market experience since leaving school. The fact that labour market experience only matters for full-time jobs reflects the idea that a part-time job is probably not a job an individual will make a career out of, but only a means to help pay for some of the living expenses of attending school.

Utility at time t depends on consumption $c(t)$ in period t , and on whether the individual is in school (and working part-time) or out of school (and working full-time). The individual's life cycle utility (i.e., present discounted value of utility) can be expressed as

$$V(S, c(t)) = \int_0^S e^{-\rho t} [u(c(t)) - \phi(t)] dt + \int_S^\infty e^{-\rho t} u(c(t)) dt \quad (1.2)$$

where ρ is the subjective discount factor. Finally, the intertemporal budget constraint

²⁸Although tuition fees are the only direct costs mentioned in the [Card \(2001\)](#) model, one can think of $T(\cdot)$ as including all direct costs related to schooling. If the best alternative to living in university residence was to go to school from home, then food and lodging costs would also need to be included in the $T(\cdot)$ function.

takes the form

$$\int_0^\infty e^{-Rt} c(t) dt = \int_0^S e^{-Rt} [p(t) - T(t)] dt + \int_S^\infty e^{-Rt} y(S, t) dt \quad (1.3)$$

where R is the borrowing/lending rate.

Although I have provided the mathematical representation of the model, I do not take the model at face value, but more as guidance on how to better understand the rise in university enrolment observed in COVID-19 times. As such, I leave the derivation of the first-order condition with respect to schooling, and how the exogenous variables affect the optimal value of schooling to the appendix A.1. Nonetheless, I believe that showing the mathematical representation helps better see the different ways education choices can be affected.

1.5.2 Theoretical Predictions

Provision of education - cost of education

COVID-19 brought about important changes to the provision of post-secondary education in Canada. One went from an in-person learning approach, to one where remote learning became the norm. Online learning could be synchronous where the course was offered in real time and at a specific date and time, or asynchronous where the course did not have an assigned date and time. In the former case, many universities would also offer a recording of the lectures that a student could watch at their leisure. Even when universities started going back to in-person learning in the 2021 academic year, the approach was typically reserved for smaller classes, and professors were strongly encouraged to still offer remote access options. These changes to the provision of education affected the cost of attending university.

For those deciding to attend university directly out of high school, they could now remain at their parents' home and thus incur lower food and lodging costs. One could also see a cost saving (i.e., lower commuting costs) for those whose housing decision remained unaffected because their family lived within commuting distance of a university.²⁹ For older individuals that had left home and had their own lives, it meant that with the more flexible learning environment they could more easily juggle going to school while remaining attached to their career. Within the human capital model, these changes can be reflected in lower direct costs of attending university, i.e., $T(t)$, but also in the fact that older individuals do not have to sacrifice their higher wage, i.e., $Y(S, t)$, that went with their

²⁹Given that university tuition fees often cover bus passes, one is referring to the opportunity cost of time spent commuting.

career job when attending university. As such, one could expect enrolment to increase for both age groups in COVID-19 times.³⁰

It should be noted, however, that the cost of education could have increased for some groups, such as those with young children. The uncertainty regarding their children's schooling (whether it would switch to online learning and parents would need to be at home to supervise), or the provision of daycare (an outbreak at the daycare could result in all children being sent home) could have imposed greater cost on this group.

Economic recession/recovery - opportunity cost of time

The COVID-19-led recession was initially very severe. Although the economy did rebound in the months that immediately followed, it took some time for the economy to go back to pre-pandemic levels. This meant that for much of 2020 and 2021, jobs were hard to come by.³¹ Within Card's representation of the human capital model, this can be interpreted as a decrease in full-time wages, i.e., $Y(S, t)$, over the COVID-19 period. This implies that the opportunity cost of going to school is now lower.³² As such, one can expect post-secondary enrolment to increase during these hard economic times.

However, this is not the focus of this paper. I am trying to understand the COVID effect beyond the pure opportunity cost channel, and this why I control for the overall (provincial) unemployment rate even in my basic regressions (i.e., section 1.4.2), and also when I will explore the merits of the cost of education hypothesis.³³ Said differently, the unemployment rate will capture the business cycle effect. As such, the COVID variable measures any remaining COVID effect. But given that the effect of the COVID-19-led recession was very heterogeneous and unlike any other recession, it is possible that controlling for the overall (provincial) unemployment rate does not fully account for the business cycle effect. To address this issue, I will also rely on unemployment rates for more narrowly defined subpopulations (i.e., age and gender).

³⁰Alternatively, the ability to work online (i.e., remotely) can be seen as reducing the cost of working for older workers. As such, one could see more people who are in school deciding to work, leaving enrolment unchanged. But the fact that I observe an increase in enrolment for older women does not favour this conjecture.

³¹When examining the demand side, Jones et al. (2023) find that job postings did rebound fairly quickly, but it tooks some time to fully recover to pre-pandemic levels, and the recovery was not uniform across occupations.

³²Recall that within Card's framework, an individual cannot go to school while having a full-time job (i.e., a career job), so one could think of it as the $Y(s, t) - P(t)$ differential being smaller.

³³To focus on the opportunity cost channel and precisely measure its effect, would require many more years of data, i.e., more variation in the unemployment rate as in Alessandrini (2018).

Provision of education - learning styles

There exists substantive education and psychology literatures that look at this issue. The idea be that not all individuals learn the same way, and students learn is best when the teaching method that focus on learning styles. The VARK model (Fleming and Mills, 1992), for example, reflects the idea that sensory preferences matter. The VARK acronym, where V is visual, A is aural, R is reading-writing and K is kinesthetic reflects this idea.³⁴ If a person prefers the visual (V) they learn better by seeing or observing say figures or equations. An aural (A) person can learn better from speech. For kinesthetic (K) persons, they learn from touch, hearing, smell, taste, sight and hands-on experience. The evidence with respect to the importance of VARK in a university setting, particularly with respect to gender differences, is mixed. Some find that gender differences matter (Wehrwein et al., 2007), while others do not (Alkhasawneh et al., 2008). It should be noted that in many cases where gender differences are observed, they tend to be small in importance (Slater et al., 2007).³⁵ When the VARK approach is used to specifically look at online learning in the pre-COVID era, the evidence is again mixed.³⁶

There are other different learning characteristics which could cause online learning differences across genders, such as independence, self-regulation, persistence and multi-task ability. Some researchers find that females outperform their male counterparts in online studying because of stronger independent learning skills (Price, 2006), stronger self-regulation (Alghamdi et al., 2020), better multitasking abilities (Jeong and Fishbein, 2007), and being more persistent and committed (Richardson and Woodley, 2003). However, males demonstrate more stable attitudes towards online learning (Nistor, 2013). Having said this, some researchers point out there are no significant differences across genders for the younger people such as millennials (Harvey et al., 2017). Lastly, some researchers find that males and females respond differently to competition (Morin, 2015b; De Paola et al., 2015).³⁷ This may matter because the competitive environment may have lessened in COVID-19 times since online learning was more in isolation (less face to face peer competition).

Having said this, the dramatic change in the provision of education in COVID-19 times, with its greater dependence on online learning for *everyone*,³⁸ could now be more (or less)

³⁴The preferences are determined by the VARK questionnaire.

³⁵More than half of both genders prefer multiple modes of learning styles (56.1% males versus 56.6% female), but for unimodal styles, there are some gender differences, for example, single V (2.4% males versus 7.5% females), single A (4.9% males versus 5.6% females), single R (9.8% males versus 11.3% females), or single K (26.8% males versus 18.9% females).

³⁶Drago and Wagner (2004) is an example where the satisfaction with online course did vary. Those that are aural and read-write learners tend to be more satisfied with online styles.

³⁷Specifically, Morin (2015b) finds males' academic outcomes are better than females in more competitive academic environments. De Paola et al. (2015), however, demonstrate that females can do as well as males in a competitive environment.

³⁸Prior to the advent of COVID-19, a person could choose whether, in certain circumstances, to take

favourable for certain subgroups. Sensory preference,³⁹ and the ability to self-regulate could now matter more.⁴⁰ Within Card (2001)’s framework one could therefore see a change in the disutility parameter (i.e., $\phi(t)$) of going to school versus work, which in turn would influence the decision to go to school. Although presented as a possible explanation, its exploration is beyond the scope of the paper. The dataset that I rely upon for my empirical analysis does not have the necessary information to address this possibility. It should be noted that the existing evidence to date is still preliminary and inconclusive (Zapalska, 2022; Liu et al., 2021).

1.5.3 Findings

I start by exploring the source of change for the older age group as it provides guidance on how to better understand the findings of the younger age group.

Older group (25 to 29)

As previously discussed, older individuals are very attached to the workforce. The greater majority work, and if so it is typically full-time. Furthermore, they are most likely working at a job they plan to make a career in.⁴¹ Therefore, it is natural to look at whether the increase in university enrolment for older women is driven by those who are employed. Column (1) of table 1.4, which is equivalent to column (9) of table 1.3, shows the results for the full sample of older women, whereas column (2) is restricted to those who are not employed. When focusing on the employed (i.e., column (3)), the COVID effect remains very present, albeit a little smaller, and still statistically significant. Since most women are employed, one can surmise that it is the employed women that are driving the results. The COVID results for full-time and part-time (i.e., columns (4) and (5)) are both economically and statistically significant, but the effect is larger for the latter group. These results point towards the cost of education channel; It is easier (less costly) for older women to go to school while working during COVID-19 times.

Yet, if it is now easier to juggle a career and go to school in COVID-19 times, why does one not also see an enrolment effect for older men? One possibility is that men and women work in different occupations, and the ones favoured by women better reward education. As such, the drop in the cost of education is sufficient to encourage these

an online course. As such, this person may not have been representative of the typical university student.

³⁹The group that may be relevant to this study is those that have an A-preference as they are best suited to learning by listening to recorded lectures (a feature of online schooling).

⁴⁰Adam et al. (2017) describe self-regulating as the ability to manage one’s own learning. It can be thought that the learners who have a self-regulating ability can self plan, organize, instruct, monitor and evaluate themselves during the learning process.

⁴¹This is in direct contrast to young people who will, in most cases, take any job that can help pay for some of the living expenses while attending university.

older women to upgrade their skills, but not for older men. If one focuses on the ten broad occupational categories of the 2016 National Occupational Classification, one can observe some commonality in the choice of occupation. For example, in the years just prior to the advent of COVID-19, ‘Sales and Services’ is an important occupation category for both genders. Nonetheless, there are significant occupational differences. The other top occupational categories for older women are ‘Business, Finance and Administration’, ‘Education, Law and Social Community and Government Services’ and ‘Health’. On the other hand, ‘Trades, Transportation and Equipment Operators’, is male dominated and is by far the largest occupation category for older men (representing almost 30% of all occupations), and it is followed (in order of importance) by ‘Sales and Services’, and ‘Natural and Applied Sciences’. I use the prevalence of graduate degrees in each occupation to gauge occupations that favours having workers with more education.⁴² If one looks at the years just prior to COVID-19, the broad occupations categories that have more educated workers are in order of importance: ‘Education, Law and Social Community and Government Services’, ‘Health’, ‘Natural and Applied Sciences’, and ‘Management’—occupations that as a group are more favoured by women. Column (6) shows the regression findings when I further restrict my sample of older women to those that are in these ‘highly skilled’ occupations, whereas column (7) shows the results for their counterparts (i.e., older women in occupations that require less education). That the COVID effect is now larger (smaller) in highly (lowly) educated occupations supports the claim that older employed women go back to school to upgrade their skills; they do so when the return of going back to school is worth it.⁴³

A natural next step would be to examine whether graduate enrolment did in fact increase in COVID-19 times for older women. Data limitations, however, prevent me from directly addressing this issue; one can observe whether an individual is enrolled in a university, but not the type of program. Nonetheless, one can get a good approximation by carrying out the same regressions as before, i.e., where university enrolment is still the dependent variable, but with a more restricted sample based on educational attainment. Column (8) of table 1.4 shows the results when restricting the sample to individuals that already have a post-secondary certificate, diploma or degree. The COVID effect is larger (as compared to those that do not possess post-secondary qualifications) and statistically significant. These findings are in line with the idea that these already qualified older women are upgrading their skills.

One would expect those who can work remotely (i.e., telework) have a lower opportunity

⁴²More precisely, I look at the proportion of the eligible population (i.e., 15 years and up including both genders) in each occupation that have a university certificate, diploma or degree above the bachelor’s level.

⁴³It is possible that some of the occupations that favour having more educated workers such as education and health are more exposed to the virus risk, and as such, COVID-19 changed the benefit of retraining. Having said that, the effect for these occupations is still present when I exclude education and health occupations.

cost of attending university than those who have to work on-site, as they can more easily juggle work and schooling. Columns (1) and (2) of table 1.5 show the results for those that can and cannot work remotely, respectively. To identify occupations/jobs that can be done remotely, I utilize the telework-feasibility indicator constructed by Deng et al. (2020). As expected, the COVID effect is larger for those that are employed in telework-susceptible occupations. As a final check of the cost education channel, I look at family factors, particularly the presence of young children. For older women with young children at home, there is now an extra dimension to the cost of education—one related to the uncertainty regarding children’s schooling and daycare during pandemic times. Although the net effect is unclear,⁴⁴ the COVID effect for this group, if any, should be smaller than for those without young children. My empirical findings confirm this point. Only for those with no young children at home is the COVID effect both economically and statistically significant. Finally, it is not unreasonable to assume a gradient effect when dealing with older children, and this what I find in the data. The COVID effect is larger when dealing with older women whose youngest child is 6 to 12, and again larger when focusing on 13 to 17 year olds.

Although not closely tied to Card (2001)’s human capital model, and as such not discussed in section 1.5.2, there is a possibility that COVID-19 may have affected the benefits of holding certain occupations. Workers in harder hit sectors (e.g., service sector) or in sectors more exposed to viral risk (e.g., health and education) may have wanted to switch professions, thus requiring retraining (i.e., going back to school). Given that my findings are driven by those very attached to the workforce (i.e., the full-time employed), one would need to see these workers retain their full-time employment status while retraining for a new profession. I do not, however, see an enrolment effect when focusing on sales and service occupations. This is not surprising given my finding of a null effect for occupations that have less educated workers, of which sales and services are an important component. Having said this, I do see a difference when one narrows down the occupations that favour more education to just health and education—the COVID effect increases by 50% and it is still statistically significant despite the reduced sample size. It should be noted that it is hard to separate the cost of education story from the benefit of a job story in the data, as previous findings could also be interpreted through the benefit of education lens. For example, it is easier for a person with no young children at home to retrain in a new profession (even if the classes had not been online). Having said that, the fact that I observe a larger effect for jobs that can be carried out remotely would favour the cost of education story. Irrespective, it is not unreasonable to surmise a complementary effect. Having online classes would definitely make it easier to retrain for a new profession while working full-time at one’s current profession.

⁴⁴The online dimension of post-secondary education would reduce the cost of education, whereas the uncertainty with respect to their young children’s education and daycare would increase it.

I replicate the same regressions for tables 1.4 and 1.5 but for older males only. The conclusions are very different. There is no university enrolment increase no matter which specific subgroup one focuses on. It suggests the interpretation that since the drop in cost is small, and therefore only makes a difference for women, who face higher return to education (because of the occupations they choose).

My findings suggest that the cost of education, and possibly the benefit of education, play a key role in the rise of university enrolment for older women, yet it is possible that the overall unemployment rate does not account for the full effect of the business cycle in table 1.3. As such, this section would be trying to explain a ‘spurious’ effect. To verify this possibility, I re-estimate equation (1.1), but where the unemployment rate is more narrowly defined, as to better reflect the economic conditions faced by the age-gender subgroups. For the older women regressions, for example, I tried using the unemployment rate for all women, and the unemployment rates of 25 to 39 year olds. In all cases I still observe similar COVID patterns as seen in columns (8) and (9) of table 1.3, and most importantly, those of tables 1.4 and 1.5. As a final check, I focus on the occupation dimension. More precisely, I take advantage of the fact that the LFS asks the occupation of not just the employed, but also of those who are out of work for less than one year. As such I can estimate occupation-specific unemployment rates by province across time. I therefore replicated my tables using occupation-specific unemployment rate (defined at the broad occupation level).⁴⁵ Again the main conclusions remain unchanged.

Younger group (17-24)

The age range of the younger group is only eight years (as compared to 15 for the older group), yet it is nevertheless a heterogeneous grouping. Teenagers are much less attached to the labour market than young adults, whether one focuses on employment or full-time employment conditional on being employed. In fact, along these dimensions, young adults have more in common with the older age group than they do with teenagers. As such, to better understand the source of change for the younger individuals, I carry out regression analysis for teenagers (17-19) and young adults (20-24) separately.

Panel A of table 1.6 shows the regression results (by gender) for teenagers, whereas panel B focuses on young adults. Teenagers are clearly driving the young women’s COVID findings. The effect for teenage women is 6.1 p.p. (column (1) of panel A), as compared to

⁴⁵It should be noted that as compared to the cases where I do not impose an employment restriction (e.g., table 1.3), the samples are now smaller. Said differently, I must drop the out-of-work individuals who were not employed in the past year as I cannot assign them a province-by-occupation unemployment rate. It is therefore possible that the choice of sample and the choice of unemployment both matter, but that they end up cancelling each other out. To make sure that my results are not affected by the choice of sample, I redid all my tables using the provincial unemployment rate, but where I drop those with no occupation information. My results are essentially the same.

only 1.8 p.p. for young adult women (column (1) of panel B). When focusing along the labour market characteristics dimension for female teenagers, one can see that the COVID effect for the not employed (i.e., column (2)) and the part-time employed (i.e., column (5)) are similar in magnitude to the case where I do not condition on labour market status. Given these two subgroups account for the greater majority of teenage women, I can say that it is the less attached that are key to the female teenage findings.⁴⁶ If that is the case, one might surmise that this holds true because schooling is their main activity. This is what I find in the data (see table 1.7).⁴⁷ Across the board, the rise in female teenage enrolment is for full-time studies as shown in panel A. Finally, it is interesting to note that female teenagers employed part-time show similar effect as male teenagers employed part-time. It can explain partially by the broad occupations distribution for part-time employed female teenagers and male teenagers. According to LFS public-use files and the ten broad occupational categories of the 2016 National Occupational Classification, in the year just prior to the advent of COVID-19, most of part-time employed teenagers work in ‘Sales and Services’ category (i.e., 79.1% of part-time employed female teenagers and 77.4% of part-time employed female teenagers are in ‘Sales and Services’ category). That category was hit hard in COVID-19 times. Thus, the similar COVID effects express that the benefit of education for the teenagers is similar across gender.

If the cost of education is important in explaining my findings I should see a greater effect for those for which this would matter the most. Table 1.8 shows the results when I condition on family income. More precisely, when I restrict the sample to those whose usual place of residence is their parent’s home, and whose economic family earnings are below the 75th, 50th and 25th percentiles.⁴⁸ It should be noted that I must narrow my age range to 17-18 year olds to ensure that those away at university are nonetheless treated as part of the parent’s dwelling.⁴⁹ The COVID effect for these young women gets larger as

⁴⁶As a robustness check, I redefined part-time as only including those that usually work less than 20 hours per week (as opposed to 30 hours). The COVID effect is very similar, which confirms that it is those that are partially attached that are key to my findings.

⁴⁷I verify this by re-running equation (1.1), but where the dependent variables are full- and part-time university enrolment.

⁴⁸A teenager is considered to be living at home if he/she is the ‘son or daughter’, ‘grandchild’, ‘son/daughter-in-law’, ‘foster child’ of the reference person. I use the full LFS sample when determining these thresholds. Finally, these thresholds are measured as of September of each year.

⁴⁹The criteria to be included in the survey is that the individual usually lives in the surveyed dwelling. *“For persons with more than one residence in Canada, their usual place of residence is the place where the person lives most of the time, with the following exceptions: . . . The usual residence of students is that of their parents, if they return to live with their parents during the year even if they live elsewhere while attending school or working at a summer job (Statistics Canada, 2018a).”* As such, one can expect that a first-year university student living in a university residence from September to April (which is very common in the first year of university) will be considered part of his/her parent’s households. The situation becomes more complicated in later years as the student may have signed a one-year lease and may only come back for infrequent visits, and in this case the family home may not be the usual place of residence anymore. In addition, where the student is counted matters because the family income variable in the LFS master files only measures the income of family members that live in the same dwelling. As such, restricting the attention to teenagers when focusing on geography and family income, i.e., 17-18

one moves down the family income distribution. By the time I focus on the bottom 25 percentile, the magnitude of the COVID effect doubles in size. This is consistent with the cost of education story where the effect should be larger for the low income family.

Geographical location should also matter. A person whose family home is far from a university campus would have had to move to attend university prior to the advent of COVID-19, whereas they could now attend online. As such, the cost savings should be more substantial for this group as compared to those whose family home is close to a university. Similarly, one would expect significant cost savings (in terms of commuting time) for those studying from home, but who would face a substantive commute (e.g., students living in the suburbs of large metropolitan areas). Unfortunately, the LFS does not provide the address, nor the postal code, and as such I cannot measure the distance from a university. I can, however, determine whether a person lives in an urban or rural area, and whether he/she lives in a CMA or a CA and if so which one. Finally, I can identify who lives in a (primary) core or a secondary core.⁵⁰ It should be noted that CMAs and CAs can only have one core, and given their sizes CMAs can have multiple secondary cores.

Table 1.9 shows the results for 17-18 year olds whose usual place of residence is their parent's dwelling by various geographical areas, and then by family income. Given the above discussion, the column headings are for the most part self-explanatory, except for the CMA* and CA* notations which designate CMAs and CAs that have a university within their boundaries, respectively. There are universities in all but except two CMAs (i.e., 33 out of 35), whereas only 19 out of 115 provincial CAs have a university (typically the main campus of a small university or a satellite campus). At first glance one would think that a simple urban-rural comparison would suffice, as universities are typically found in urban settings. Yet, just focusing on this breakdown would be misleading, and this for multiple reasons: first, the level of education is very different across the rural-urban dimension. In addition to the distance from a university, this probably reflects the fact higher education is less necessary in some rural areas. So even with significant cost savings, the benefits of higher education in rural areas that are very far from population centres may not warrant going to university. Second, the level of education also varies across population centres, with the larger one, i.e., ones typically found in CMAs, being much more educated. Finally, CMA can cover very large areas, and as such, some population centres within CMA, typically secondary cores, can be far from universities typically found

years of age, is most appropriate.

⁵⁰The LFS uses the 2016 Census of Population geographical definitions where the core is defined as the population centre with the largest population around which a CMA or CA is delineated. The core of a CMA must have a population of at least 40,000, whereas for a CA it must be in the 10,000–39,999 range. A secondary core is a population centre with 10,000 or more individuals within a CMA (and in many cases much more), that is not situated in the core. See [Statistics Canada \(2018b\)](#) for a more detailed discussion of these concepts.

in core population centres.

Panels A and B of table 1.9 show that for teenage women there is some evidence suggesting that proximity to a university matters, particularly when I start to focus on households with lower family income. Although I present columns (1) through (4) for the sake of completeness, I believe that for the reasons mentioned above, columns (5) through (9) are most telling. One can see that as one focuses on CMAs and CAs that have a university, and condition on lower family income (i.e., below 75th percentile), one sees a larger COVID effect when one moves away from the core. This is also true when I further restrict my attention to CMAs with a university, where the greater majority of the population lives. The effect becomes particularly large for those residing in secondary cores—large urban centres, that are, in many cases, far from the (primary) core of CMAs.

I now revisit the benefits of a job channel, but for the younger age group. Given that it is teenagers who are less attached to the workforce (i.e., full-time students) that are driving the results, and that the type of occupation they tend to hold is very different than for their older counterparts, I would be hard pressed to argue that it is a retraining issue—that they want to change career midstream—which is driving my teenage findings. Having said, this does not preclude that it may play some roles. If I restrict my sample to those that work in sales and services, the most predominant occupation for this age group, I do see the COVID effect increase for those that work full-time.

The evidence for young men is less clear-cut. This is not surprising given that one is dealing with a smaller overall COVID effect (i.e., only 1.3 p.p.) that was not statistically significant.⁵¹ The COVID effect is in fact a little smaller for teenage men (i.e., 1.0 p.p.) than it is for young adult men (i.e., 1.5 p.p.), and neither is statistically different from zero. There is some indication of an effect for those partially attached to the work force (i.e., part-time employed) for both subgroups. In the case of teenage men it is both economically very large and statistically significant at the 1% level. The idea that these teenage men are only partially attached to the workforce is reinforced by the following additional findings: first, the results still stand when I define part-time as less than 20 hours of work, and second, the effect is due to an increase in full-time studies (see table 1.7). What is surprising, however, is that there is nothing there for those that are not employment. Although, conditioning on family income on its own does not seem to matter for males (i.e., table 1.8), I do see an effect when I also account for geographical location of the family home (i.e., table 1.9), but the effect is more muted than for females, and it is not statistically significant. Finally, It is possible that high school boys/men were more adversely affected by COVID-19, resulting in lower high school graduation rates for this group. As such, one does not see an increase in their university enrolment simply because

⁵¹It should be noted, however, that when I cluster at the province level and account for the small number of clusters (as opposed to using heteroskedasticity-robust standard errors), it is close to being significant at 10% level.

fewer men had the prerequisites to go to university (i.e., having completed high school). This is not borne out in the data, at least not for the early stages of the pandemic. In fact, there was an increase in high school graduation rates (and on-time graduation rates) for both genders in 2019-2020, and the increase was higher for men both in relative and absolute terms (Statistics Canada, 2022a).⁵²

As I did with older individuals in section 1.5.3, I verified for the possibility that the overall (provincial) unemployment rate may not have accounted for the full effect of the business cycle by relying on (provincial) unemployment rates for more narrowly defined subpopulations (i.e., age and gender). This does not alter my main findings.

1.6 Robustness Checks

In this section I carry out four robustness checks. First, I verify the sensitivity of my findings, allowing for the fact that applications to post-secondary (in particular university) must be done months in advance. Second, I slightly expand (decrease) my sample to include more (fewer) pre-COVID years. Third, I cluster standard errors at the province and the province-year level. In the former case, I also account for the small number clusters. Finally, I re-estimate the regression equation using a Probit model. My main findings are not sensitive to these robustness checks.⁵³

1.6.1 Timing of Enrolment Decision

The evidence so far indicates that where I observe a COVID effect is at the university level. Yet, the decision to enrol in university is a multi-step decision: First, the individual must apply, typically months in advance. Second, conditional on receiving an offer(s), he/she must decide which school to attend (if any). Finally, he/she may subsequently change his/her mind, and decide to not attend, or defer attendance, even after having accepted a university's offer.

The application process and its associated deadlines can vary from one university to the next, and also across programs within the same university. There is nonetheless much commonality across schools. In the Ontario case, applications must be done through the Ontario Universities' Application Centre (OUAC) portal. Students can begin to apply as of early October, and the preliminary deadline for secondary students to apply for university

⁵²This does not rule out the possibility of a medium to long term effect, i.e., an accumulation effect of COVID policies such as school closures that went well into the 2020-2021 school year. I cannot explore this possibility, however, as graduation rates data for 2020-2021 were not available at the time of the writing of this paper.

⁵³I focus on the results of table 1.3 as they are at the core of my findings. Having said this, the main findings of subsequent tables are also robust to these checks.

is mid-January. OUAC refers to it as the equal opportunity deadline. It should be noted that this is not a hard deadline in that some schools will start making offers to stronger students as applications roll in, and many programs will stay open (for applications) into the spring and early summer but space may be limited.⁵⁴ Having said this, OUAC monthly application numbers clearly show that the greater majority of applications occur prior to this deadline.⁵⁵

Table 1.10 carries out the same regressions as in table 1.3, but where I account for the fact that the decision to apply is made prior to September. This is operationalized in the following way: the COVID variable for period t equals one if, as of the period t decision month, we are in COVID-19 times. To be consistent, the unemployment rate which reflects economic conditions is similarly defined.⁵⁶ For ease of presentation, only the COVID coefficient estimates and their associated standard errors are shown.

Relying only on September enrolment data, panel A of table 1.10 shows results for three possible decision months: i) September—the contemporaneous month which replicates the results of table 1.3, ii) June—the month when most programs close to applications, and iii) January—the date by which most applications are in. The COVID effect, when treating June as the decision month, are very similar to those that rely on the contemporaneous month (i.e., September). This should come as no surprise as the choice of June only changes the values of the unemployment rate variable (i.e., I now use June rates), not the COVID variable.⁵⁷ When treating January as the decision month, I still see the same patterns, but the standard errors are larger and in a couple of cases one loses some statistical significance. This holds true because I have less variation to work with; the COVID variable now equals one only in 2021.

To address this issue, I expand the sample to also include January enrolment data (see panel B). I first carry out regressions when the decision month is contemporaneous with the enrolment data.⁵⁸ Including additional enrolment data does not affect the main

⁵⁴Students will continue to apply even after the deadline. The reasons are various: students may do poorly in a certain course; or get experience that makes them want to change programs; or meet someone fun who is planning to attend a university where they have not applied. Another way to think of the mid-January date is that it is the deadline that allows for equal opportunity to apply for a program before program space becomes more restricted or closes. Much of this information is based on an email conversation held in August 2022 with a manager (Communications and Events) at OUAC.

⁵⁵OUAC publishes application data from February through September. The statistics published in February are for the period from October of the previous year (the application opening month) to mid-January of the current year (the deadline). After that, OUAC provides monthly updates.

⁵⁶For example, assume that January is the decision month. In this case, the COVID variable for individual i in 2020 will equal zero because as of January 2020, COVID-19 had yet to manifest itself. The unemployment rate variable for individual i in 2020 will be the provincial unemployment rate of the province he/she resides in as of January 2020.

⁵⁷In this case, the COVID variable equals one in year t if as of June of year t one is in COVID-19 times. This would still only hold true in 2020 and 2021.

⁵⁸The decision month is September for September enrolment data, and January for January enrolment data.

patterns. When I use January as the decision month, however, I still have enough variation in the COVID variable to precisely identify the COVID effect.⁵⁹ Not only are the patterns again very similar, but the results are still statistically significant. As a group, these findings indicate that my main results are robust to the choice of decision month.

1.6.2 Sample Periods

Although I have presented evidence that the pre-COVID years have been stable enrollment—wise, it is nonetheless important to verify the sensitivity of my results to the number of pre-COVID years included in my sample.

Table 1.11 carries out the same regressions as in table 1.3, but for slightly different sample period. Only COVID coefficient estimates (and their standard errors) are shown. Furthermore, for the sake of comparison, panel A replicates the results of table 1.3, i.e., it shows results that are based on the 2017-2021 period. Although I relied on three pre-COVID years for my main analysis, I could have as easily relied on two to match the number of years observed in COVID-19 times. Panel B shows the findings when I reduce the sample to the 2018-2021 period. The results are essentially the same. If anything, the standard errors tend to be a little larger, which is to expected as restricting the number of years reduces the sample size. When I expand my sample period to include four and five pre-COVID years (see panels C and D) the general patterns remain, but the COVID effects are somewhat amplified. This latter result should come as no surprise given that there is a slight dip in post-secondary enrolment in 2016. This was one of the reasons why I chose to start my sample as of 2017. Having said this, what matters is that the main patterns remain.

1.6.3 Clustering

In this section, I take a deeper look at the construction of my standard errors. Although the COVID effect is national, the decision rules/regulations regarding COVID (with a lockdown being the extreme case) are made at the provincial level.⁶⁰ As such, this opens the possibility to cluster at the province-year or province level. In the former case, it would generate a reasonable number of clusters (i.e., 50 clusters), but may not be most appropriate due to the possibility of unaccounted within-province serial correlation. Clustering at the province level would account for such serial correlation, but would result in an insufficient number of clusters (i.e., only 10 clusters). We address the small number of clusters issue following the approach suggest in Roodman et al. (2019).

⁵⁹The COVID variable equals one in three enrolment period: January 2021, September 2022 and January 2022.

⁶⁰There are some exceptions such as international travel which falls under federal jurisdiction.

Table 1.12 presents the COVID coefficient estimates of table 1.3, followed by the p-values for the different clustering approaches mentioned above. I only report p-values because the boottest program (boottest is freely available) does not generate standard errors. For the sake of comparison, I also report the p-values when relying on heteroskedasticity-robust standard errors as is done in the main analysis of table 1.3. The p-values when clustering at the province-year level are systematically lower. As discussed above, this may not be the best approach as it does not account for unobserved within-province serial correlation. When I cluster at the province level, the results are very similar to my baseline approach. Furthermore, accounting for the small number of cluster does not materially change my conclusions either.

1.6.4 Probit Model

I re-estimate my main findings (i.e., tables 1.1 to 1.9) using a Probit model (instead of the Linear Probability Model). It does not affect any of my conclusions. In fact, the marginal effect estimates of the COVID variable (and associated standard errors) are very similar to the ones where I rely on the Linear Probability Model. For the marginal effect of Probit results see appendix tables A.1 to A.9.

1.7 Conclusion and Discussion

In this paper I rely on master files data of the LFS for the 2017-2021 period to see how post-secondary enrolment was affected in COVID-19 times, and explore the source of change. In addition to contributing to the Canadian COVID-19 literature, the paper also contributes to the post-secondary enrolment literature, and in particular, to papers that look at how important external events can affect enrolment decisions.

I find that university enrolment increased in COVID-19 times for both young (17-24) and older (25-39) women, and the effects are economically and statistically significant. For men, I only observe the effect in the younger age group, and it is more muted (as compared to young women) and not statistically significant. Surprisingly, college enrolment was unaffected by COVID-19, and this holds true across gender and age groups. For both younger and older women, the drop in the cost of education that followed the advent in COVID-19 is key. The channels through which it operates, however, differs across the two age groups. For older women the evidence points to the notion that due to online schooling one did not have to sacrifice a career job to go back to university and upgrade one's skills in COVID-19 times. For younger women the evidence supports the direct cost of education channel, i.e., it is now less costly to attend university because they can now study from home.

Given the lack of existing Canadian evidence (and the limited international evidence), I see this paper as a first step in understanding how this COVID shock affected post-secondary enrolment in Canada. More work needs to be done. In particular, in explaining why younger men were not affected in the same way as younger women. It may be that learning styles matter, and that young women could better cope with online learning, an issue that I could not address with my data.

1.8 Figures and Tables

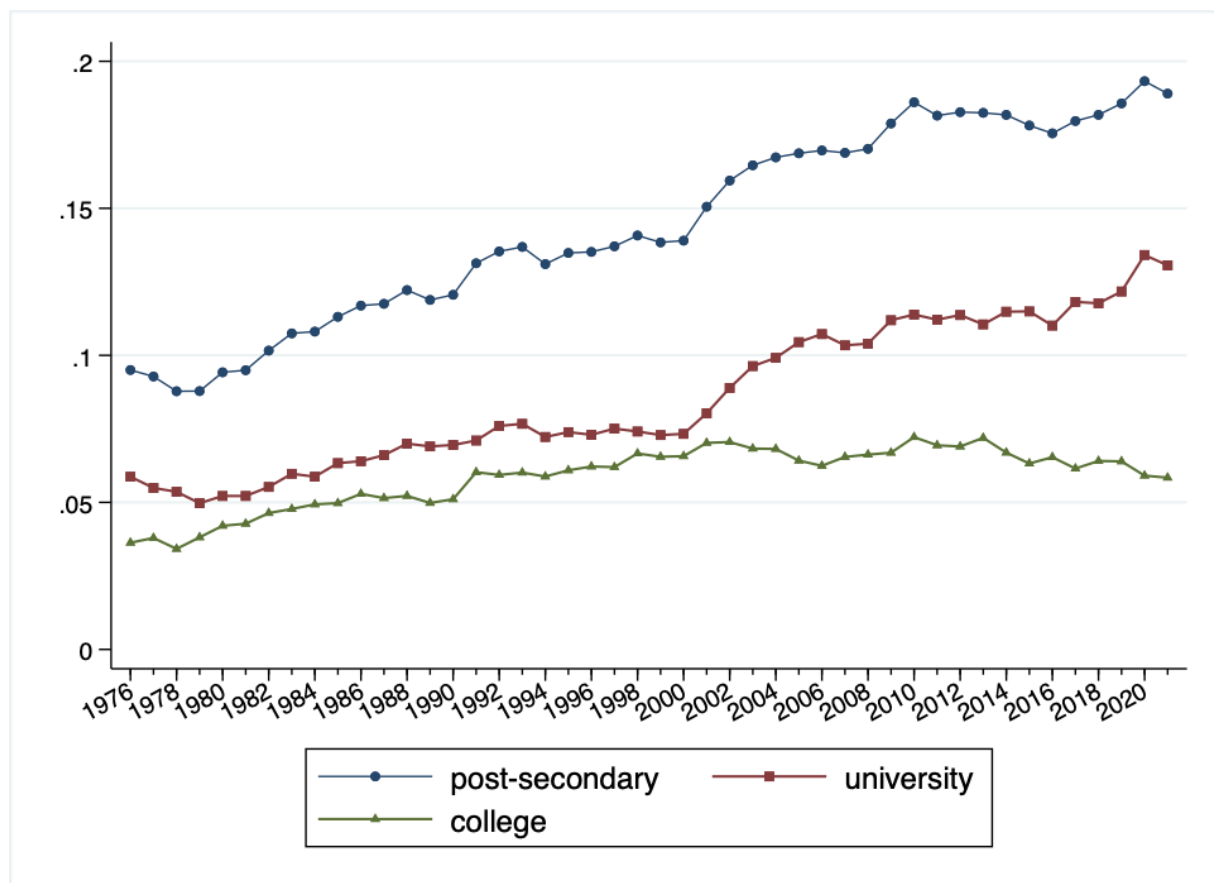


Figure 1.1: Post-secondary enrolment rate, 17-39, 1976-2021 (Sep. only), by institution type. Source: LFS master files.

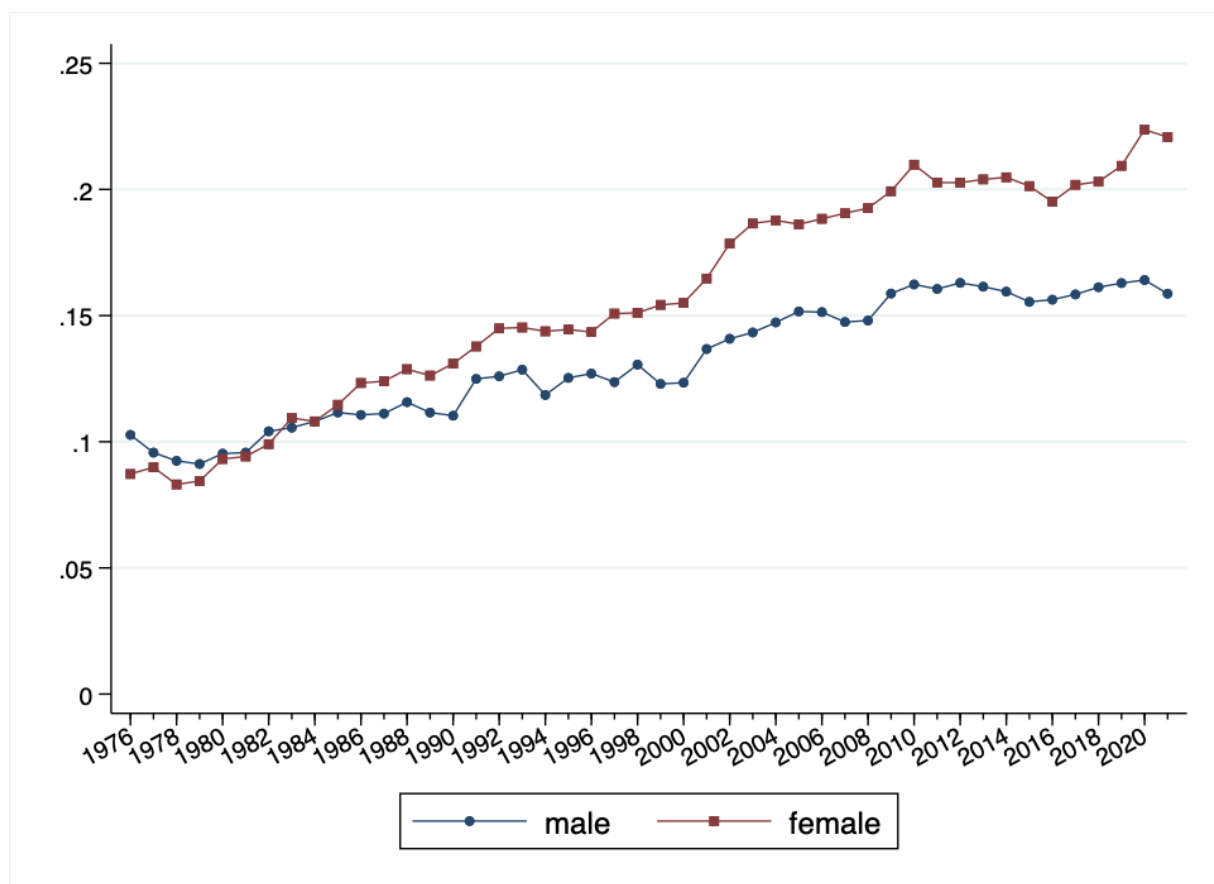


Figure 1.2: Post-secondary enrolment rate, 17-39, 1976-2021 (Sep. only), by gender. Source: LFS master files.

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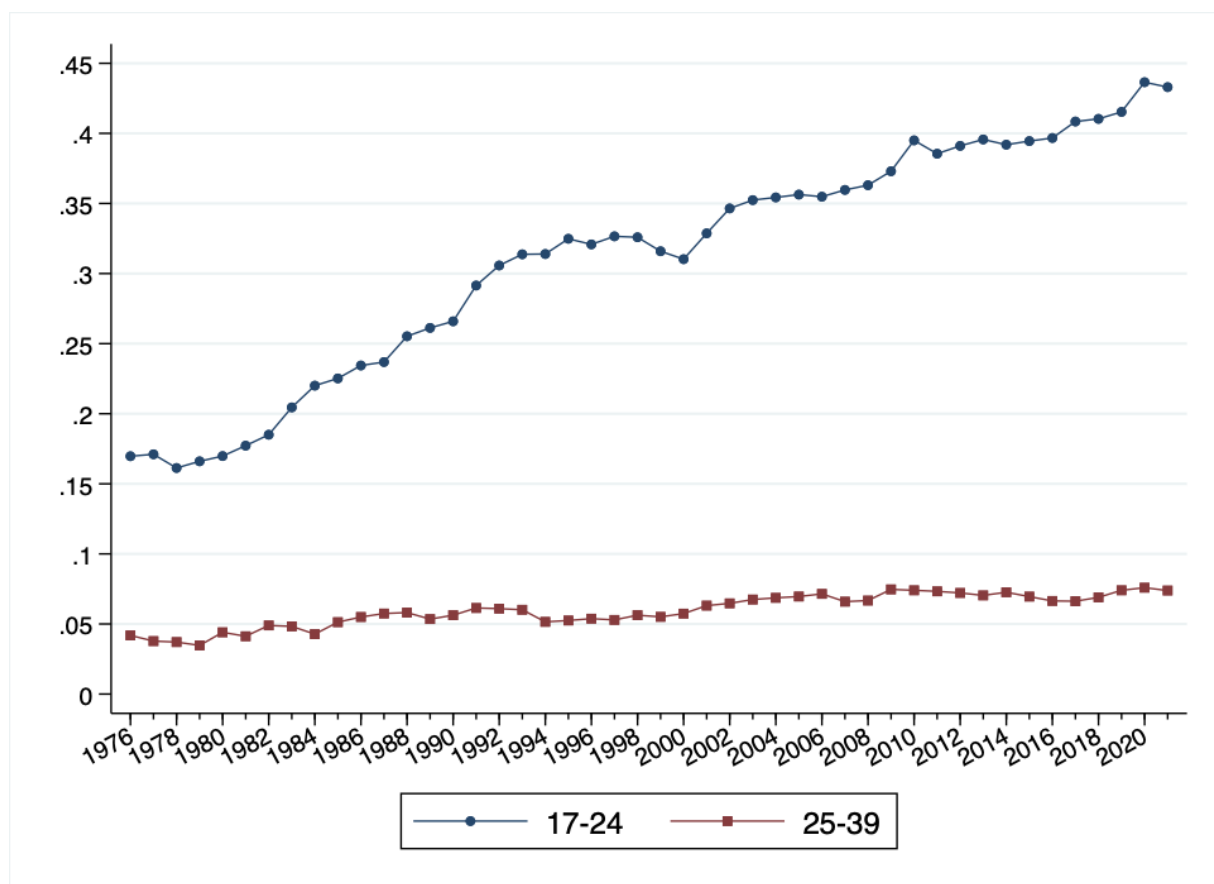


Figure 1.3: Post-secondary enrolment rate, 17-39, 1976-2021 (Sep. only), by age group. Source: LFS master files.

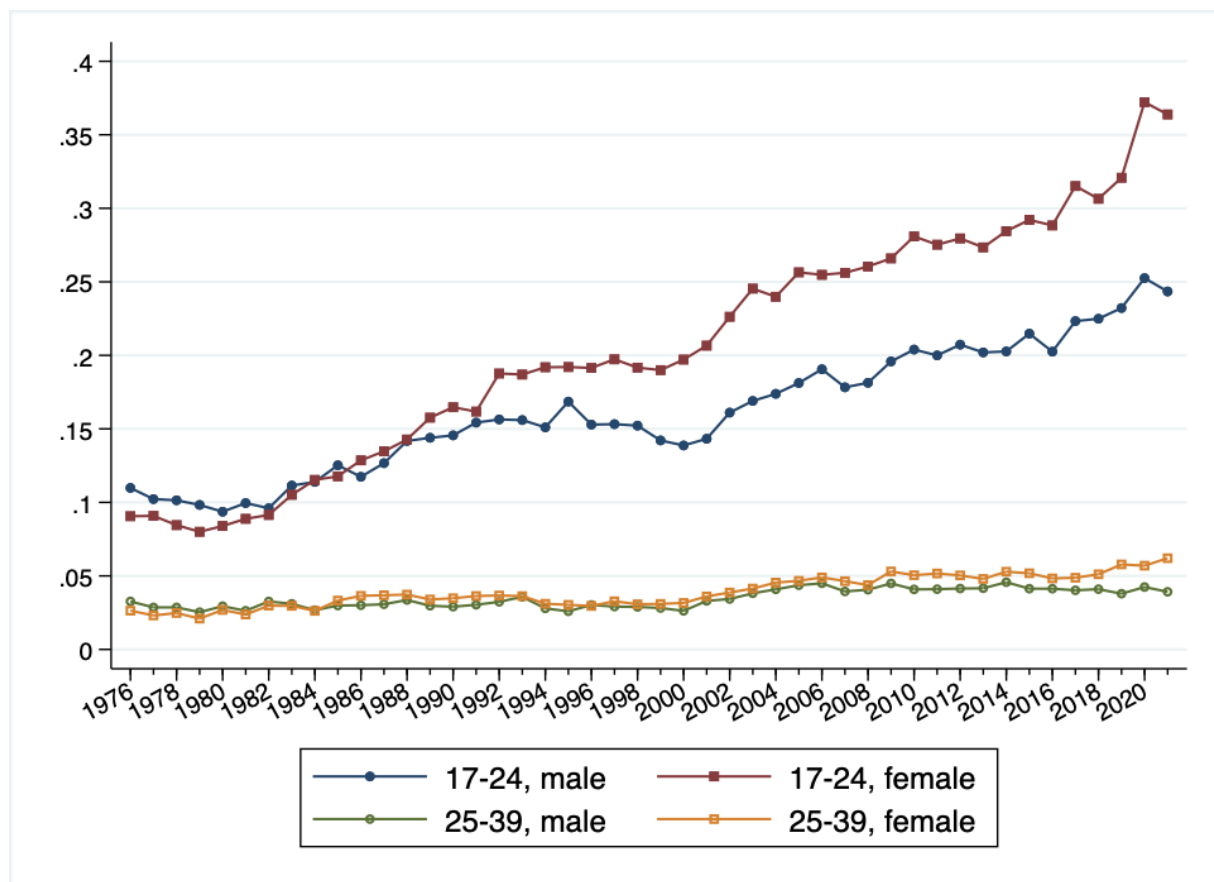


Figure 1.4: University enrolment rate, 17-39, 1976-2021 (Sep. only), by age and by gender. Source: LFS master files.

Table 1.1: Post-secondary enrolment results

	17-39			17-24			25-39		
	All	Male	Female	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
COVID	.012*** (.004)	.004 (.005)	.020*** (.006)	.022** (.009)	.015 (.013)	.031** (.014)	.007** (.004)	-.001 (.004)	.016*** (.005)
Female	.061*** (.003)	—	—	.126*** (.006)	—	—	.031*** (.002)	—	—
Married	-.061*** (.003)	-.042*** (.003)	-.078*** (.004)	-.183*** (.010)	-.159*** (.015)	-.198*** (.014)	-.028*** (.002)	-.020*** (.003)	-.038*** (.004)
Age	-.094*** (.002)	-.086*** (.003)	-.102*** (.003)	.887*** (.027)	.723*** (.037)	1.060*** (.038)	-.061*** (.005)	-.057*** (.007)	-.066*** (.007)
Age squared	.001*** (.000)	.001*** (.000)	.001*** (.000)	-.022*** (.001)	-.018*** (.001)	-.026*** (.001)	.001*** (.000)	.001*** (.000)	.001*** (.000)
Unemployment rate	-.062 (.152)	-.011 (.203)	-.124 (.225)	-.185 (.364)	-.145 (.504)	-.264 (.525)	-.087 (.133)	.008 (.166)	-.189 (.208)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean enrol. (2017-19)	.178	.155	.201	.406	.355	.461	.067	.056	.078
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a post-secondary institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a constant. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 1.2: College enrolment results

	17-39		17-24		25-39	
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
	(7)	(8)	(9)	(10)	(11)	(12)
COVID	.001 (.003)	.001 (.004)	.002 (.004)	.001 (.007)	.002 (.009)	-.001 (.010)
Female	.013*** (.002)	— (.004)	— (.004)	.015*** (.004)	— (.004)	— (.004)
Married	-.011*** (.002)	-.010*** (.002)	-.013*** (.003)	-.037*** (.007)	-.048*** (.009)	-.032*** (.010)
Age	-.049*** (.001)	-.048*** (.002)	-.049*** (.002)	.098*** (.019)	.090*** (.026)	.103*** (.026)
Age squared	.001*** (.000)	.001*** (.000)	.001*** (.000)	-.003*** (.000)	-.003*** (.001)	-.003*** (.001)
Unemployment rate	-.178* (.096)	-.208 (.127)	-.148 (.143)	-.581** (.241)	-.578* (.334)	-.589* (.349)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean enrol. (2017-19)	.062	.057	.066	.142	.135	.150
N	145,818	72,522	73,296	45,686	23,612	22,074
				100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a college institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a constant. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table 1.3: University enrolment results

	17-39			17-24			25-39		
	All (1)	Male (2)	Female (3)	All (4)	Male (5)	Female (6)	All (7)	Male (8)	Female (9)
COVID	.011*** (.004)	.004 (.005)	.018*** (.005)	.022*** (.009)	.013 (.012)	.032** (.013)	.006* (.003)	-.001 (.004)	.012*** (.005)
Female	.049*** (.002)	—	—	.111*** (.006)	—	—	.020*** (.002)	—	—
Married	-.049*** (.002)	-.032*** (.003)	-.065*** (.004)	-.146*** (.009)	-.111*** (.013)	-.166*** (.012)	-.018*** (.002)	-.012*** (.002)	-.026*** (.003)
Age	-.046*** (.002)	-.038*** (.002)	-.053*** (.003)	.789*** (.024)	.633*** (.032)	.957*** (.036)	-.046*** (.004)	-.043*** (.006)	-.049*** (.006)
Age squared	.001*** (.000)	.000*** (.000)	.001*** (.000)	-.019*** (.001)	-.015*** (.001)	-.023*** (.001)	.001*** (.000)	.001*** (.000)	.001*** (.000)
Unemployment rate	.116 (.138)	.198 (.182)	.024 (.207)	.396 (.345)	.433 (.459)	.324 (.518)	-.087 (.110)	.041 (.140)	-.222 (.171)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean enrol. (2017-19)	.116	.098	.134	.264	.220	.312	.044	.037	.051
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a constant. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 1.4: University enrolment results, female, 25-39, by labour market characteristics

	All		Not Employed		Employed		Employed		Employed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
COVID	.012*** (.005)	.018 (.013)	.011** (.005)	.009* (.005)	.028* (.016)	.018** (.008)	.003 (.006)	.010* (.006)	.007 (.006)	
Mean enrol. (2017-19)	.051	.081	.043	.035	.082	.056	.032	.050	.022	
N	51,222	10,741	40,481	32,991	7,490	19,137	21,344	29,673	10,808	

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of females born in Canada or is (or ever was) a landed immigrant, 25 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). High skilled occupations (i.e., column (6)) are the broad occupational categories where there is a high prevalence of graduate degrees. Post-secondary education (i.e., column (8)) refers to those that have attained a post-secondary certificate, diploma or degree. All regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table 1.5: University enrolment results, female, 25-39, by type of work and presence of young children at home

	Employed		All		Employed	
	Remote Work	Other	Young Child	Other	Young Child	Other
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	.016*	.008	.004	.013**	.006	.012*
	(.009)	(.006)	(.005)	(.006)	(.006)	(.007)
Mean enrol. (2017-19)	.051	.039	.028	.063	.024	.052
N	13,558	26,923	18,864	32,358	13,746	26,735

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of females born in Canada or is (or ever was) a landed immigrant, 25 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). Remote work occupations (i.e., column (1)) are the occupations that are carried out remotely, and young children (i.e., columns (3) and (5)) refers to those individuals who have a young child under the age of six at home. All regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table 1.6: University enrolment results, 17-24, by age group and labour market characteristics

	Female			Male		
	All	Not Emp.	Emp.	All	Not Emp.	Emp.
	(1)	(2)	(3)	(6)	(7)	(8)
			Full-time		Full-time	
			(4)		(9)	
			Part-time		Part-time	
			(5)		(10)	
<i>Panel A: Teenagers</i>						
COVID	.061*** (.019)	.055* (.028)	.075*** (.024)	.108** (.042)	.073*** (.028)	.038* (.020)
Mean enrol. (2017-19)	.282	.343	.226	.087	.260	.121
N	8,604	4,099	4,505	1,025	3,480	4,478
<i>Panel B: Young adults</i>						
COVID	.018 (.017)	.033 (.032)	.016 (.020)	.021 (.019)	.045 (.034)	.023 (.017)
Mean enrol. (2017-19)	.328	.488	.255	.082	.503	.135
N	13,470	4,444	9,026	5,452	3,574	9,858
				14,487	4,629	7,536
						2,322

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 24 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 1.7: Full- and part-time university enrolment results, 17-19, by gender and labour market characteristics

	Female					Male				
	All	Not Emp.	Emp.	Full-time		All	Not Emp.	Emp.	Full-time	
				(4)	(5)				(8)	(9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Panel A: Full-time enrolment</i>										
COVID	.052*** (.019)	.045 (.028)	.065*** (.024)	.075** (.033)	.067** (.028)	.008 (.015)	-.019 (.023)	.034* (.019)	-.001 (.012)	.070*** (.026)
Mean enrol. (2017-19)	.276	.340	.217	.065	.254	.188	.261	.113	.029	.161
N	8,604	4,099	4,505	1,025	3,480	9,125	4,647	4,478	1,774	2,704
<i>Panel B: Part-time enrolment</i>										
COVID	.010** (.005)	.010 (.007)	.010* (.006)	.033 (.028)	.006 (.004)	.002 (.003)	-.001 (.003)	.004 (.006)	-.001 (.007)	.008 (.008)
Mean enrol. (2017-19)	.006	.003	.009	.022	.006	.006	.003	.008	.005	.010
N	8,604	4,099	4,505	1,025	3,480	9,125	4,647	4,478	1,774	2,704

Notes. Dependent variable: In panel A, a binary variable equal to one if the individual is enrolled in a full-time university institution (and zero otherwise). In panel B, a binary variable equal to one if the individual is enrolled in a part-time university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 19 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 1.8: University enrolment results, 17-18, by economic family earnings

	Women			Female			Male			Male		
	Member of the Parents' Dwelling			Member of the Parents' Dwelling			Member of the Parents' Dwelling			Member of the Parents' Dwelling		
	All	p75	p50	p75	p50	p25	All	p75	p50	p75	p50	p25
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
COVID	.073*** (.021)	.058*** (.022)	.061** (.025)	.086*** (.030)	.118** (.048)	.023 (.016)	.010 (.017)	-.014 (.021)	-.002 (.028)	-.023 (.036)		
Mean enrol. (2017-19)	.225	.231	.206	.199	.211	.144	.146	.140	.140	.139		
N	5,819	5,284	3,395	2,197	1,128	6,230	5,706	3,588	2,245	1,116		

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 18 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). Living at home means the respondent's relationship to the reference person is son or daughter, grandchild, son/daughter-in-law, or foster child. p75, p50 and p25 indicate subsamples of teenagers whose economic family earnings are below the 75th percentile, 50th percentile, and 25th percentile. All regressions include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table 1.9: University enrolment results, 17-18, by geographical area

	All		All		CMA*/CA*		CMA*		CMA*	
	Urban	Rural	CMA*/CA*	Other	Core	Other	Core	Other	Core	Sec. Core
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(9)
<i>Panel A: Female</i>										
COVID	.077***	.046	.080***	.034	.077***	.091	.081***	.089	.270*	
	(.025)	(.034)	(.026)	(.029)	(.029)	(.066)	(.029)	(.074)	(.147)	
Mean enrol. (2017-19)	.237	.170	.249	.150	.252	.234	.253	.239	.200	
N	4,287	1,532	3,780	2,039	3,016	764	2,790	631	99	
<i>Panel B: Female, bottom 75th percentile of family income</i>										
COVID	.068**	.062	.075**	.045	.053	.194**	.058*	.195**	.414**	
	(.029)	(.040)	(.030)	(.036)	(.033)	(.076)	(.034)	(.085)	(.169)	
Mean enrol. (2017-19)	.209	.157	.219	.144	.229	.159	.230	.164	.065	
N	2,739	1,011	2,355	1,395	1,906	449	1,766	373	67	
<i>Panel C: Male</i>										
COVID	.026	.009	.033	.001	.035	.032	.037	.020	.031	
	(.019)	(.025)	(.021)	(.017)	(.024)	(.046)	(.025)	(.049)	(.105)	
Mean enrol. (2017-19)	.153	.097	.169	.068	.177	.121	.178	.123	.152	
N	4,652	1,578	4,055	2,175	3,232	823	2,923	697	115	
<i>Panel D: Male, bottom 75th percentile of family income</i>										
COVID	-.001	.014	.010	-.002	.003	.046	.006	.046	.011	
	(.025)	(.028)	(.027)	(.020)	(.031)	(.052)	(.032)	(.058)	(.152)	
Mean enrol. (2017-19)	.150	.088	.164	.067	.176	.091	.178	.093	.092	
N	2,883	1,027	2,490	1,420	1,987	503	1,792	415	71	

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a full-time university institution (and zero otherwise). The sample in panel A consists of female individuals born in Canada or is (or ever was) a landed immigrant, 17 to 18 years of age, over the 2017-2021 period (Sep. data only). The samples in panel B is restricted to female respondents whose family income is in the bottom 75th percentile. Panels C and D are similarly defined, but for males. The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). CMA and CA are census metropolitan area and census agglomeration, respectively. The LFS uses the 2016 Census of Population geographical definitions where the core is defined as the population centre with the largest population around which a CMA or CA is delineated. The core of CMA must have a population of at least 40,000, whereas for a CA it must be in the 10,000-39,999 range. A secondary core is a population centre with 10,000 or more individuals within a CMA (and in many cases has much more), that is not situated in the core. CMAs and CAs can only have one (primary) core, but given their sizes CMAs can have multiple secondary cores. The CMA* and CA* notations designate CMAs and CAs that have a university within their boundaries. All regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table 1.10: University enrolment results, external environment

	17-39			17-24			25-39		
	All	Male	Female	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Panel A: Sep. enrol. data</i>									
COVID (Sep., contemp. month)	.011*** (.004)	.004 (.005)	.018*** (.005)	.022*** (.009)	.013 (.012)	.032** (.013)	.006* (.003)	-.001 (.004)	.012*** (.005)
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222
COVID (Jun.)	.010*** (.004)	.001 (.005)	.020*** (.006)	.023** (.010)	.010 (.013)	.039** (.015)	.005 (.003)	-.002 (.004)	.012*** (.005)
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222
COVID (Jan.)	.015*** (.005)	.002 (.007)	.029*** (.008)	.029** (.013)	.011 (.018)	.050** (.020)	.006 (.004)	-.005 (.006)	.018*** (.007)
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222
<i>Panel B: Sep. & Jan. enrol. data</i>									
COVID (contemp. month)	.012*** (.003)	.008*** (.004)	.016*** (.004)	.026*** (.007)	.023** (.009)	.031*** (.010)	.004* (.002)	-.001 (.003)	.009*** (.003)
N	327,784	163,200	164,584	103,069	53,279	49,790	224,715	109,921	114,794
COVID (Jan.)	.013*** (.003)	.005 (.005)	.022*** (.005)	.026*** (.008)	.019* (.011)	.034*** (.013)	.007** (.003)	-.003 (.004)	.017*** (.004)
N	327,784	163,200	164,584	103,069	53,279	49,790	224,715	109,921	114,794

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The sample for panel B covers the September 2017 to January 2022 period. The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). The unemployment rate is measured as of the same month as the COVID variable. All regressions are weighted and include a female binary variable, a married binary variable, age and age squared, the unemployment rate, province fixed effects, and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 1.11: University enrolment results, various sample periods

	17-39		17-24		25-39				
	All	Male	Female	All	Male	Female			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Panel A: 2017-2021 sample period</i>									
COVID	.011*** (.004)	.004 (.005)	.018*** (.005)	.022*** (.009)	.013 (.012)	.032** (.013)	.006* (.003)	-.001 (.004)	.012*** (.005)
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222
<i>Panel B: 2018-2021 sample period</i>									
COVID	.011*** (.004)	.004 (.005)	.018*** (.006)	.023** (.010)	.013 (.013)	.035** (.015)	.005 (.003)	.000 (.004)	.010*** (.005)
N	112,251	55,853	56,398	34,961	18,136	16,825	77,290	37,717	39,573
<i>Panel C: 2016-2021 sample period</i>									
COVID	.017*** (.003)	.008* (.004)	.026*** (.005)	.038*** (.007)	.027*** (.010)	.052*** (.011)	.007** (.003)	-.001 (.003)	.014*** (.004)
N	179,106	89,020	90,086	56,573	29,178	27,395	122,533	59,842	62,691
<i>Panel D: 2015-2021 sample period</i>									
COVID	.016*** (.003)	.006* (.004)	.026*** (.004)	.039*** (.007)	.025*** (.009)	.055*** (.010)	.005* (.002)	-.003 (.003)	.012*** (.004)
N	212,445	105,455	106,990	67,844	34,953	32,891	144,601	70,502	74,099

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a female binary variable, a married binary variable, age and age squared, the unemployment rate, province fixed effects, and a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%, ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 1.12: University enrolment results, various clustering approaches (p-values reported)

	17-39		17-24		25-39	
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(4)	(5)	(6)
COVID						
het.-robust s.e. (p-value)	.011	.004	.018	.022	.013	.032
clust. province and year (p-value)	(.002)	(.413)	(.001)	(.013)	(.271)	(.015)
clust. province (p-value)	(.000)	(.124)	(.000)	(.000)	(.024)	(.005)
boottest (p-value)	(.009)	(.133)	(.005)	(.020)	(.028)	(.083)
	(.011)	(.133)	(.013)	(.017)	(.118)	(.099)
N	145,818	72,522	73,296	45,686	23,612	22,074
				100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a female binary variable, a married binary variable, age and age squared, the September unemployment rate, province fixed effects, and a constant. p-values are in parenthesis. Source: LFS master files.

Chapter 2

Canadian Job Stability Patterns in the Post-Great-Recession Period

2.1 Introduction

Claims that the employer-employee relationship has changed, that workers are now as easily disposable as other resources have been around since the late-1980s/early-1990s. Proponents of this conjecture argue that technological change and the rise of international trade, i.e., globalization, are the root causes of the demise of ‘stable’ jobs, with the rise of the gig economy being recently added to the list of causal factors. Yet the job stability literature (Canada: [Heisz \(2005\)](#); [Brochu \(2013\)](#), U.S.: [Neumark et al. \(1999\)](#)) had, until recently, not found any evidence to support this claim. In fact, the early Canadian evidence suggests that jobs had become more stable in the 1990s and into the 2000s, with compositional changes (ageing of the workforce and to a lesser extent increased educational attainment) and the increased job stability of women having played key roles in explaining the new Canadian patterns that arose ([Brochu, 2013](#)).¹ The advent of better U.S. tenure data, particularly for low-tenure workers, has spurred renewed interest in the employment relationship. The new U.S. evidence suggests that the employment relationship has changed but not uniformly across workers ([Molloy et al., 2024](#)).

In this paper, we rely on the Canadian Labour Force Survey (LFS) to update the existing Canadian job stability evidence beyond the Great Recession.² Due to the many similarities between the Canadian and U.S. labour markets, the richness of the LFS (which we discuss below) may shed light on the changes in job stability not just for Canada, but also for the United States. A secondary goal of this paper is to document job stability patterns of vulnerable populations, i.e., individuals of Indigenous identity living off-reserve

¹Tenure data limitations prevented the early U.S. job stability literature from drawing stronger conclusions regarding secular changes, let alone explore the source of change.

²We can, for example, see whether the recent changes observed in the U.S. are also present in Canada.

and immigrants, that had yet to be examined in Canada due to previous data limitations. The exploration of this additional dimension will help provide a fuller picture of how these vulnerable groups are performing in the labour market, which in turn can provide guidance to policy-makers on how to best help them.³

The richness of the LFS tenure data is critical to our empirical strategy. We favour a retention rate approach as our empirical strategy because a retention rate is a direct measure of job stability.⁴ A job is stable if it has a high probability of continuing into the next period. Therefore, a well-conditioned retention rate is less sensitive to labour market inflows and outflows than in-progress measures such as mean tenure or the proportion of long-term jobs (20 years or more).⁵ Identifying long-term secular changes using a retention rate approach requires consistent and detailed tenure data made available at frequent and regular intervals over multiple decades. The LFS meets these stringent criteria.⁶

We find that the employment relationship became more stable following the Great Recession. It can best be described as a ratchet effect with job stability increasing during the Great Recession, only to stabilize at historically high levels in the subsequent expansionary period.⁷ A systematic negative male-female gender gap has now emerged, with female jobs being more stable than male ones. Finally, the rise in the stability of low-tenure jobs has persisted into the post-Great Recession period, and this increase is broadly based. These patterns hold for both cross-sectional and panel approaches.

Rising educational attainment, but not ageing of the workforce, plays a role in explaining new job stability patterns, both at the aggregate level and for low-tenure jobs. However, for the latter, some of the rise remains unaccounted for. More precisely, when focusing

³We recognize that individuals of Indigenous identity and immigrants are two very distinct groups. They face very different economic situations and not surprisingly they tend to have their own literature. Nonetheless, they are vulnerable groups in the sense that they both have encountered labour market difficulties, and in both cases the job stability dimension has yet to be explored.

⁴A retention rate is the probability that a job continues into the next period.

⁵An inflow of workers into the labour market will, by construction, bring down the mean (in-progress) tenure, not because jobs have become less stable but simply because there are now more new jobs. The effect of a large inflow, such as the significant inflow of women into the workforce in the 1970s and early 1980s, will be long-lasting. Even if these new entrants had very stable employment relationships from when they first joined the labour market, changes in, say, the proportion of jobs with tenure of 20 years or more would only start to be observed 20 years later. A similar story holds true for outflows. One has observed in Canada (and the U.S.) a decline in labour force participation of prime-aged men, particularly the less-educated. If those that now leave the labour market tended to have less stable jobs, one will see a spurious improvement in in-progress measures. Note that they are characterized as in-progress measures because the tenure counts how long an individual has been with their current employer as of the time of the survey, i.e., the tenure spell is still in-progress.

⁶It should be noted that labour market transitions play a central role in search models; within these models, the employer-employee match is a key feature. There is much empirical work (Brochu, 2013) suggesting that very low-tenured jobs are much less stable, which aligns with the class of search models where match quality is only fully revealed once the match is formed.

⁷That one sees an increase in job stability during the Great Recession is not unexpected, as this has occurred in all previous recessions since the mid-1970s when LFS microdata first became available. What is noteworthy is that one did not see a reversion during the long post-Great Recession expansionary period that followed.

on all-tenure workers, education explains all of the small increase for men, whereas for women it explains 2/3 of their rise. When focusing on low-tenure workers, however, rising educational attainment explains approximately 1/3 of the significant rise for each gender. We also conclude that the job-to-job transition which has been found to matter in the U.S. labour market has limited explanatory power for Canada. In fact, we observe that for low-tenure jobs our findings are driven by a decline in the employment to unemployment transition, and it is initiated from the employer side.⁸

Finally, we find that individuals of Indigenous identity living off-reserve who historically have poorer labour market outcomes than their non-Indigenous counterparts, also do poorly along the job stability front. For immigrants, the story is less bleak. They underperform the native-borns upon their arrival, but the assimilation pattern is strong enough that they eventually catch up and surpass them.

This paper contributes to the job stability literature as follows: we are the first to document the Canadian job stability patterns, and explore their sources of change, for the post-Great Recession period—a period of substantive economic change. We are also the first to focus on immigrants and individuals of Indigenous identity. The examination of the job stability dimension can help us better understand why these vulnerable populations have not fared as well in the labour market. Finally, by utilizing both cross-sectional and panel approaches, and showing that they give very similar results, we bridge the findings of the earlier job stability literature that tended to focus on the cross-sectional approach to more recent papers, particularly those looking at low-tenure jobs, which tend to rely more on the panel approach due to the availability of better U.S. tenure data in recent years.

Closely related to our work is [Molloy et al. \(2024\)](#) who look at how the employment relationship has evolved in the American labour market over the past couple of decades, and as we do, look for changes in the aggregate, and for an extensive number of subpopulations. They rely on the Current Population Survey (CPS) and complement their analysis using longitudinal datasets, mainly the Survey of Income and Program Participation (SIPP) and to a lesser extent the National Longitudinal Survey of Youth (NLSY).⁹ Their main focus,

⁸That job-to-job transition is an important factor in the U.S. but not in Canada has yet to be explored in the literature. It may be due to cross-country differences in the social safety net, such as health insurance and employment insurance (EI)/unemployment insurance (UI) programs. [Riddell \(2005\)](#), for example, speculates that differences in EI/UI programs, particularly the significant difference in the likelihood of an unemployed worker receiving EI/UI benefits (being higher in Canada) could explain some of the Canada–U.S. unemployment rate gap. There is also evidence that having an employer-provided health insurance (as is the case in the U.S.) can lead workers being locked-in to their jobs ([Madrian, 1994](#); [Garthwaite et al., 2014](#)). This could, in the case of poor matches, have implications for job-to-job transitions.

⁹Although the CPS is the U.S. counterpart of the LFS, i.e., both are national household labour force surveys which are the official source of employment and unemployment data for their respective countries, tenure questions are not part of the regular monthly questionnaire in the CPS. They are only asked in select supplements. Since 1996, the tenure supplements are now held every two years (either January or February). This means that in their analysis using the CPS, which is the main component of their paper,

however, is in providing a comprehensive examination of the changing distribution of job tenure. They do not find any significant change in the mean tenure, but they do find differences in the tails of the tenure distribution. They document a broadly based decline in the importance of short-term jobs (across a broad range of worker characteristics) which appears to be related to a decline in job-to-job transitions. Finally, Molloy et al. (2024) observe a decrease in the importance of long-term jobs (20 years or more) for older men, which has been counterbalanced by a rise for older women.

Also related to our work are the papers that have focused on the declining importance of jobs of short duration in the U.S. (Hyatt and Spletzer, 2013, 2017; Pries and Rogerson, 2022). In particular, Pries and Rogerson (2022), relying on the Quarterly Workforce Indicators (QWI), conclude that a significant part of the decline in labour market turnover observed over the last two decades can be accounted by a decline in employment spells of short duration (one to two quarters), and this result is present across a variety worker and firm characteristics. Of most relevance to our paper, they find that the rise in the retention rate of these short-duration employment spells (one or two quarters) is a key factor in the observed change.

Finally, this paper contributes to a broader literature that relies on labour market transitions to better understand the workings of the labour market. It has, among others, been used to enhance our comprehension of labour market states (Jones and Riddell, 2006, 2019),¹⁰ to get a fuller picture of the effect of labour market policies (minimum wage: Brochu and Green (2013); Dube et al. (2016); Brochu et al. (2023)), and to get a better sense of how the labour market behaves over the business cycle (Campolieti, 2011; Shimer, 2012; Fujita and Ramey, 2009; Elsby et al., 2015) and specifically, over the recent COVID-19 recession and subsequent recovery (Brochu, Cr  chet and Deng, 2020; Jones et al., 2023; Lal  , 2024).

The rest of the paper is divided as follows. Section 2.2 presents the data and provides an overview of the empirical approach relied upon in this paper. Section 2.3 documents the new job stability patterns and section 2.4 explores the source of change. In section 2.5 we further examine the job stability patterns using a panel approach. Finally, section 2.6 concludes.

they must focus on in-progress tenure measures (i.e., in-progress tenure duration) rather than retention rates. For the part of their analysis that follows a retention approach, they mainly rely on the SIPP.

¹⁰More precisely, they utilize labour market transitions to show that the traditional labour market states are in fact quite heterogeneous. For instance, individuals who want a job but are not actively looking for one, and thus counted as out of the labour force, have more in common with the unemployed than non-participants.

2.2 Data and Empirical Approach

For our empirical analysis, we rely on Canadian Labour Force Survey (LFS) master files data over the 1977 to 2022 period. The LFS is a large monthly household survey (i.e., approximately 55,000 households are interviewed each month) that gathers labour market information of the Canadian adult population.¹¹ It is the official source of employment and unemployment data for Canada.

The richness of the LFS tenure data is key to this study. As part of the regular questionnaire, and dating back to 1976, the LFS asks respondents that are employed when they started working for their present employer, and the in-progress tenure duration is recorded in months. This allows us to construct a precise and consistent measure of job stability spanning four and a half decades.

We restrict our sample to individuals between the ages of 20 to 65 living in one of the Canada's ten provinces. The upper age limit is kept relatively high as to be comparable with the recent literature, and it also reflects the fact that 65 is the typical retirement age in Canada. We exclude those living in the territories (representing less than 1% of the Canadian population) as the survey design is somewhat different for these areas, which would affect the comparability of the findings.¹²

As is commonly done in the job stability literature (Neumark et al., 1999; Brochu, 2013; Pries and Rogerson, 2022; Molloy et al., 2024), we rely on a retention rate approach to explore for changes in job stability. It is a direct measure of job stability and is less sensitive to labour market inflows than in-progress measures such as in-progress mean tenure. The retention rate is simply the probability that a worker will stay with the same employer for one more period. More precisely, the retention rate for workers with characteristics c who have been (continuously) employed with the same employer for s periods as of time t can be written as

$$R_t^{s,c} = \frac{N_{t+1}^{s+1,c}}{N_t^{s,c}} \quad (2.1)$$

where the denominator is the number of workers with s periods of tenure and characteristics c as of time t , with the numerator representing the number that continued with their present employer into the next period.

For the first part of our analysis we estimate the retention rates using a cross-sectional estimator previously relied upon in the job stability literature (Neumark et al., 1999; Heisz,

¹¹More precisely, the target population of the LFS consists of the civilian non-institutional population 15 years and up, excluding those living on Indigenous reserves.

¹²Some of the differences include the length of stay in the survey (territories: 24 months) and the frequency of interviews (territories: every three months). Furthermore, non-response is a much more serious issue in the territories. See Brochu and Cr  chet (2022) for more details.

2005; Brochu, 2013). The estimator takes the form

$$\hat{R}_t^{s,c} = \frac{\tilde{n}_{t+1}^{s+1,c}}{\tilde{n}_t^{s,c}} \quad (2.2)$$

where $\tilde{n}_t^{s,c}$ is the sum of the base weights of individuals with tenure s and characteristics c at time t . The estimator takes advantage of the fact that the base weights of repeated cross-sections like the LFS (and the CPS for the U.S.) represent the inverse probability of being chosen. As such, the denominator (numerator) of equation (2.2) directly estimates the denominator (numerator) of equation (2.1). One can rely on repeated cross-sections, i.e., use a different cross-section for the numerator, because for a worker to have $s + 1$ periods of tenure at time $t + 1$, he/she had to have been part of the same *population* cohort that had s periods of tenure as of period t .¹³

We focus on the one-year retention rate, the probability of remaining with the same employer one more year. We do so because we are interested in identifying long-term secular trends, and by focusing on one-year rates, we can abstract from confounding seasonality issues that arise with monthly transitions. A one-year transition window is short enough to be able to fully identify changing patterns,¹⁴ and the resulting one-year rates are easily interpretable.¹⁵ The minimum conditioning characteristics for all retention rates consists of employed individuals 20 to 64 years of age, excluding full-time students, returning students, and the self-employed.

We complement our cross-sectional analysis with a panel one. We take advantage of the rolling panel design of the LFS—that households remain in the survey for six consecutive months and one-sixth are replaced each month—to construct two consecutive

¹³Having a population cohort simply implies that there is more than one period of information for each person in the population. An example will best illustrate the idea of drawing from a population cohort, and in turn, the workings of this estimator. Assume one is interested in estimating the retention rate of female workers 20 to 64 years of age with less than 12 months of tenure. The estimator is

$$\hat{R}_t^{1-11,c,20-64} = \frac{\tilde{n}_{t+1}^{13-23,c,21-65}}{\tilde{n}_t^{1-11,c,20-64}} \quad (2.3)$$

where the denominator $\tilde{n}_t^{1-11,c,20-64}$ is the sum of the base weights of workers who have been the same employer less than 12 months, have time-invariant characteristics c (i.e., are female) and are 20 to 64 years of age in year t . Although coming from a different cross-section, female workers 21 to 65 years of age with 13 to 23 months in year $t + 1$ come from the same population cohort as those in the numerator, i.e., they had to have been one year younger and had one year less of tenure in year t . It should be noted that the estimator can account for population changes, but these changes (due to immigration, emigration or deaths) must lead to a break in the tenure spell, which are relatively mild identifying assumptions. See Brochu (2011) for more details on the properties of this estimator.

¹⁴If one were to focus on a longer transition, say a four-year rate as was done in the earlier U.S. job stability literature (due to data limitation), one would have difficulty separating out cyclical from secular changes.

¹⁵Even when abstracting from the seasonality issue, focusing on rates at higher frequency, such as one-month rates, can be difficult to interpret, especially if the series is somewhat noisy, as one needs to compound the effect twelve times if one is interested in seeing the effect one year later.

month mini-panels.¹⁶ Given that one follows individuals from one month to the next, the panel retention rate estimator is simply the (weighted) proportion workers that continued with the same employer into the next period.¹⁷ It allows us to explore avenues that cannot be explored with the cross-sectional approach. Specifically, one can look at other labour market transitions (e.g., job-to-job transition) to shed light on changes in job stability.¹⁸ A second and equally important reason is that it will allow us to bridge the findings of recent papers that have focused on a panel approach to the earlier literature that tended to focus on the cross-sectional approach.

2.3 Job Stability Patterns

We start this section by examining how job stability patterns have evolved since the Great Recession.¹⁹ In the second part of the section, we look at the patterns of vulnerable groups, i.e., immigrants and those of Indigenous identity, that have yet to be explored in the job stability literature.²⁰

2.3.1 Post-Great Recession

Figure 2.1 shows the overall one-year retention rate for 1977-2021.²¹ We include earlier years to put the post-Great Recession patterns into perspective. One can see a ratchet effect with the advent of the Great Recession, i.e., the retention rate increases during the recessionary period only to stabilize at historically high levels in the expansionary period that follows.²² To put this effect in perspective, the average one-year rate over the expansionary period that followed the Great Recession (2010-2018) is 82.9%, whereas it

¹⁶See Appendix B.1 for details on the creation of the mini-panels.

¹⁷Say one is interested in the January 2010 one-month retention of female workers 20 to 64 years of age with less than 12 months of tenure. Relying on the January-February 2010 mini-panel, one would calculate the (weighted) proportion of female workers 20 to 64 years of age with less than 12 months of tenure in January 2010 that were still with the same employer in February 2010.

¹⁸The cross-sectional retention rate estimator cannot be easily adapted to address other labour market transitions. We use the job-to-job transition to illustrate this point. When using the LFS as repeated cross-sections, one can identify a new job in period $t + 1$ (i.e., job tenure will equal one month or less), but cannot identify the cohort from which it came from in period t , i.e., one cannot differentiate the group that came from another job (which would imply a job-to-job transition) from those that came from non-employment. This is in contrast to the retention rate where, as previously mentioned, one can use a synthetic cohort approach: the group of workers that have $s + 1$ periods of tenure at time $t + 1$ had to have had s periods of tenure at time t .

¹⁹As previously discussed, Heisz (2005) and Brochu (2013) provide a detailed overview of the Canadian patterns prior to the Great Recession.

²⁰This is due to data availability. Questions identifying immigrants' status and individuals of Indigenous identity were not introduced in the LFS until the mid-2000s. See section 2.3.2 for more details.

²¹Although the data extends to 2022, one-year retention rates can only be calculated up to 2021.

²²A similar effect had been noted with the recession of the early 1990s (Brochu, 2013).

averages 81.7% over the one that followed the recession of the early 1990s (1993-2006).²³ Interestingly, the countercyclical pattern observed during earlier recessions is also present around the COVID-19 one. One must take care, however, in drawing a more precise conclusion about the exact timing. The 2020 retention rate measures whether a worker who held a job *anytime* in 2020 is still with the same employer one year later. Yet, the COVID-19 recession was very short-lived, and was immediately followed by a strong recovery—all occurring in 2020. As such, the one-year retention rate for 2020 will confound the effects of the recession and the expansionary periods.²⁴ We will revisit the COVID-19 period effect when we focus on one-month retention rates later in the paper.

Figure 2.2 presents the one-year retention rate by gender. The clear gender difference—with the female rate systematically surpassing the male rate—first observed in the couple of years prior to the Great Recession continues into the subsequent expansionary period.²⁵ Such a finding is striking. It is in direct contrast to what one observes along the wage dimension where women managed to narrow the male-female wage gap over time, but never could eliminate it. Furthermore, the ratchet effect mentioned above is present for both genders, but is more prevalent for females.

In figure 2.3, we show the rates by educational attainment. The rates are from 1990 onwards because the approach to measuring education in the LFS changed as of January 1990. The focus went from measuring years of education to educational attainment. Particularly relevant to our study is the fact that the LFS added a high school graduation question, so one can in the post-1990 period separate out dropouts from those that completed their high school. Although the series is a little noisy, what is important to note is the clear educational profile, i.e., more educated workers have more stable jobs, that is present in the pre-Great Recession period continues beyond it.²⁶ Given the continued rise in educational attainment in the post-Great Recession period, i.e., more and more are attending university particularly women, this suggests that educational attainment will matter when exploring the source of change.

The most dramatic change occurs at the bottom of the tenure distribution.²⁷ Job

²³What these numbers emphasize is that one does not see an immediate reversion during the long post-Great Recession expansionary period that followed.

²⁴In addition, one cannot draw any strong conclusions for the post-COVID period, i.e., separate out cyclical from secular trends, as there is not enough years of data.

²⁵A negative male-female gap had been previously identified for prime-aged workers starting in the early to mid-2000s, but no such conclusion could be drawn at the time for the full workforce (i.e., including 55 to 64 year olds).

²⁶That more educated workers tend to have more stable jobs is a well-known phenomenon in the job stability literature (Heisz, 2005; Brochu, 2013), and is in line with the fact that more-educated workers tend to have better labour market outcomes. This could be due to the fact that more skilled workers may perform different types of jobs which are less easily replaceable than the less skilled. It could also be due to firm-specific human capital investment, there maybe more such investment for skilled workers.

²⁷Figure 2.7 presents the rates for workers with 12 or more months of initial tenure. It shows that any changes observed in the post-Great Recession period are clearly of second-order importance as compared to those seen at the bottom of the tenure distribution.

stability of workers with less than one year of tenure (see figure 2.4) rose significantly in the post-Great Recession expansionary period. It consistently surpassed the 60% in the mid-to late 2010s, whereas it had never exceeded the 56% mark prior to the Great Recession. It should be noted that this is clearly a new job effect. If one conditions on having a job for less than six months, job stability is even lower, yet still exhibits the same rising pattern. It also holds true for men and women (figure 2.5),²⁸ and (although a bit noisy) along the education dimension (figure 2.6). Table 2.1 shows the low-tenure job stability patterns along other dimensions. For ease of presentation, we focus on strong expansionary periods before and after the Great Recessions (i.e., 1987-1988, 1998-1999, 2005-2006 and 2017-2018).²⁹ Table 2.1 clearly shows that the rise in job stability of low-tenure workers is broadly based, as it can be observed along the age, education, industry, public/private and union/non-union dimensions.

2.3.2 New Dimensions

It is well documented that individuals of Indigenous identity have fared poorly in the Canadian labour market, whether it be finding a job (unemployment rate), having a job (employment rate) or the job's wages when employed.³⁰ One dimension that has yet to be explored is job stability, and this is due to data availability. Questions on Indigenous identity only became part of the LFS for the country as a whole starting in 2007.³¹ Furthermore, the Indigenous identity questions are only asked of those who are off-reserve, as individuals living on-reserves are beyond the scope of the survey. Although the greater majority of individuals that identify as First Nation Peoples live off-reserve, they are not representative of the group as a whole as they tend to have better labour market outcomes than their on-reserve counterparts. Yet, they nonetheless systematically do worse than those that do not identify as First Nations Peoples. As such, one can treat a negative Indigenous–non-Indigenous job stability gap if it exists (and it does) as a lower bound estimate. Figure 2.8 shows the one-year retention rate for individuals of Indigenous identity versus those that are not from 2007 onwards.³² The Indigenous rates are systematically lower over the Great Recession and the expansionary period that followed,

²⁸Interestingly, the negative male-female gap for low-tenure jobs dates back to the start of our sample. This is in direct contrast to the unconditional case (i.e., do not condition on initial tenure) where we observe a male-female gap, at least initially (i.e., in the early part off the sample).

²⁹We rely on a weighted average of two consecutive years' retention rates as to minimize the sensitivity of our results to the choice of start years. As such, $R_{2017,2018}^{1,11}$ is the retention rate of a randomly chosen worker with less than 12 months of tenure in year 2017 or 2018.

³⁰See, for example, George and Kuhn (1994), Pendakur and Pendakur (1998), Pendakur and Pendakur (2002), Pendakur and Pendakur (2011) and Moyser (2017).

³¹The Indigenous identity questions were in fact introduced in stages: first in Alberta starting in January 2003, then across the Western provinces the following year, and finally nationally only as of January 2007.

³²Following the recommendation of the LFS, the Indigenous identity rates are weighted using the indigenous weight variable.

i.e., on average 5.5 p.p. lower. However, they are imprecisely measured, as indicated by the wide confidence interval bands. This is not surprising given that the Indigenous population represents a very small fraction of the overall population (5% in 2021; [Statistics Canada \(2022b\)](#)). Nonetheless, the non-Indigenous–Indigenous differential is statistically significant in most years. A natural question is whether this gap can be explained by the fact that Indigenous Peoples tend to be younger and less educated. This does not appear to be the case. When re-examining the Indigenous–non-Indigenous differential focusing on narrowly defined age (and education) groups, a significant differential remains.³³ Although a bit noisier due to smaller sample sizes, one also sees a counter-cyclical pattern for individuals of Indigenous identity—the retention rate tends to increase around the two most recent recessions. Finally, figure 2.9 shows that the tenure pattern—that low-tenure jobs are less stable—also holds along the Indigenous identity dimension. Having said this, those of Indigenous identity continue to do worse than their non-Indigenous counterparts, and the gap becomes even more economically significant.³⁴

Another vulnerable group whose job stability patterns have yet to be examined is immigrants,³⁵ and data limitations are again the main culprit. Starting in January 2006, the LFS introduced questions identifying immigrant status. More precisely, the LFS now asks the respondent if he/she “*is or ever was a landed immigrant*”, and if so, the time of arrival.³⁶ As a result, one can examine the job stability of new immigrants, and also immigrants as a whole. Figure 2.10 shows that new immigrants (i.e., arrived in the last four years) have much lower job stability as compared to native-borns.³⁷ This finding is not surprising given that upon arrival they are new to the Canadian labour market. That one also sees immigrants as a whole having similar job stability patterns to that of

³³Given that one is dealing with a small subpopulation to start with, the series become noisier when we further subdivide it. Having said this, for younger age (20-39) and education (some post-secondary or less) groups, the differential is the same or larger.

³⁴We acknowledge that individuals of Indigenous identity are not a homogeneous group, as they encompass First Nations, Métis and Inuit. As part of future work, we plan on carrying out the analysis for First Nations and Métis separately. A distinct analysis for the Inuit is not possible due to small cell counts; they represent a very small proportion of the Indigenous population and tend to live in the territories.

³⁵They are considered a vulnerable group as their labour market outcomes tend to be poorer than native-borns—particularly for recent cohorts of immigrants. [Green and Worswick \(2017\)](#) provide a summary of the Canadian evidence.

³⁶The LFS asks the year of arrival, and if it is in the last five calendar years they then ask for the month of arrival.

³⁷For data limitation reasons, we define new immigrants as those that arrived in the last four years, and not five as done by Statistics Canada. To be specific about years since migration one needs to be able to identify not just the year the individual arrived but also the month. For example, a person responding in January 2020 would be considered a new immigrant by Statistics Canada if the person had arrived to Canada January 2015 onwards. This can be determined in the data because the LFS asks the month of arrival of respondents if the difference between the survey year and year of arrival is five years or less. However, a key identifying assumption of our cross-sectional estimator is that the two cross-sections be drawn from the same population cohort. As such, if one is interested in the retention rate of individuals that arrived in the last five years in year t , one needs to be able to identify those that arrived one to six years ago in year $t+1$. This is not possible because one cannot precisely measure the year $t+1$ upper bound.

the full population has two implications: first, there is an assimilation pattern. This is confirmed when one focuses instead on immigrants that landed in the last ten years, as the differential is cut in half,³⁸ and the gap eventually disappears if one conditions on less than 30 years since arrival. Second, it means that their job stability eventually surpasses those of native-borns.³⁹ Although the assimilation pattern is less steep when focusing on the highly educated (bachelor and up) they appear to converge (or more) nonetheless. These findings are in line with the immigration literature that focuses in wages/earnings, where they find an entry effect (Hou and Picot, 2016) and assimilation over time but contrary to the job stability case the wage assimilation rates are too low for the wage of immigrants to catch up to comparable native-borns (Green and Worswick, 2012).⁴⁰

2.4 Source of Change

In this section, we explore the source of change of the job stability patterns documented in section 2.3. We do so by creating counterfactual rates that hold key socio-demographic compositions constant over time.

The overall retention rate can be written as a weighted average of retention rates for G subpopulations, as long as the subpopulations are collectively exhaustive and mutually exclusive, i.e.,

$$R_t = \sum_{g=1}^G \alpha_t^g R_t^g \quad (2.4)$$

where R_t^g is the retention rate for group g at time t , and α_t^g is the proportion of the working population in year t that is in group g . One can therefore construct composition-constant counterfactuals where the proportion of each subpopulation (i.e., the α 's) are kept constant over time. A similar approach is used if one wants to do the analysis separately by gender, which is necessary in our case given the differing gender patterns. The male counterfactual, for instance, would hold constant (over time) the proportion of male workers in each subpopulation.⁴¹

³⁸Given that this group also includes new immigrants implies a faster rate of convergence.

³⁹This holds true because one is again including new immigrants that have less job stability.

⁴⁰For completeness, we also looked at job stability of low-tenure immigrants (figure 2.11). Not surprisingly, their job stability declines when one conditions on them having a new job. What is surprising, however, is that their jobs are more stable when compared to non-immigrants that are equally low tenured.

⁴¹More precisely, the male rate at time t can be expressed as

$$R_t^m = \sum_{g=1}^G \alpha_t^{g|m} R_t^{g,m}$$

Figures 2.12 and 2.13 show the age-constant counterfactual retention rates for males and females, respectively, over the 1997 to 2021 period.⁴² In both cases, the changing age structure has very little to say about the patterns observed since the Great Recession. This is in direct contrast to earlier years where ageing of the workforce significantly affected the job stability patterns, particularly for males (Heisz, 2005; Brochu, 2013). The fact that it does not anymore, is due to the concave nature of the age profile. It tends to be quite steep for workers in their 20s and 30s, but much flatter when workers are in their 50s.⁴³ As such, it is not surprising that the effect of baby boomers on the labour market as measured through job stability would taper off in later years.

Controlling for education composition, however, is a different matter. Rising educational attainment played a role in earlier years (Brochu, 2013), and continues to do so for both genders in recent years (see figures 2.14 and 2.15), as illustrated by the fact that the pre- and post-Great Recession counterfactuals look much more similar.⁴⁴ It should be noted that we can now better control for education composition than earlier studies mentioned above because we can now separate out dropouts from high school graduates. Better controlling for their relative importance does affect the education counterfactual, which in itself is not surprising given that dropouts tends to have lower job stability than high school graduates. This suggests that earlier studies may have (somewhat) underestimated the true education composition effect.

We now turn our attention to low-tenure workers. Figures 2.16 and 2.17 show that the age structure has little explanatory power for either gender. Yet, as was the case when we did not condition on initial tenure, rising educational attainment in the post-Great Recession period matters at the bottom of the tenure distribution (see figures 2.18 and 2.19). Although, the rise in job stability is more tempered when one controls for education composition, it is nonetheless still present, particularly for males. Interestingly, earlier Canadian studies (Brochu, 2013) that attempted to explain an earlier (1990s) rise in job stability of low-tenure workers drew similar conclusions regarding the role of age and education composition, and most importantly that much remained to be explained. Further exploration of the source of change for low-tenure workers requires the use of panel data.

where $R_t^{g,m}$ is the retention rate of males in subpopulation g , and $\alpha_t^{g|m}$ is the proportion of male workers that is in group g . For the male counterfactual one would replace $\alpha_t^{g|m}$ with $\alpha_{1997}^{g|m}$ (if 1997 is the start year). The female counterfactual is similarly defined.

⁴²Age is divided into nine five-year bins (i.e., 20-24, 25-29, ..., 60-64). As such, for the male counterfactual we are holding the proportion of males in each of the age bins constant at 1997 levels.

⁴³That the age profile is very steep for younger workers is in line with search models where match quality is only revealed after a match is formed. Since younger workers are, by definition, more likely to be in new jobs, they tend to have less stable jobs.

⁴⁴The education subpopulations consists of four groups: 1) high school dropout, 2) high school graduate and some post-secondary, 3) trade certificate or diploma, college and CEGEP, and university certificate below bachelor's, 4) bachelor degree and above.

Table 2.2 quantifies the importance of changing socio-demographic composition (age and education) in explaining the job stability patterns of each gender by comparing the 1997-1998 and 2016-2018 periods. It confirms that, for all tenured workers, age plays only a small role. For men it only explains 12.2% of the gap, whereas for women it is only 5.9%. It also shows quantitatively the importance of rising educational attainment. For men it explains 119.2% of the gap, which means that if educational attainment had not increased over time, one would have seen a small decrease in job stability for men. For women education explains approximately 2/3 of the gap. When focusing on low-tenure workers only education has explanatory power, explaining approximately 1/3 of the differences over time for each gender.

2.5 Panel Approach

We start this section by showing that the job stability patterns documented in section 2.3 are also present in the panel data. Using the panel approach, we then briefly revisit the COVID patterns. Finally, and most importantly, we look at how other exit transitions have fared in the post-Great Recession period which will help us better understand the new job stability findings, particularly at the bottom of the tenure distribution.

For our panel approach, we rely on one-month retention rates calculated using two consecutive-months mini-panels.⁴⁵ We present twelve-month moving averages (i.e., the average of the current and past eleven months) as to abstract from seasonal issues.⁴⁶ The only exception is when we focus on the COVID-19 period. Relying on twelve-month moving averages can help better identify long-term secular changes, but when trying to understand the timing of cyclical changes, the unadjusted rates are more revealing.

As with the cross-sectional approach, one sees a secular increase over time in overall job stability (figure 2.20),⁴⁷ a positive male-female gap turning negative in the second half of the sample (figure 2.21), the presence of a positive education profile (figure 2.22), and substantive increases in job stability of low-tenure workers in the 1990s that continued into the post-Great Recession expansionary period (figure 2.23).⁴⁸ The similarities across approaches also extend to individuals of Indigenous identity, i.e., they fare worse than their non-Indigenous counterparts (figure 2.24), and immigrants, i.e., there is an entry effect with some assimilation over time (figure 2.25). Furthermore, when focusing on

⁴⁵We repeated our analysis below but relying instead on three-month transitions, as is typically done in the U.S. literature that focus on low-tenure jobs. Our key findings remain unchanged. See appendix figures B.1 to B.5 for more details.

⁴⁶This means that for all the one-month rate figures, the series will start as of December 1977.

⁴⁷Each 12-month moving average rate represents the average of the rates from the current month and the previous 11 months. As a result, it will take some months for the effect of COVID-19 to be fully reflected in the moving average.

⁴⁸The cyclical components previously discussed are also present in these panel series.

low-tenure workers (i.e., initial tenure of less than one year) one again observes similar gender, education, Indigenous, and immigrant patterns (see figures 2.26 through 2.29). The importance of having the panel and cross-sectional approaches generating very comparable patterns goes beyond this paper; it is of value to the literature as a whole. It means that the findings of the early job stability literature which have tended to focus on the cross-sectional approach are comparable to those of some recent papers that have relied on panel methods.

We now revisit the COVID patterns briefly discussed in section 2.3.1, but using the panel approach. Relying on one-month (unadjusted) rates will provide a clearer picture of how job stability was affected from one month to the next. Figure 2.30 shows that overall job stability dropped very suddenly with the advent of COVID-19, and that the recovery was also very rapid. Such findings are in line with the Canadian COVID-19 literature that focuses on transitions between the three labour market states (Brochu and Cr  chet, 2022; Jones et al., 2023; Lal  , 2024).⁴⁹ Such a finding is not surprising given the dramatic (and well-documented) changes in the employment to non-employment transition over the COVID-19 downturn and subsequent recovery. Equally consistent with this existing literature is the lack of any significant gender differences (figure 2.31). Of interest, are the job stability patterns of low-tenure workers that are presented in figure 2.32. As one would expect in a recession, the decline in job stability at the onset of COVID-19 is larger for low-tenured workers. Having said this, the impact on longer-tenured workers is nonetheless very significant. That it affected all tenured workers is in line with the COVID-19 literature that concludes that the effect of COVID-19 was broadly felt.

We now turn our attention to other exit probabilities to better understand the source of change of the new job stability patterns. Doing so is informative as a transition out of a job can occur for one of two reasons: the individual transitions to a new job with a new employer, or to non-employment (i.e., unemployment or out of the labour force).

To start, we focus on low-tenure workers. Figure 2.33 shows the one-month job-to-job (jtoj) and employment to non-employment (EN) transition rates for workers with less than one year of tenure. Although one sees a drop in both series, it is the dramatic fall in the EN rate that is driving the rise in job stability of low-tenured workers. This is most apparent in the post-Great Recession expansionary period, where the jtoj rate has remained fairly flat whereas the EN rate continues its decline. In figure 2.34 we break down the EN transition into two components, the employment to unemployment (EU) rate and the employment to out of the labour force (EO) rate. Not surprisingly, the EU rate tends to be more sensitive to the business cycle and systematically larger. Yet, they both experience decreases over time, with the decline being somewhat more important for the EU transition. We now explore who initiates the separation, the employer (layoff) or the employee (quit). Figure

⁴⁹Jones et al. (2023) further divide non-participants into those that want a job and those that do not.

2.35 clearly shows that the fall in the EN transition is employer driven. The same holds true if one looks at the EU and EO rates separately. Table 2.3 quantifies the importance of each transition by comparing 1997-1998 and 2016-2018, two strong expansionary periods. It confirms the findings discussed above. j-t-j transitions are not the driver, EU and EO transitions both playing a role (with the former being more important) and these findings are clearly employer driven.

For the sake of completeness we now return to the overall rate. The conclusions drawn are similar to those of low-tenure workers. The EN rate is what drives the observed changes since the Great Recession (figure 2.36), and if one disaggregates the EN rate one sees a decline in the transition to unemployment and to out of employment (figure 2.37). Finally, the changes continue to be employer driven (figure 2.38).

2.6 Conclusion

Using a rich source of Canadian tenure data, we document job stability patterns since the Great Recession, and explore the source of change. Furthermore, we examine the patterns of Peoples of Indigenous identity living off-reserve and immigrants, two vulnerable groups on which, due previous data limitation, the literature has been silent.

Our study draws the following conclusions: first, jobs have become more stable since the Great Recession in the aggregate, and particularly for women and low-tenure jobs. Second, rising educational attainment plays a role in explaining the new overall pattern, and some of the increase for low-tenure jobs. Furthermore, unlike for the U.S., job-to-job transitions are not key to our findings. It is the employment to non-employment transitions, particularly to unemployment, that drive our findings, and it comes from the employer side. Finally, we find that individuals of Indigenous identity living off-reserve and new immigrants tend to have less stable employment relationship. There is, however, a strong assimilation profile for the latter which means that their job stability eventually catches up and surpasses native-borns.

As future work, we plan to explore for changes at the top of tenure distribution, and further examine the gender differences with a focus on the potential role of occupation and industry.

2.7 Figures and Tables



Figure 2.1: One-year retention rate. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

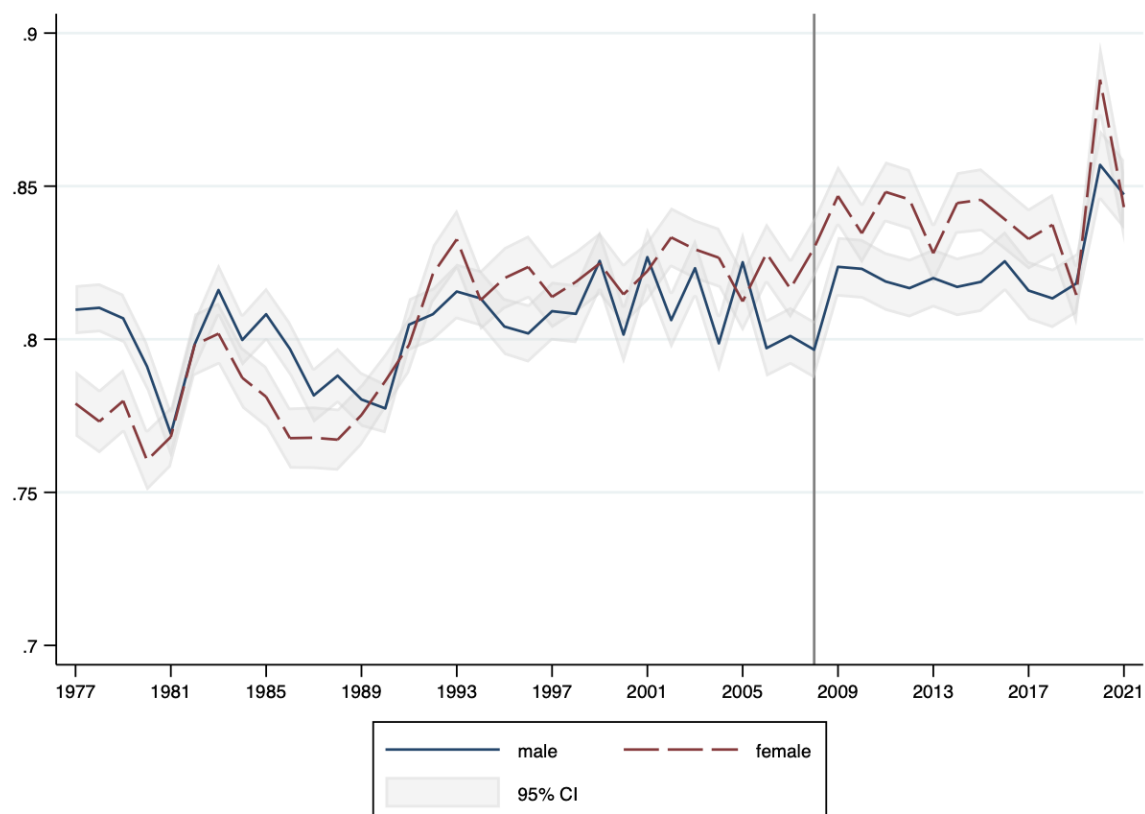


Figure 2.2: One-year retention rate, by gender. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

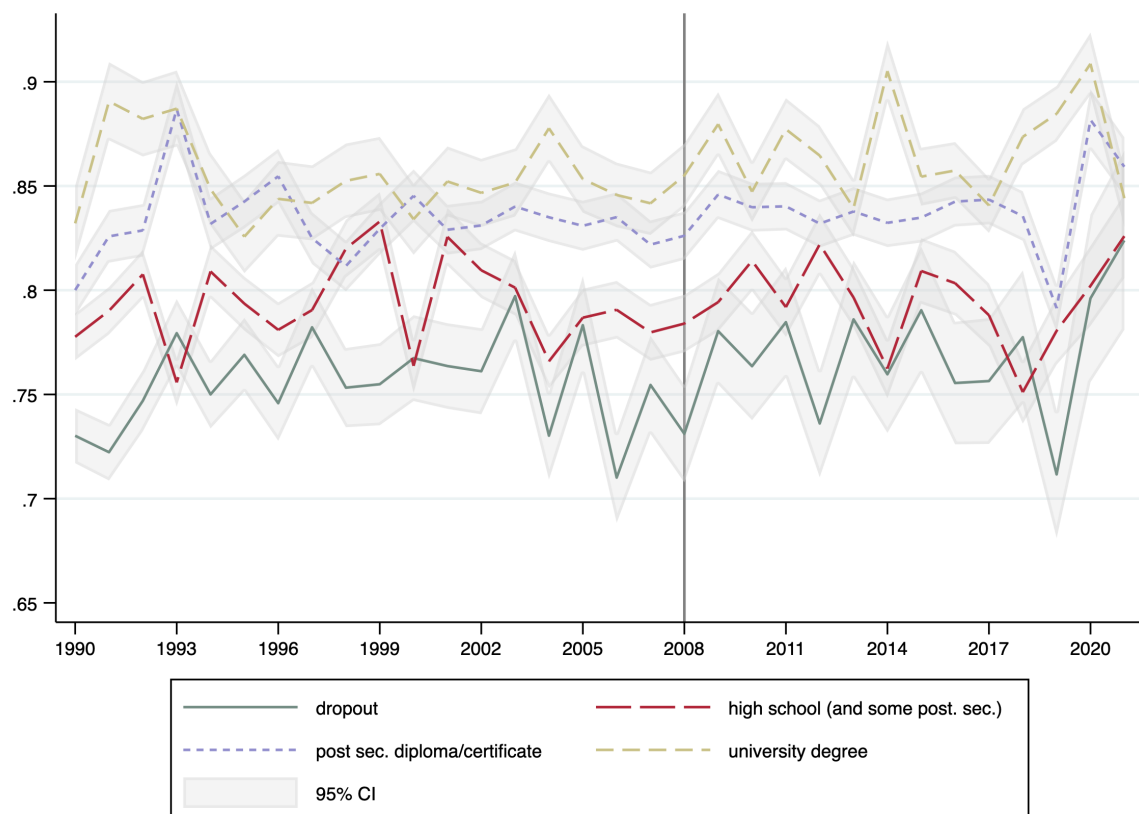


Figure 2.3: One-year retention rate, by education attainment. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.



Figure 2.4: One-year retention rate, by initial tenure. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

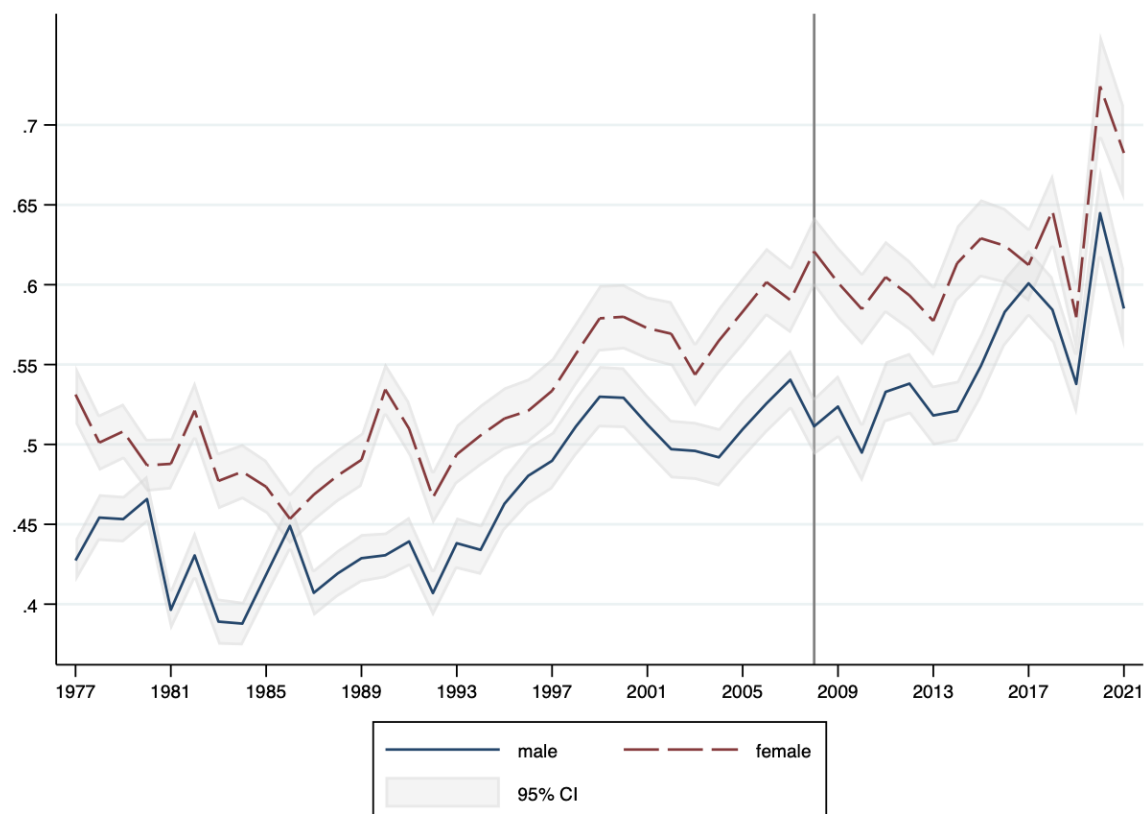


Figure 2.5: One-year retention rate, initial tenure less than one year, by gender. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

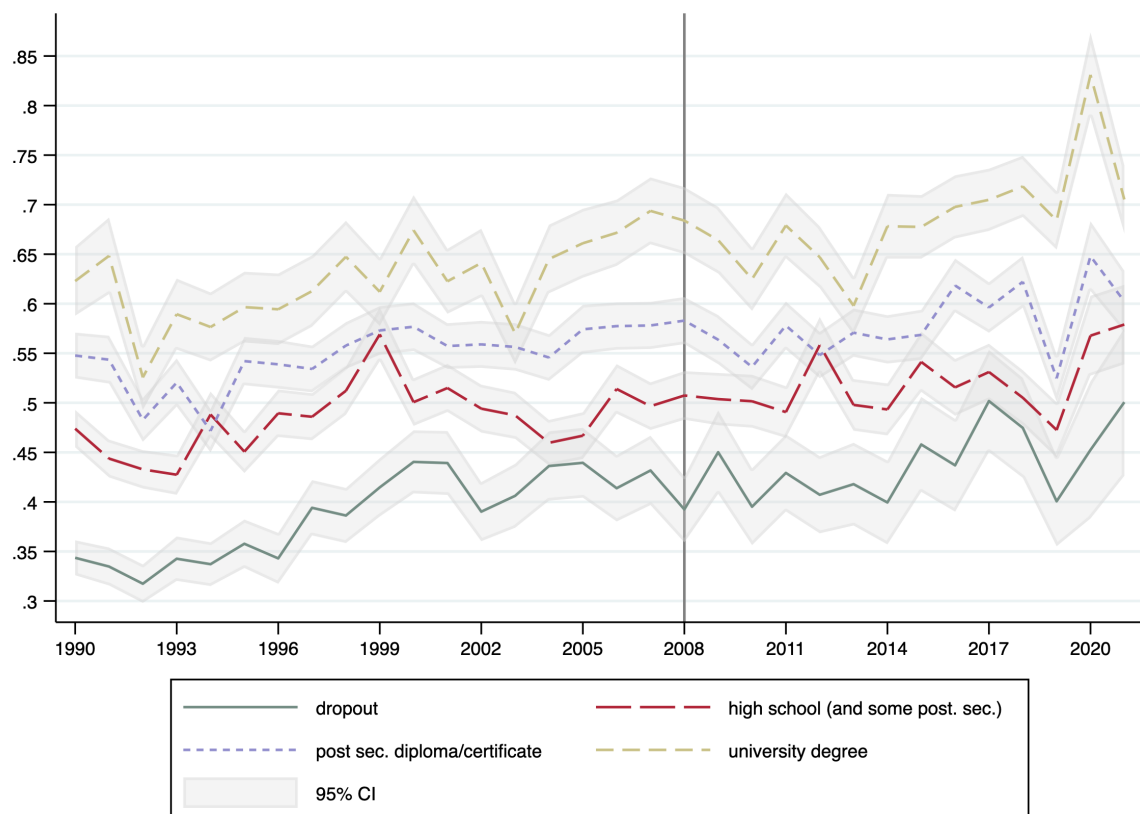


Figure 2.6: One-year retention rate, initial tenure less than one year, by education attainment. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

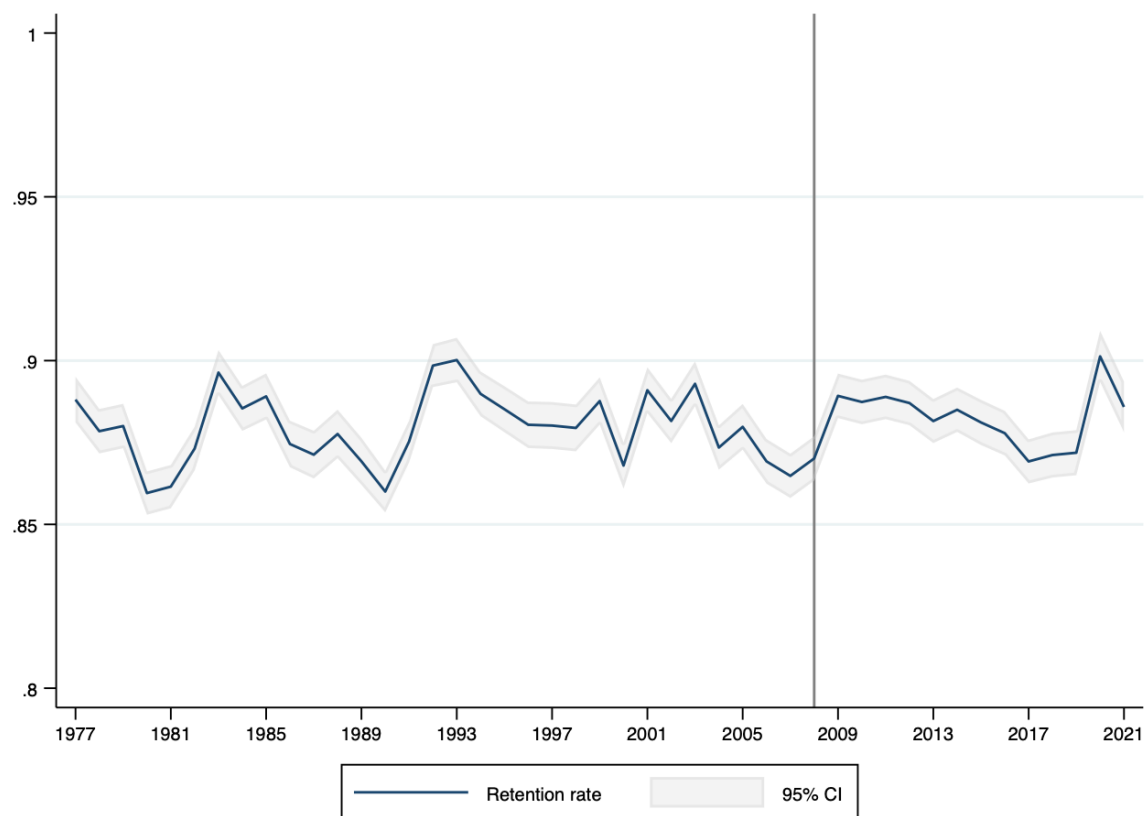


Figure 2.7: One-year retention rate, initial tenure of twelve or more months. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

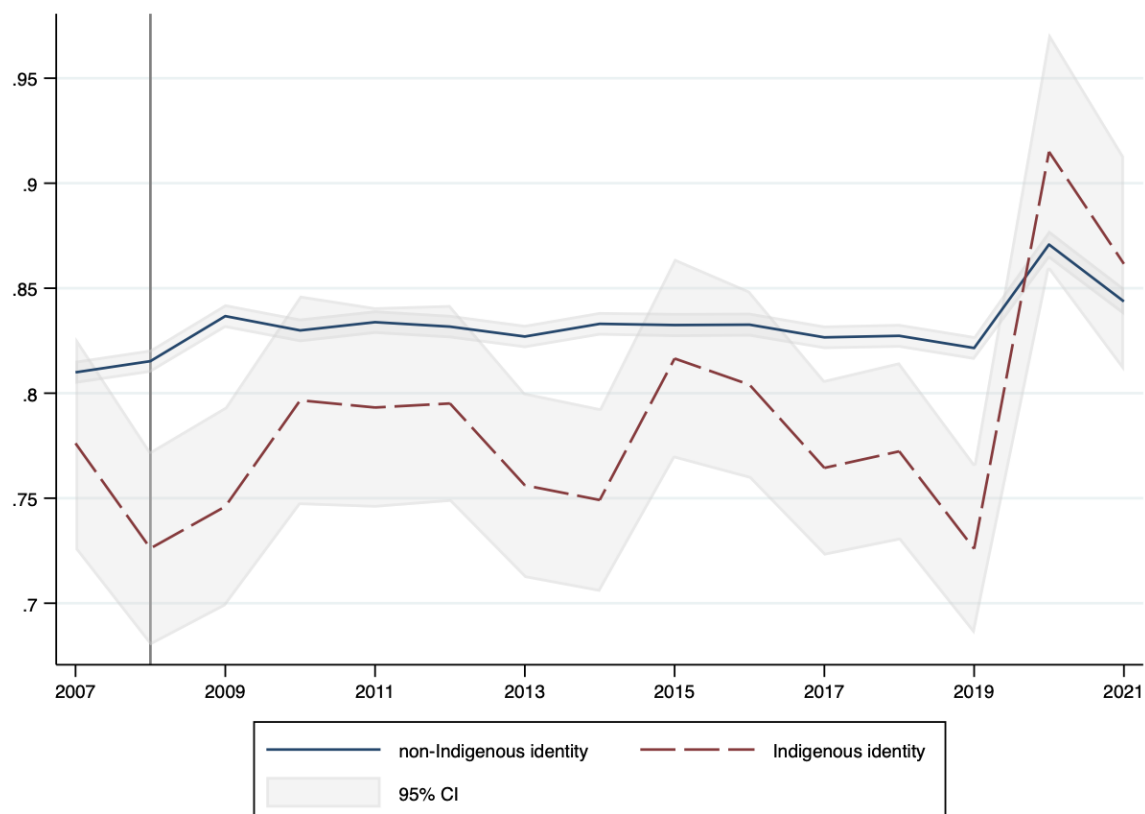


Figure 2.8: One-year retention rate, by Indigenous identity. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

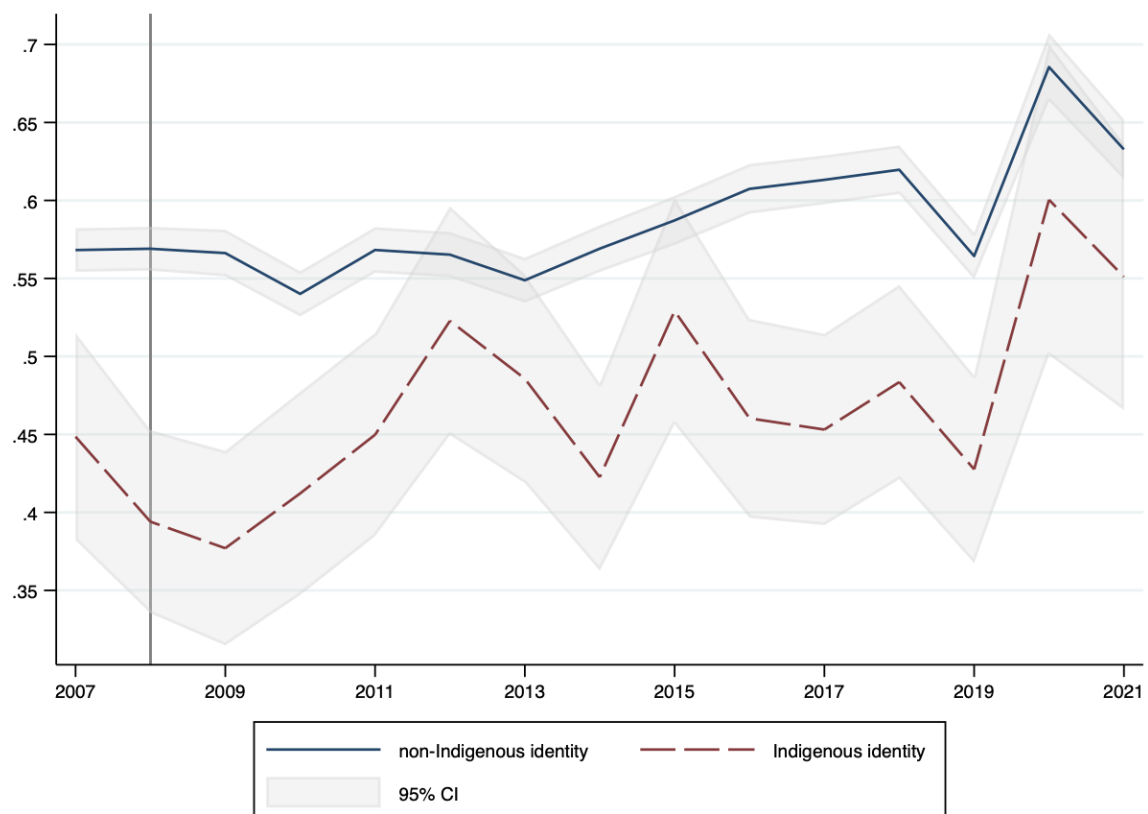


Figure 2.9: One-year retention rate, initial tenure less than one year, by Indigenous identity. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.



Figure 2.10: One-year retention rate, by immigrant status. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

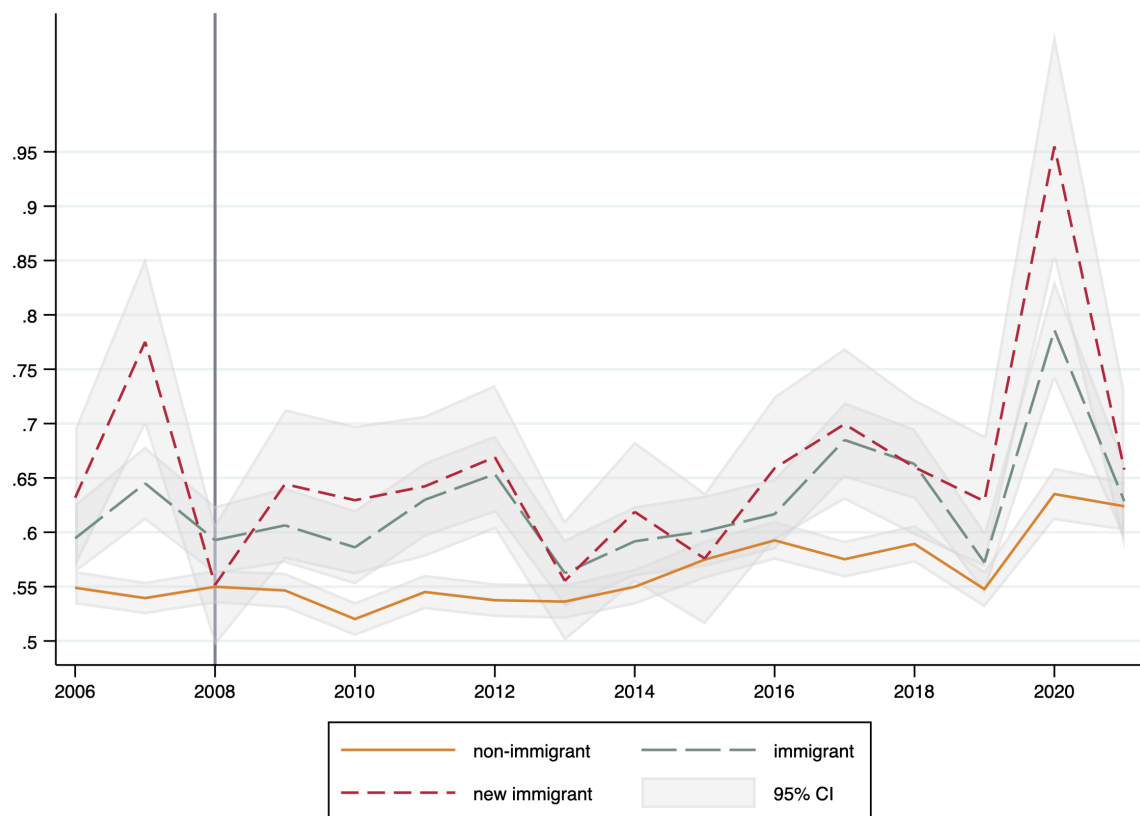


Figure 2.11: One-year retention rate, initial tenure less than one year, by immigrant status. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

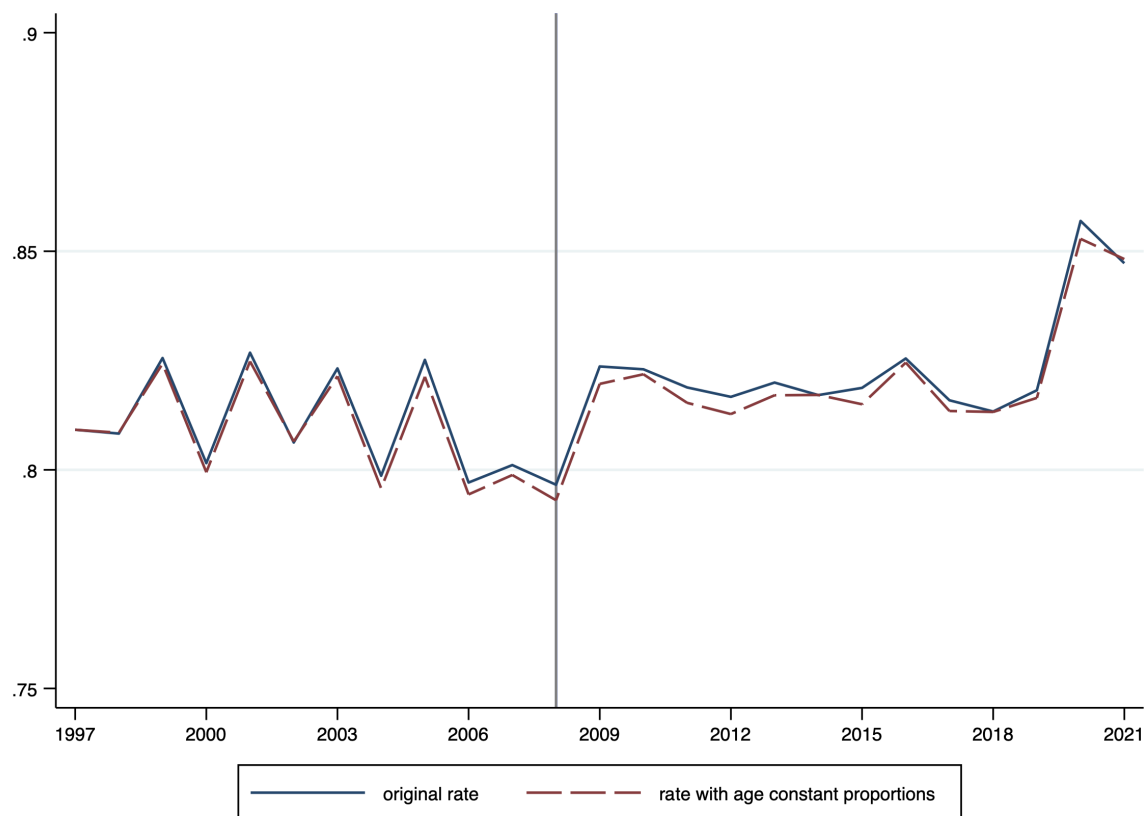


Figure 2.12: One-year retention rate counterfactual, male - holding age composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

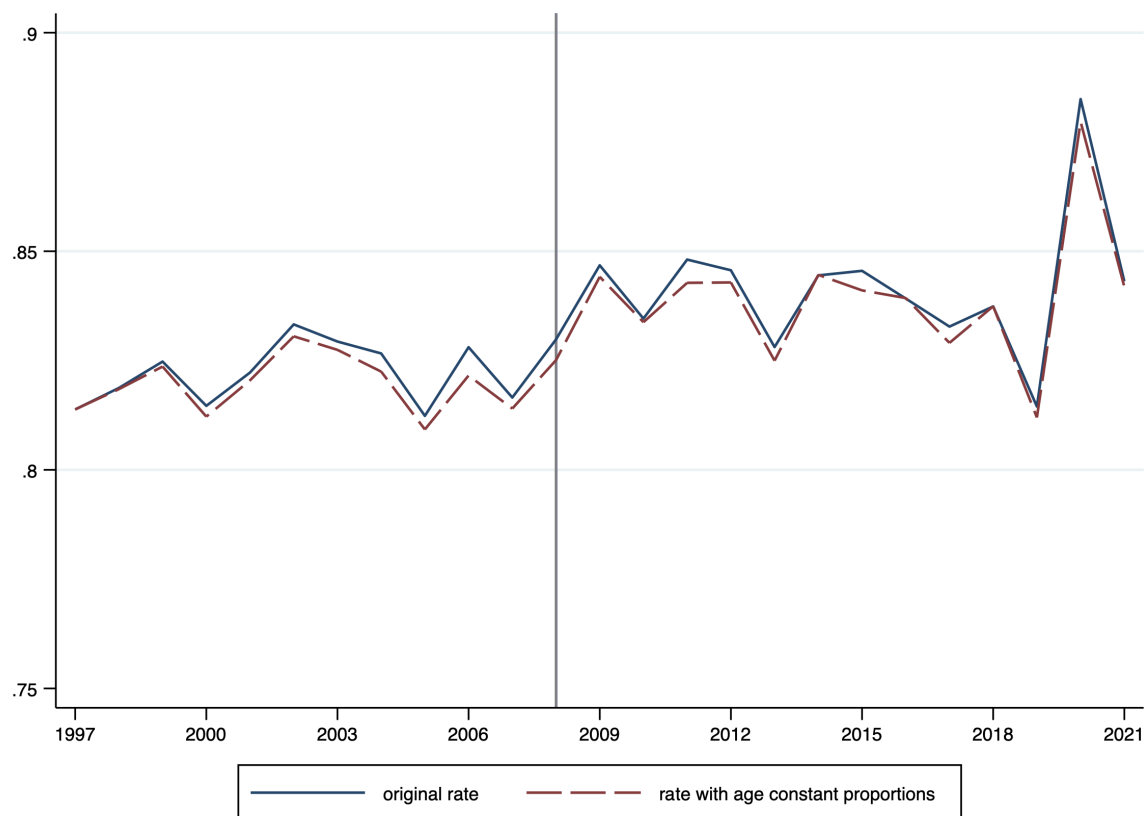


Figure 2.13: One-year retention rate counterfactual, female - holding age composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

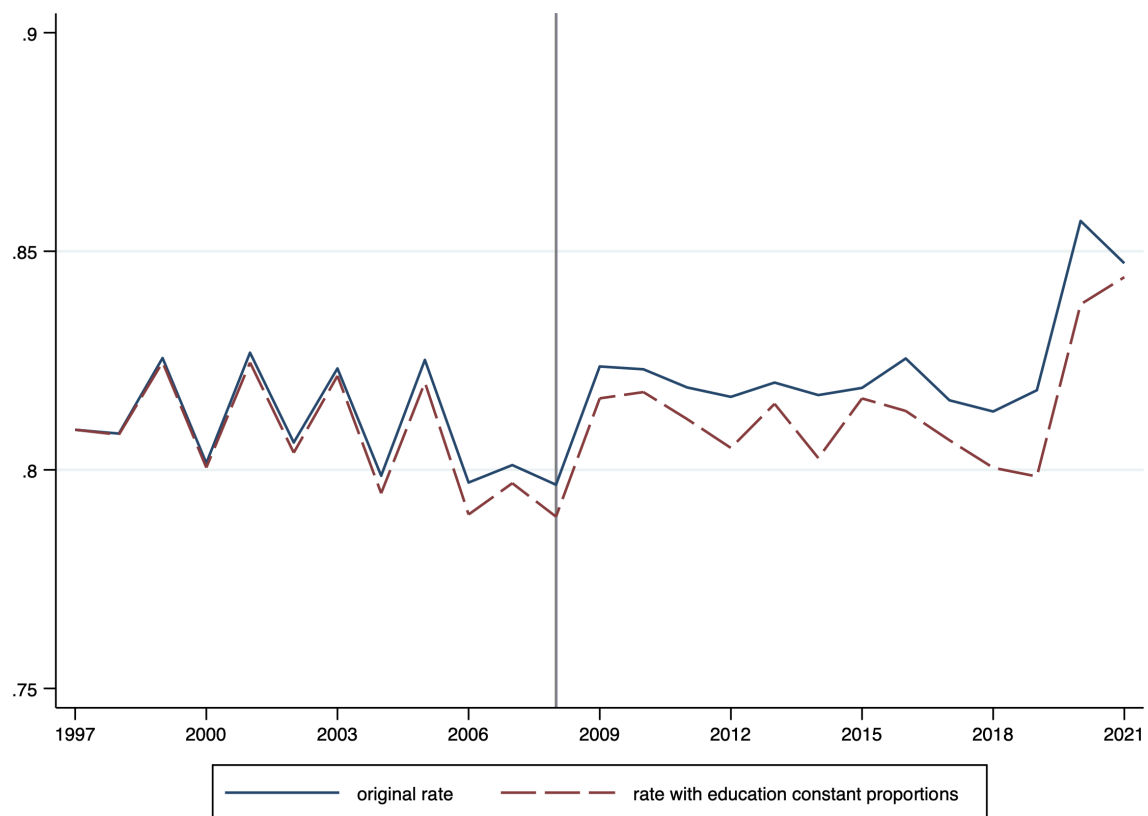


Figure 2.14: One-year retention rate counterfactual, male - holding education composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

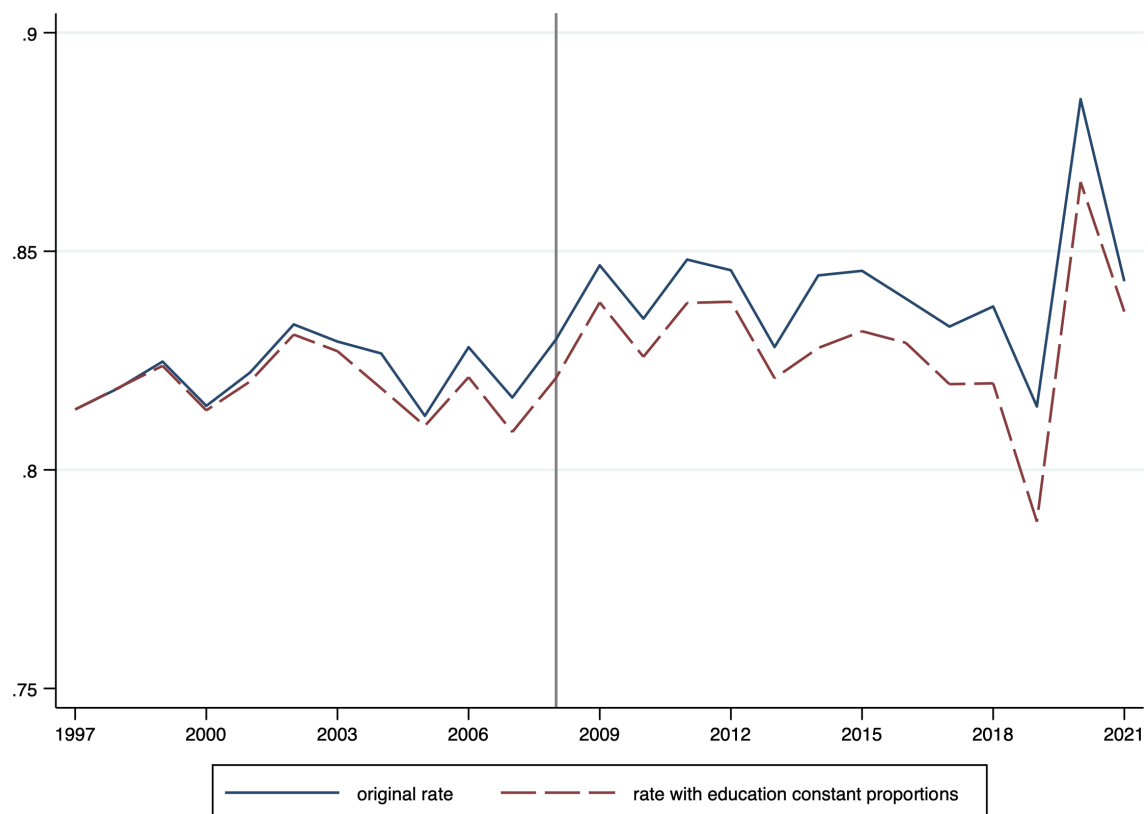


Figure 2.15: One-year retention rate counterfactual, female - holding education composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

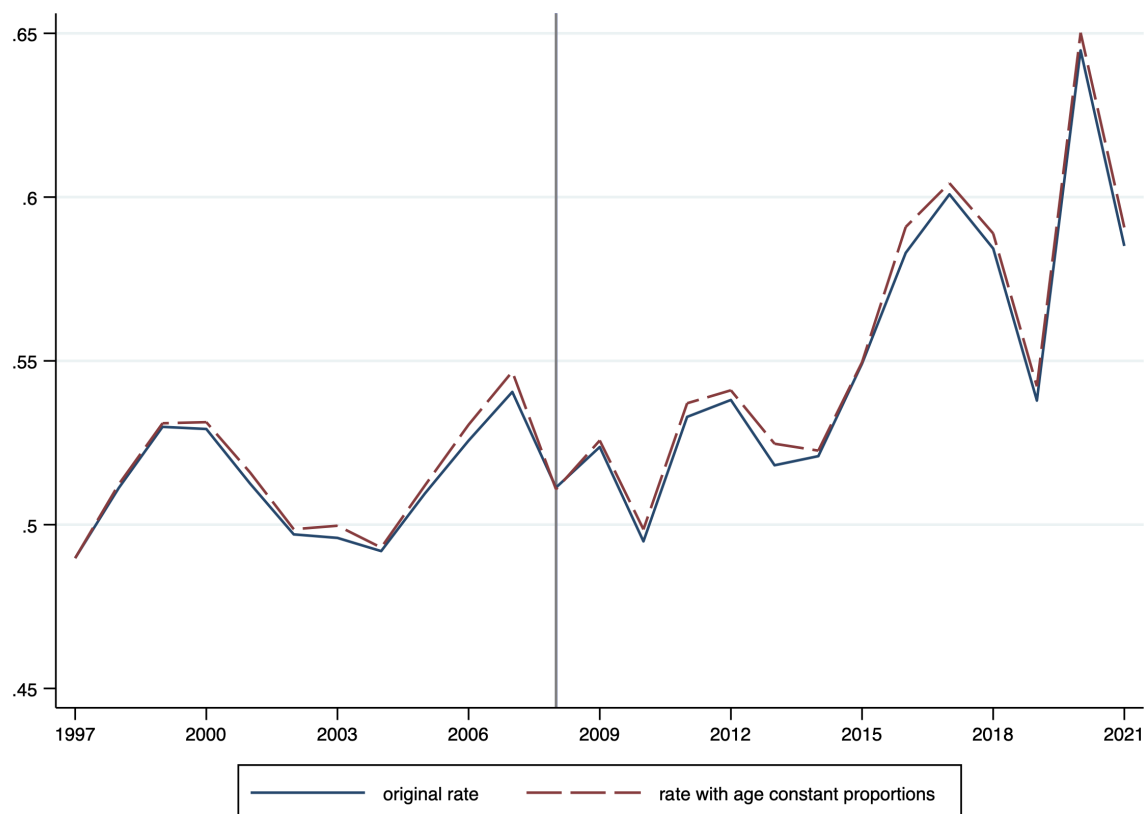


Figure 2.16: One-year retention rate counterfactual, male and initial tenure less than one year - holding age composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

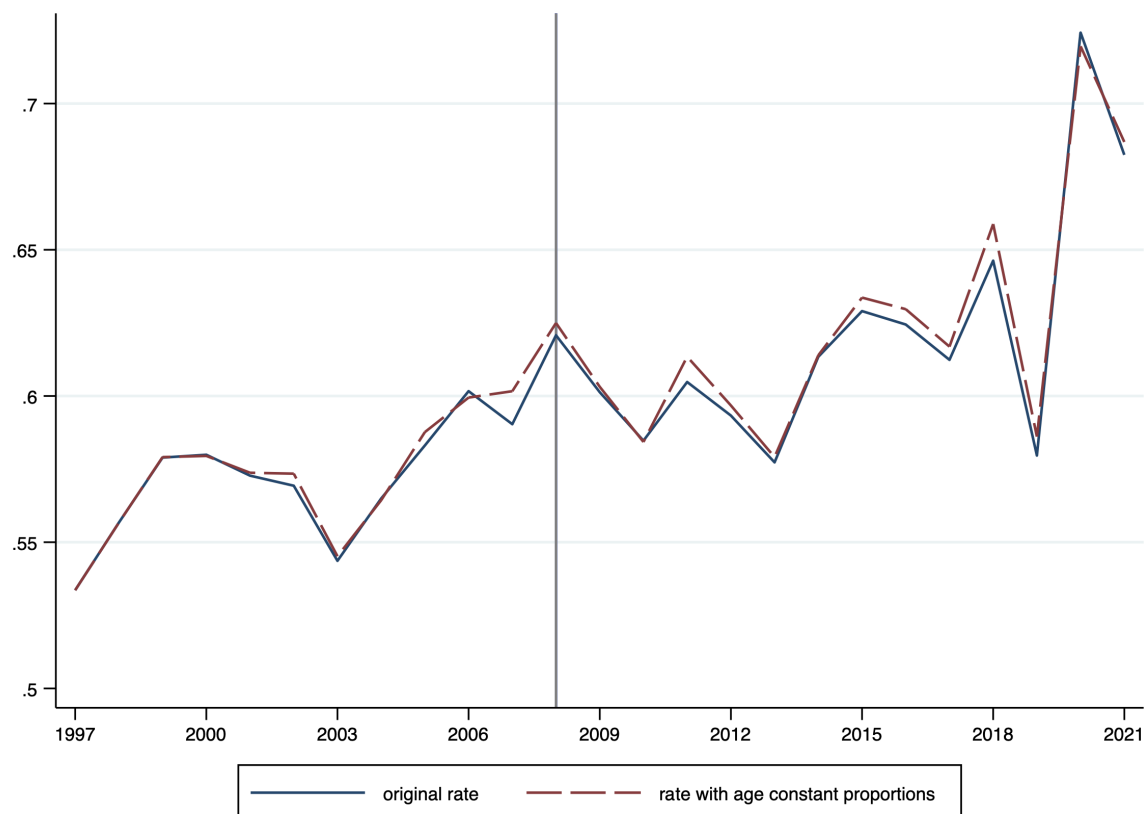


Figure 2.17: One-year retention rate counterfactual, female and initial tenure less than one year - holding age composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

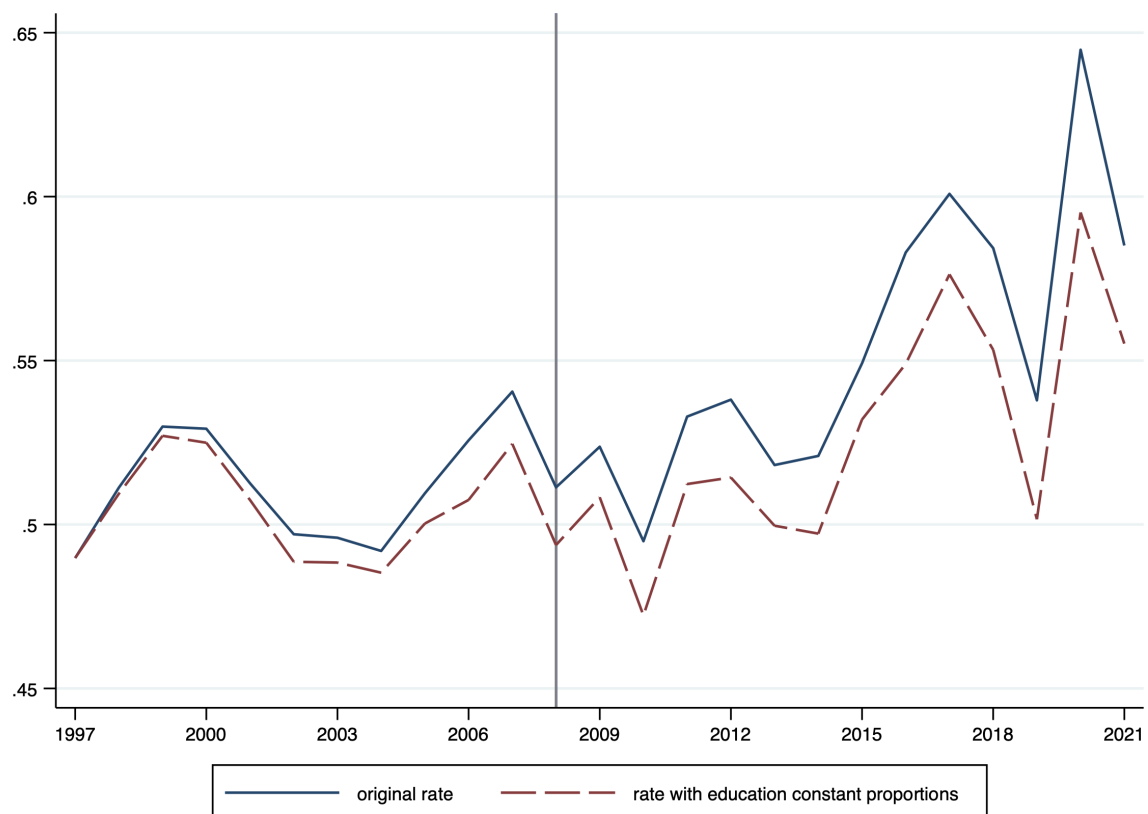


Figure 2.18: One-year retention rate counterfactual, male and initial tenure less than one year - holding education composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

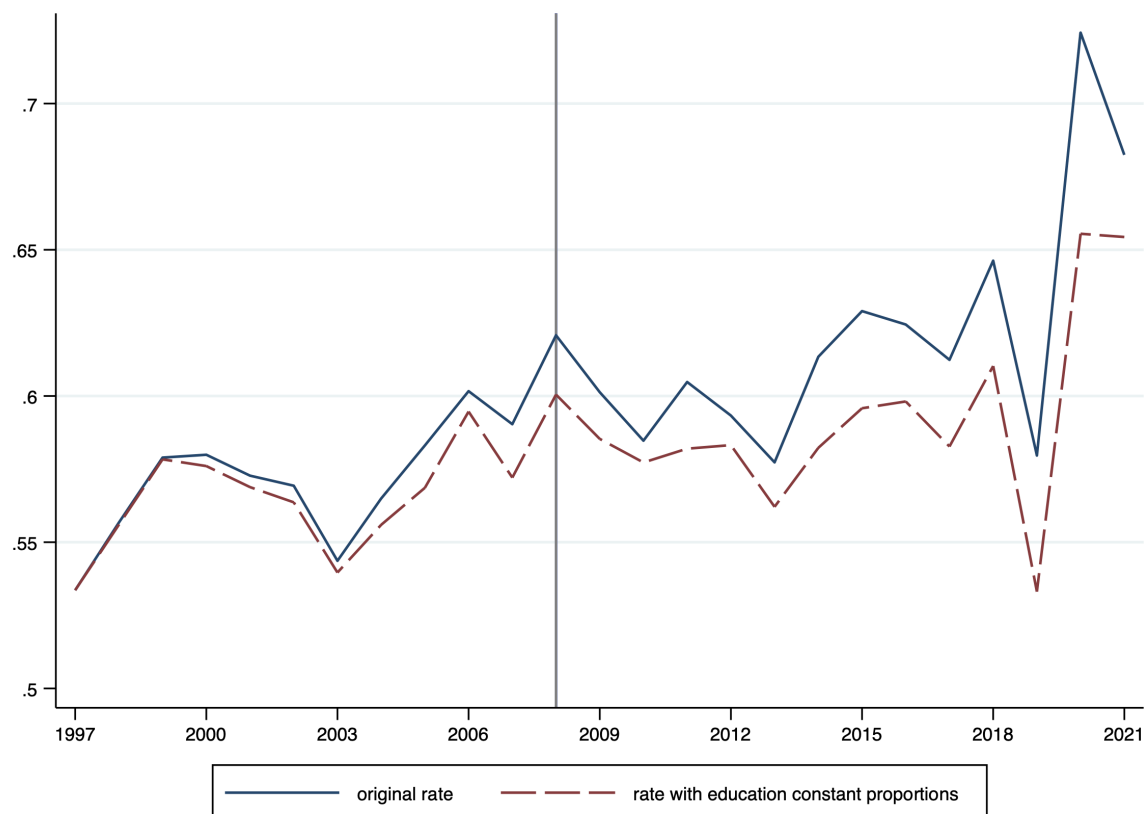


Figure 2.19: One-year retention rate counterfactual, female and initial tenure less than one year - holding education composition constant. The vertical line indicates the start year of the Great Recession (2008). Source: LFS master files.

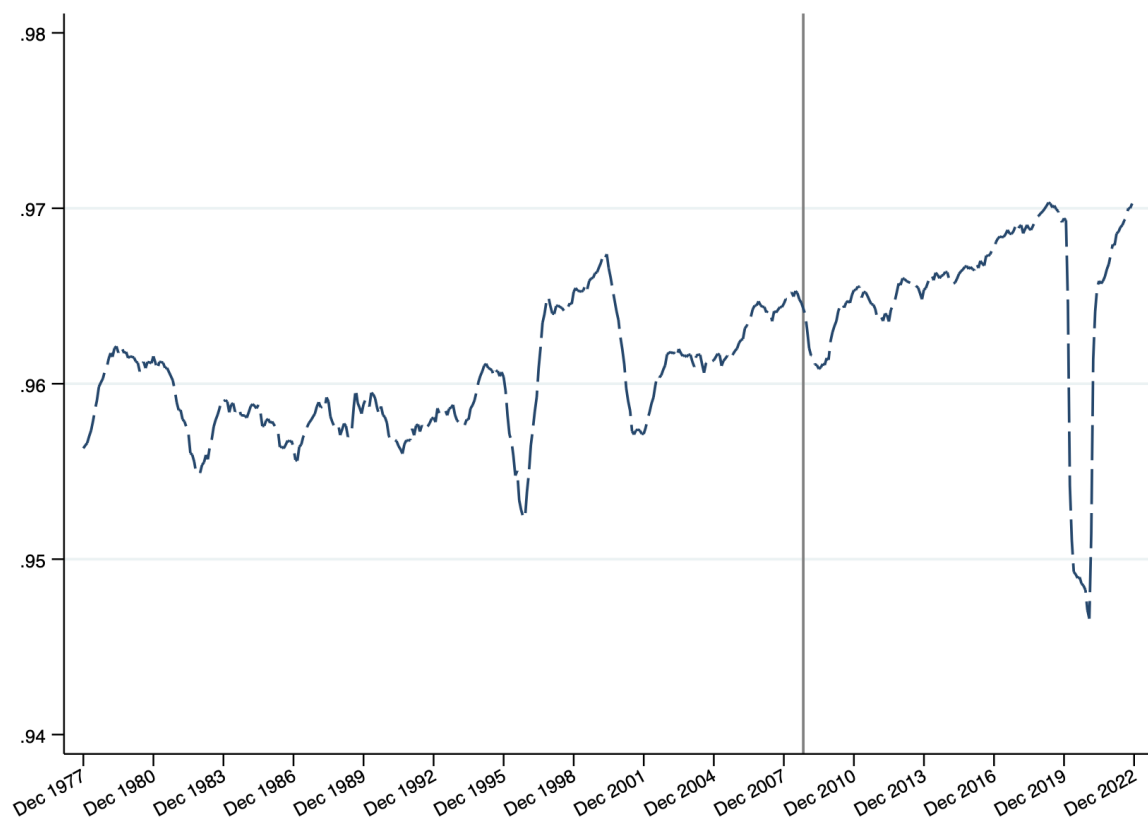


Figure 2.20: One-month retention rate. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

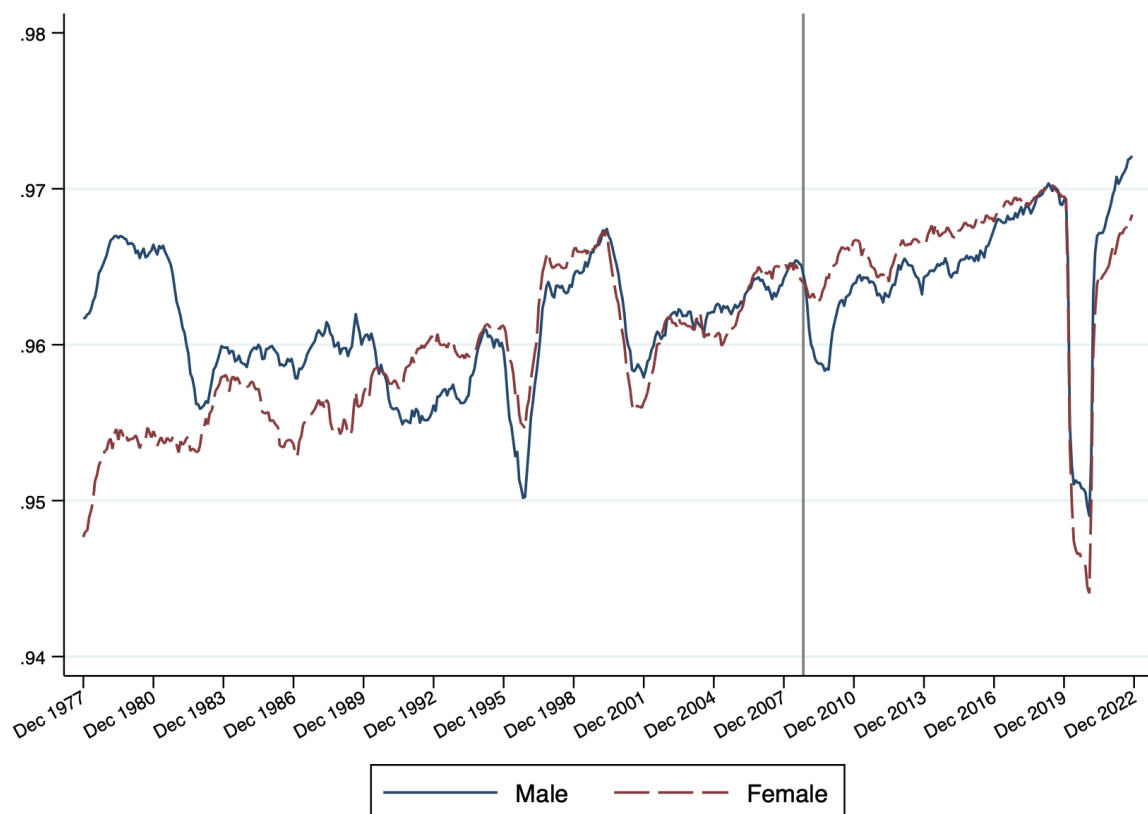


Figure 2.21: One-month retention rate, by gender. The figure shows 12-month moving average. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

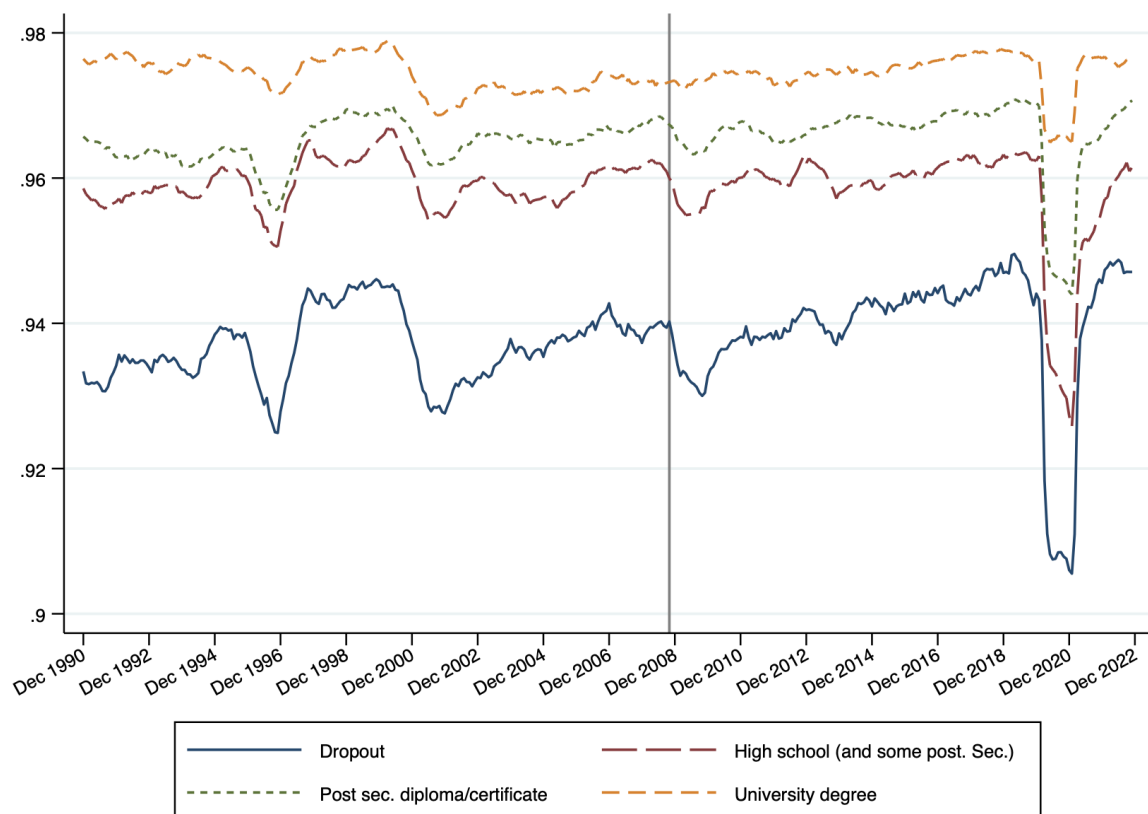


Figure 2.22: One-month retention rate, by education attainment. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

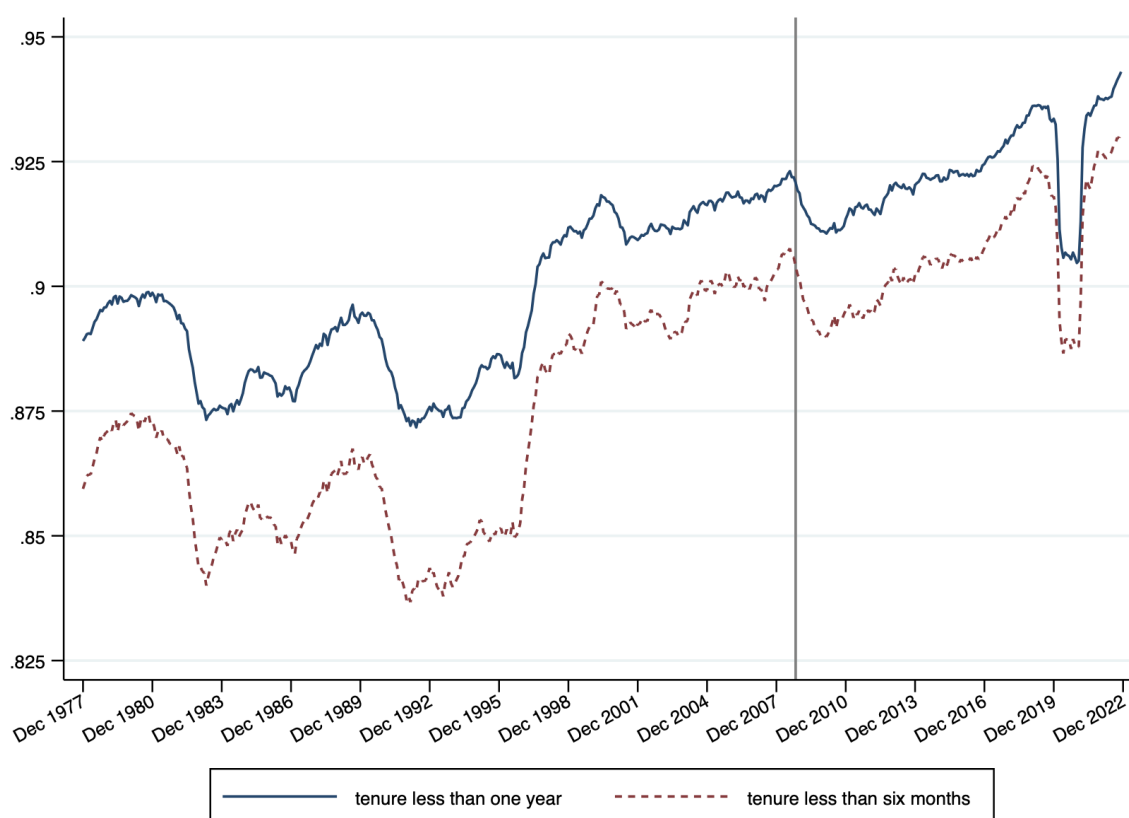


Figure 2.23: One-month retention rate, by initial tenure. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

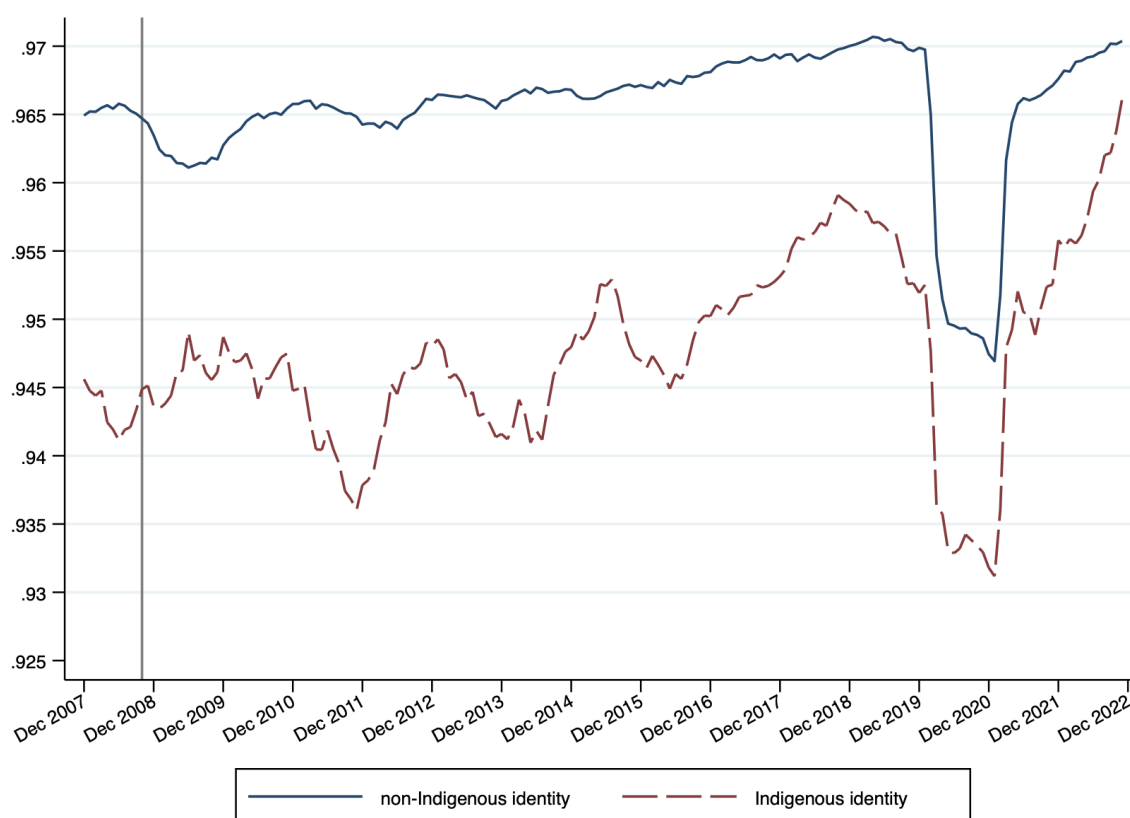


Figure 2.24: One-month retention rate, by Indigenous identity. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

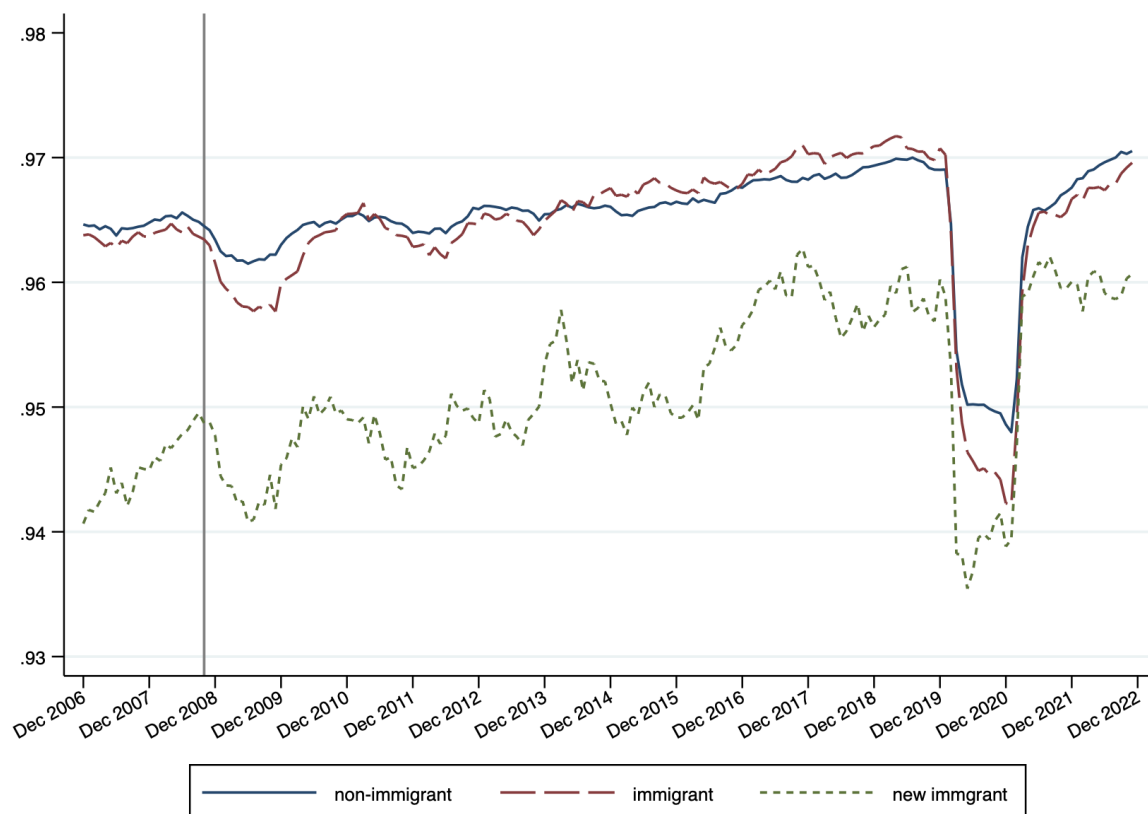


Figure 2.25: One-month retention rate, by immigrant status. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

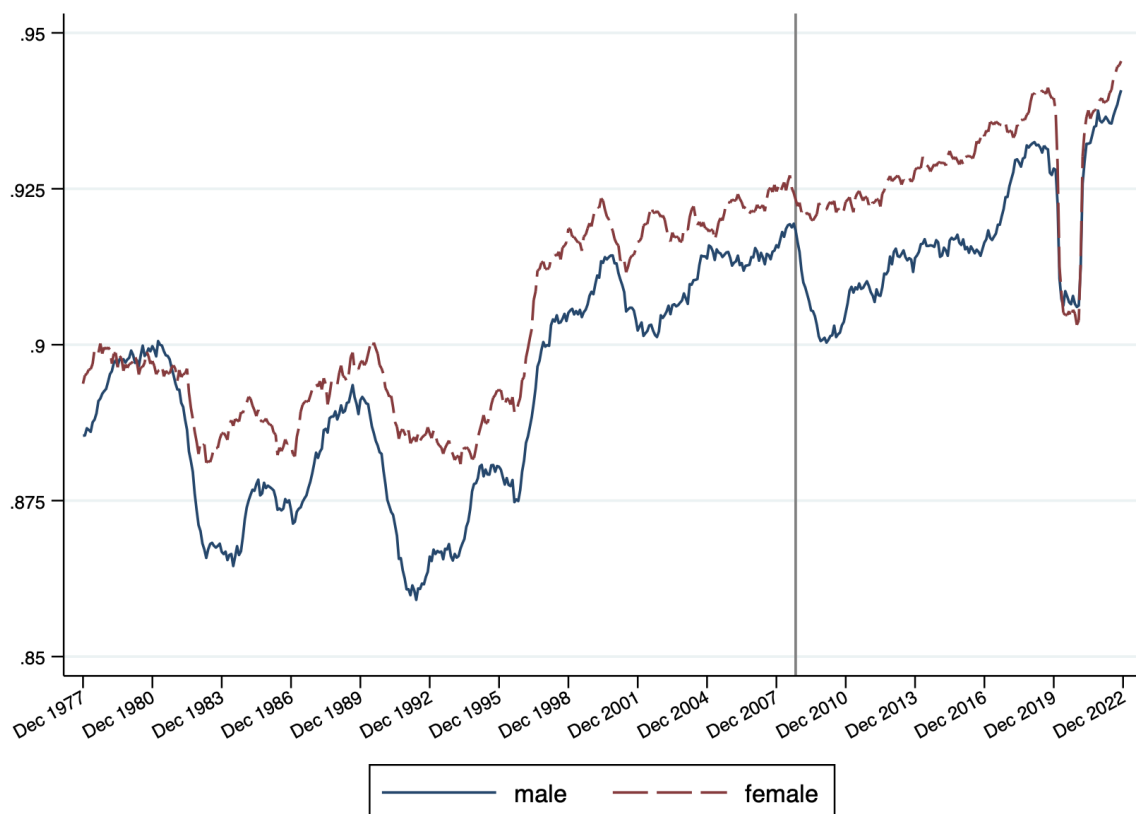


Figure 2.26: One-month retention rate, initial tenure less than one year, by gender. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

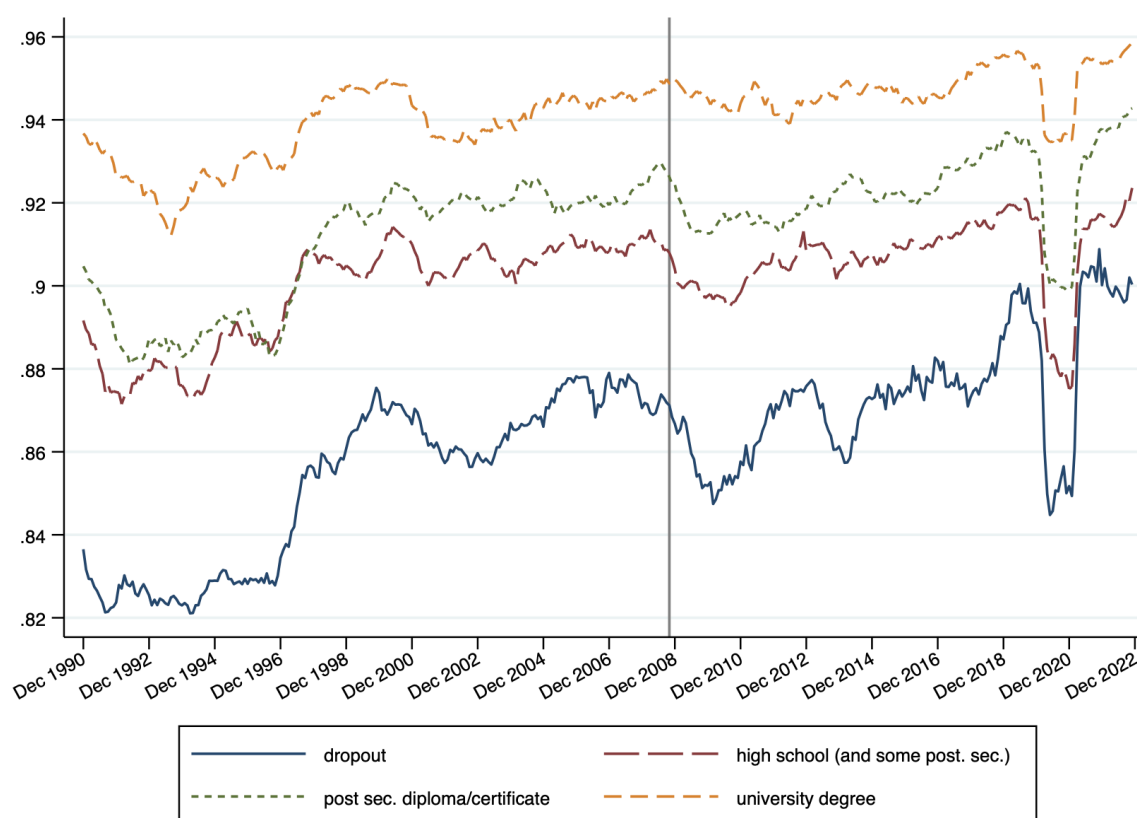


Figure 2.27: One-month retention rate, initial tenure less than one year, by education attainment. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

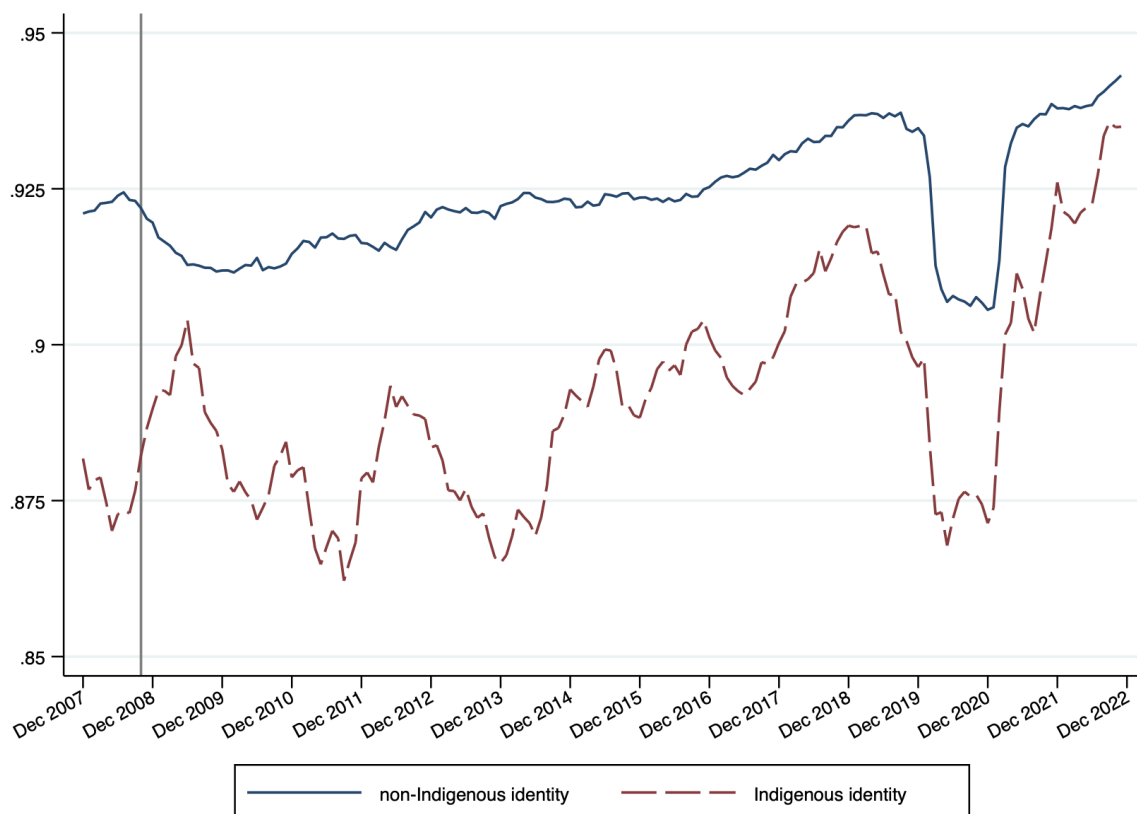


Figure 2.28: One-month retention rate, initial tenure less than one year, by Indigenous identity. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.



Figure 2.29: One-month retention rate, initial tenure less than one year, by immigrant status. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

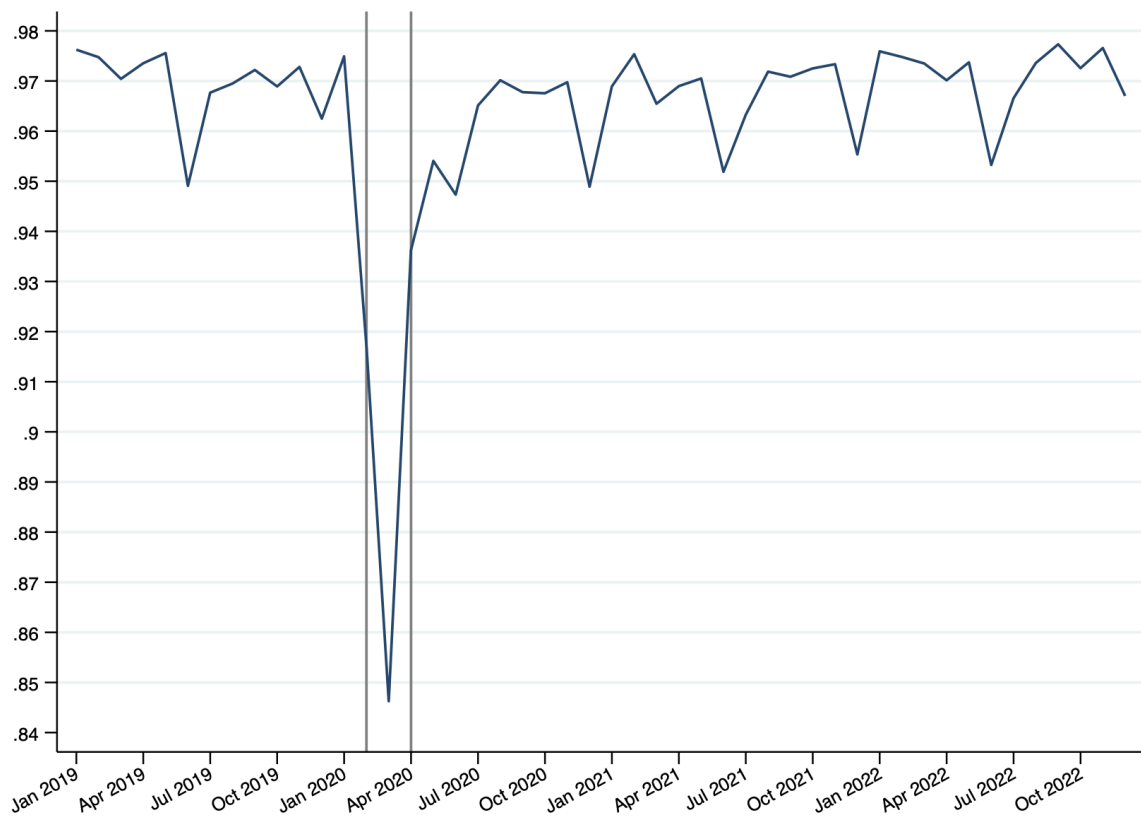


Figure 2.30: One-month retention rate in COVID-19 times. The vertical lines indicate the start and end month of the COVID-19 recession (February 2020 and April 2020). Source: LFS master files.

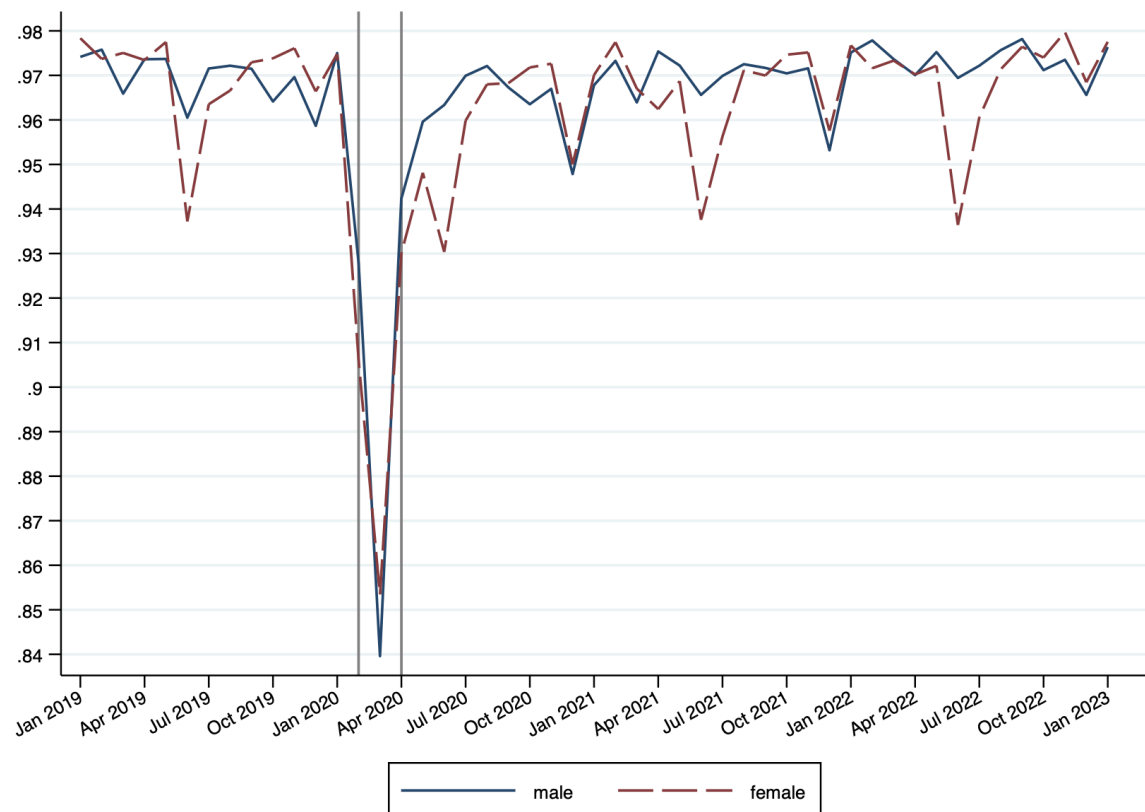


Figure 2.31: One-month retention rate in COVID-19 times, by gender. The vertical lines indicate the start and end month of the COVID-19 recession (February 2020 and April 2020). Source: LFS master files.

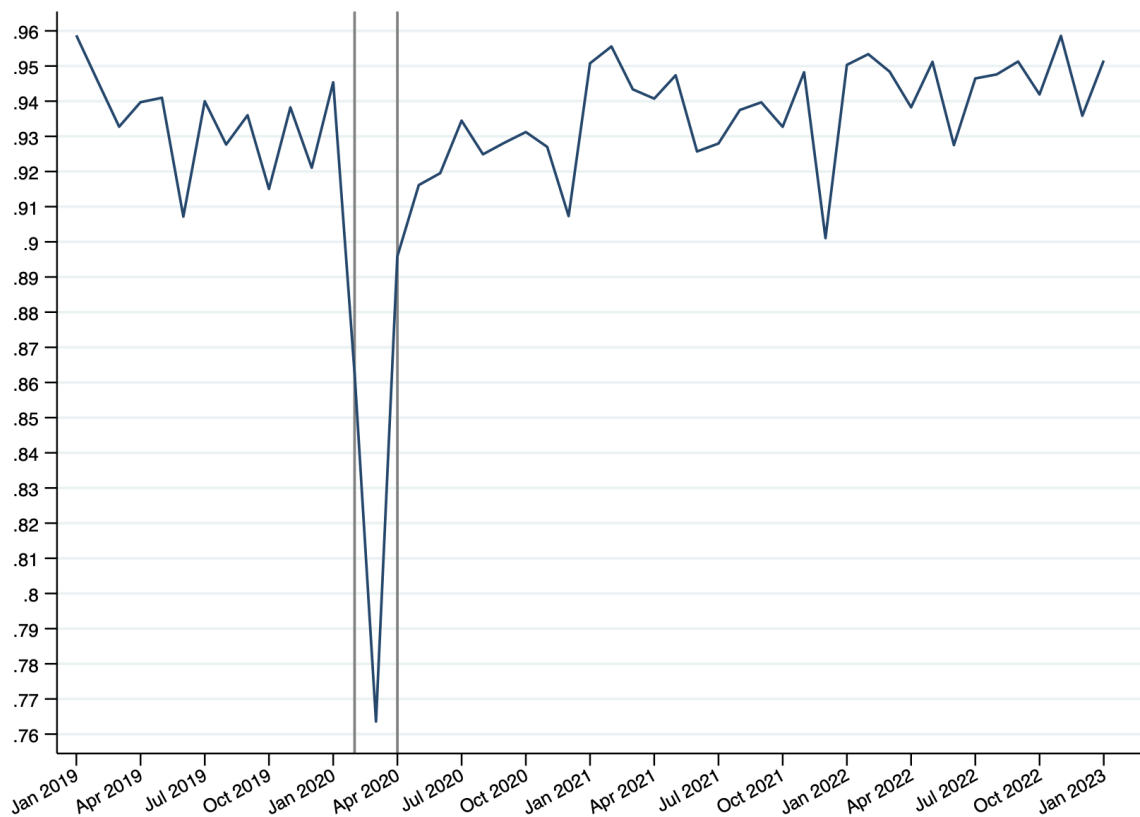


Figure 2.32: One-month retention rate in COVID-19 times, initial tenure less than one year. The vertical lines indicate the start and end month of the COVID-19 recession (February 2020 and April 2020). Source: LFS master files.

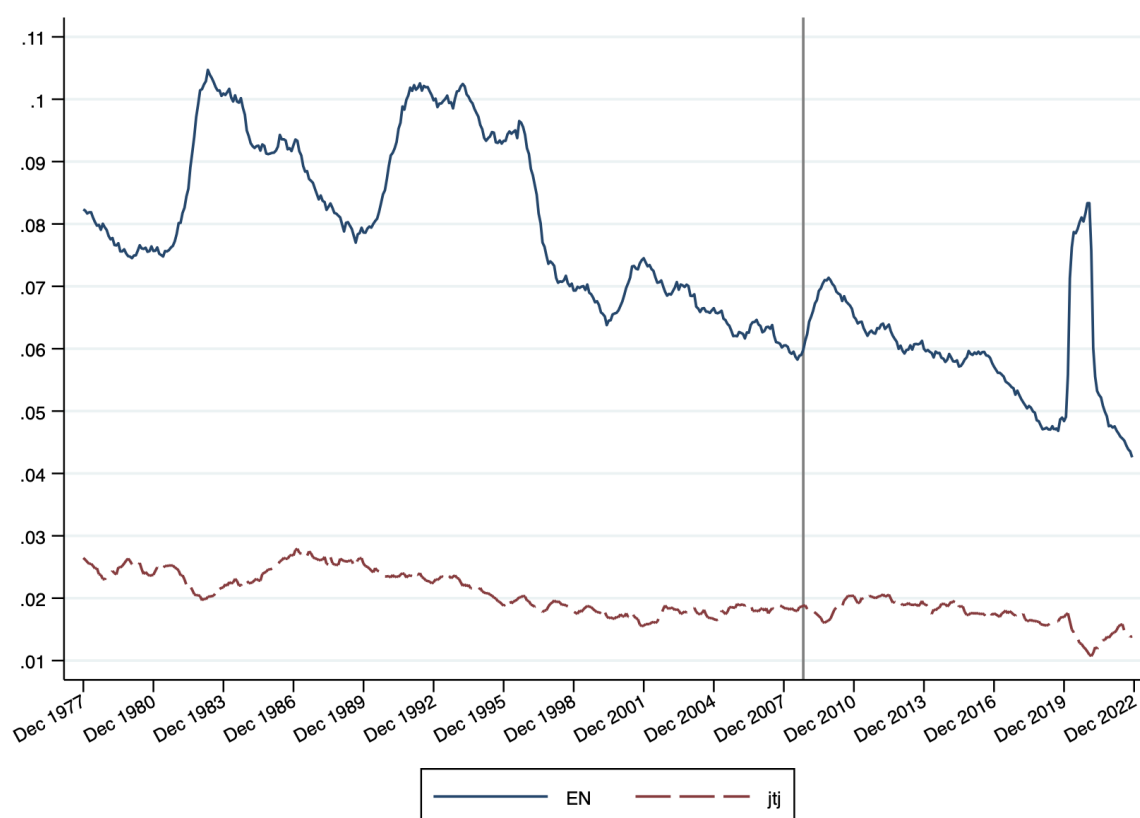


Figure 2.33: One-month EN and jtj rates, initial tenure less than one year. The EN rate is the employed to not-employed transition. The jtj rate is the job-to-job transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

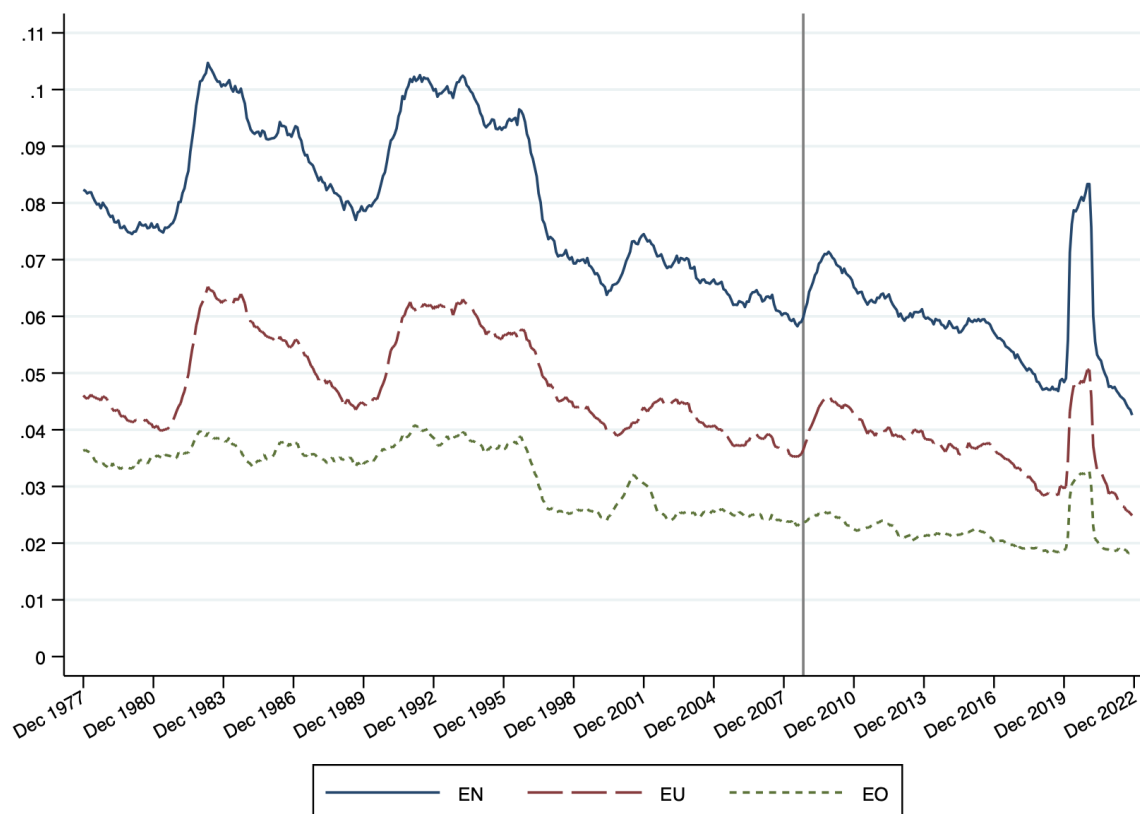


Figure 2.34: One-month EN, EU and EO rates, initial tenure less than one year. The EN rate is the employed to not-employed transition. The EU rate is the employed to unemployed transition. The EO rate is the employed to out of the labour force transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

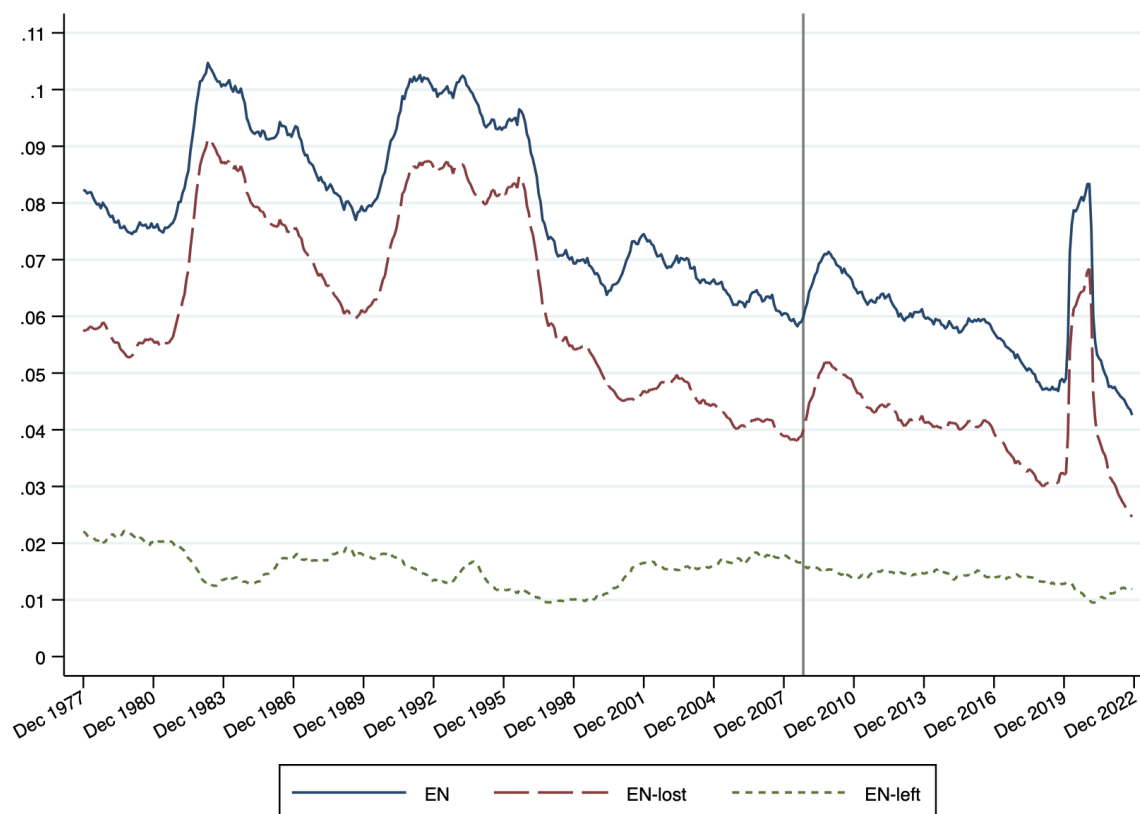


Figure 2.35: One-month EN, EN-lost, EN-left rates, initial tenure less than one year. The EN rate is the employed to not-employed transition. The EN-lost rate is the employed to not employed due to a layoff transition. The EN-left rate is the employed to not-employed due to a quit transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

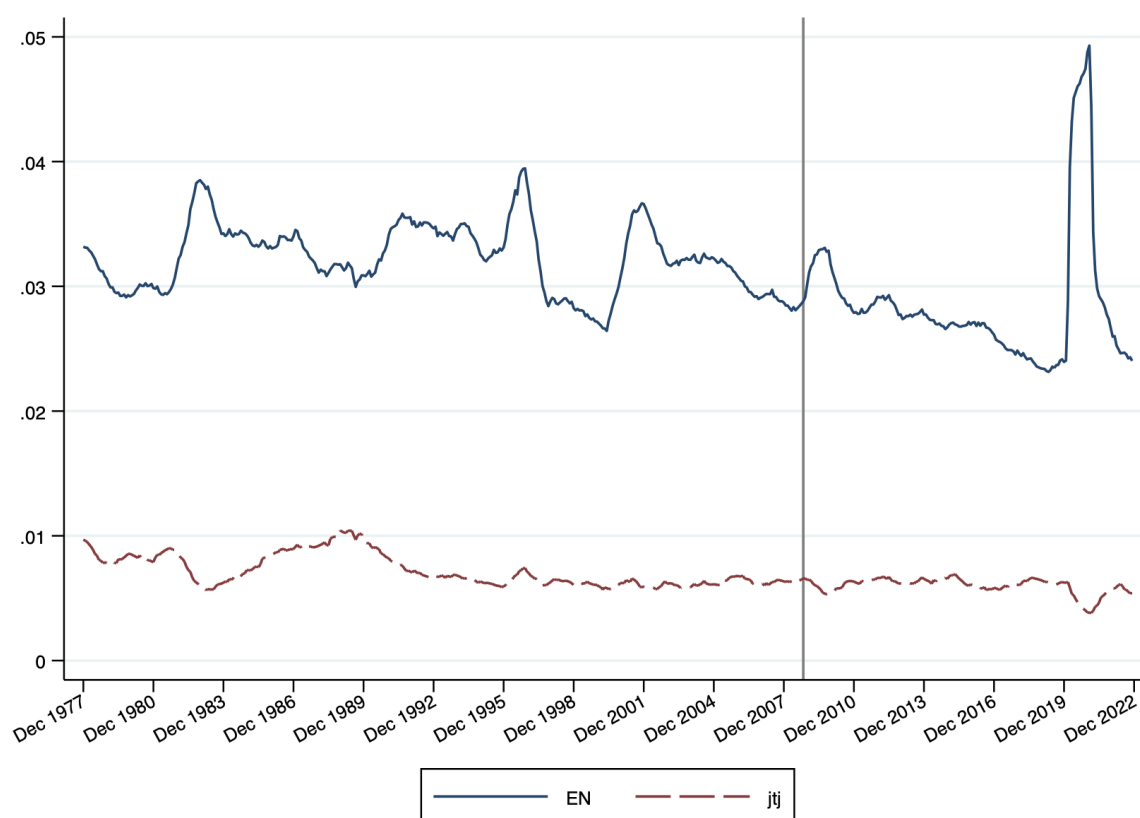


Figure 2.36: One-month EN and jtj rates. The EN rate is the employed to not-employed transition. The jtj rate is the job-to-job transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

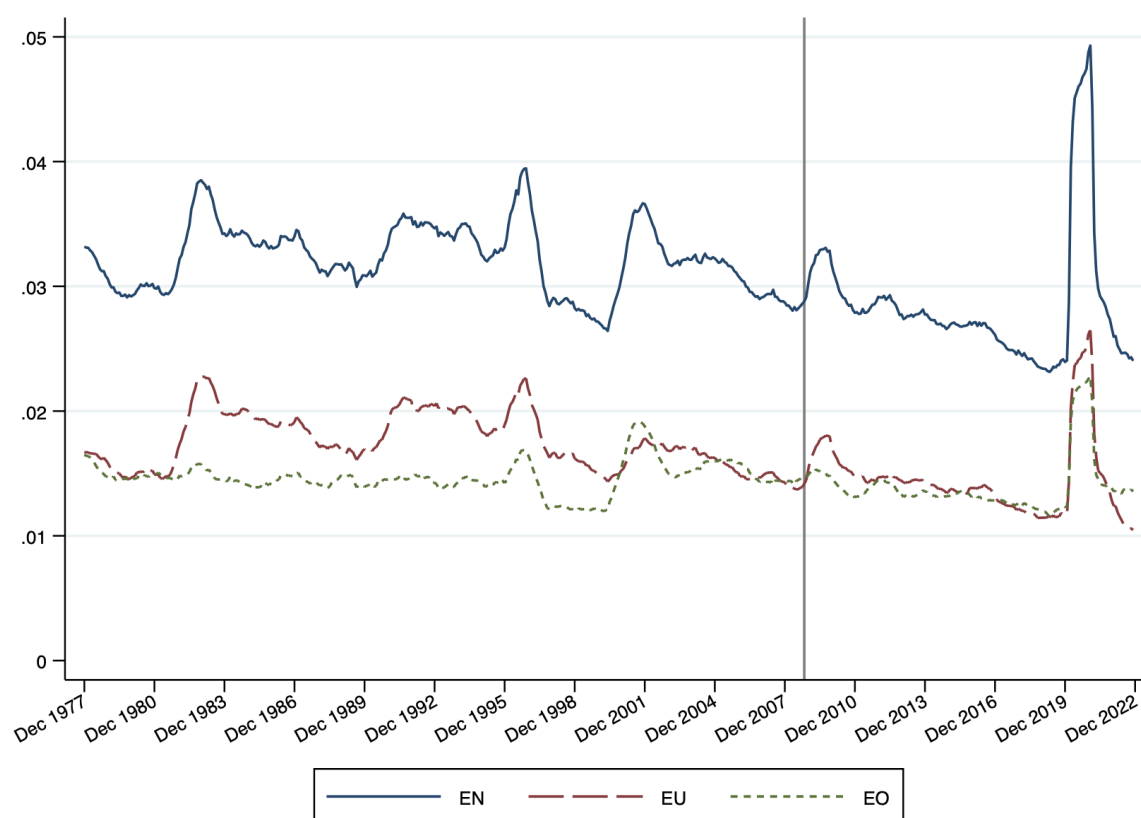


Figure 2.37: One-month EN, EU and EO rates. The EN rate is the employed to not-employed transition. The EU rate is the employed to unemployed transition. The EO rate is the employed to out of the labour force transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

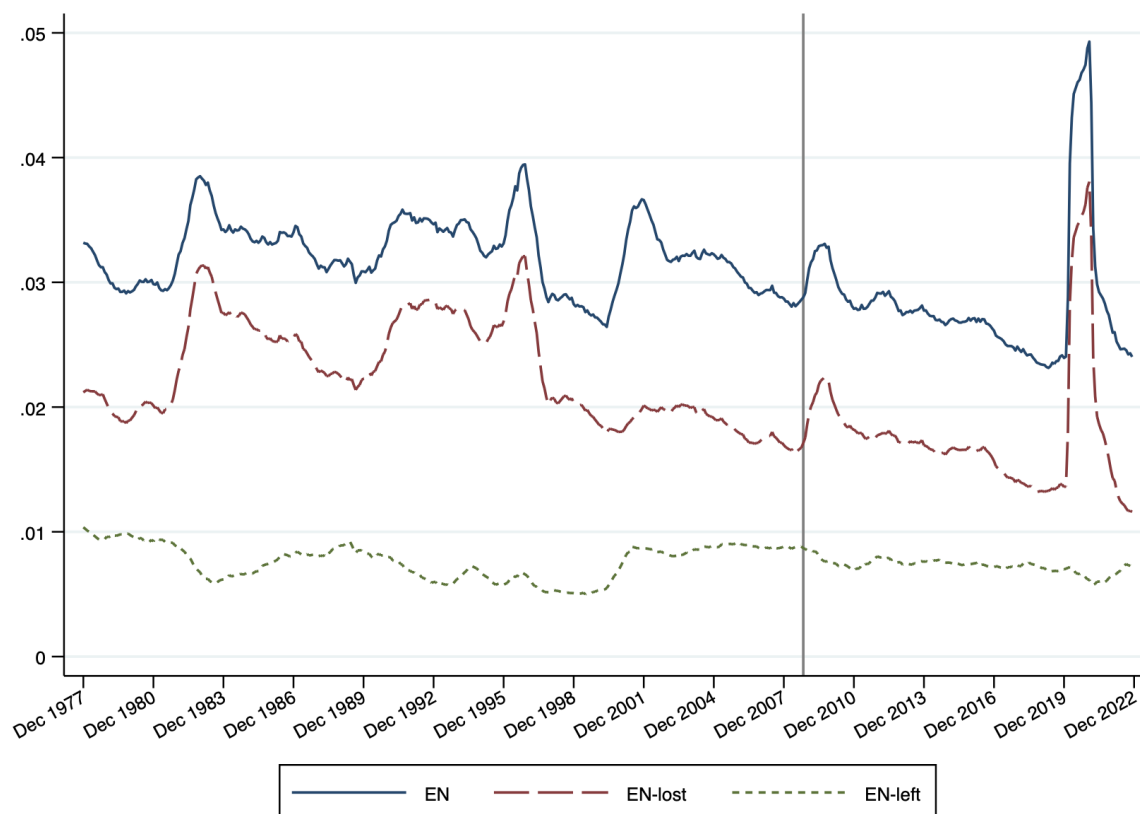


Figure 2.38: One-month EN, EN-lost, EN-left rates. The EN rate is the employed to not-employed transition. The EN-lost rate is the employed to not-employed due to a layoff transition. The EN-left rate is the employed to not-employed due to a quit transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

2 Canadian Job Stability Patterns in the Post-Great-Recession Period

Table 2.1: One-year retention rates, tenure less than one year, across business cycles, by gender, industry, age, education and region

	<i>R1987,1988</i>	<i>R1998,1999</i>	<i>R2005,2006</i>	<i>R2017,2018</i>
Overall	.443 (.004)	.544 (.005)	.553 (.005)	.610 (.006)
Male	.413 (.005)	.521 (.007)	.518 (.007)	.592 (.007)
Female	.475 (.006)	.568 (.007)	.593 (.008)	.630 (.008)
<i>Industry</i>				
Goods	.401 (.007)	.500 (.009)	.513 (.010)	.542 (.011)
Services	.461 (.005)	.560 (.006)	.568 (.006)	.632 (.007)
Public	.514 (.011)	.623 (.015)	.705 (.017)	.704 (.017)
Private	.430 (.004)	.531 (.005)	.531 (.005)	.595 (.006)
Union	-	.647 (.013)	.664 (.013)	.718 (.014)
Non Union	-	.520 (.005)	.527 (.005)	.585 (.006)
<i>Age</i>				
20-29	.426 (.005)	.522 (.007)	.519 (.008)	.574 (.008)
30-39	.471 (.008)	.577 (.010)	.588 (.011)	.660 (.012)
40-49	.456 (.011)	.561 (.012)	.578 (.012)	.673 (.015)
50-64	.432 (.014)	.502 (.015)	.541 (.014)	.564 (.013)
<i>Education</i>				
Dropout	-	.401 (.010)	.427 (.012)	.488 (.018)
High school (and some post Sec.)	-	.540 (.009)	.490 (.009)	.518 (.010)
Post sec. diploma/certificate	-	.565 (.009)	.576 (.009)	.610 (.009)
University degree	-	.629 (.013)	.667 (.012)	.712 (.011)
<i>Region</i>				
Atlantic	.334 (.012)	.382 (.013)	.442 (.016)	.505 (.019)
Quebec	.409 (.008)	.535 (.011)	.547 (.011)	.610 (.012)
Ontario	.516 (.007)	.591 (.009)	.586 (.009)	.633 (.009)
Prairies	.413 (.009)	.519 (.011)	.546 (.011)	.601 (.013)
British Columbia	.394 (.011)	.566 (.015)	.546 (.014)	.611 (.014)

Notes. A weighted average of two consecutive years' retention rates is used as to minimize the sensitivity of our results to the choice of start years. Union includes union member and not a union member but covered by a collective agreement. Standard errors are in parentheses. Source: LFS master files.

Table 2.2: Decomposition across business cycles (1997-1998 and 2016-2018)

	All tenures		Tenure less than one year	
	Composition effect	Remaining effect	Composition effect	Remaining effect
	(1)	(2)	(3)	(4)
<i>Age decomposition</i>				
Male	.001	.008	-.005	.094
	12.21%	87.79%	-5.97%	105.97%
Female	.001	.019	-.007	.090
	5.88%	94.12%	-9.01%	109.01%
<i>Education decomposition</i>				
Male	.011	-.002	.030	.059
	119.21%	-19.21%	33.60%	66.40%
Female	.014	.007	.031	.052
	67.55%	32.45%	37.13%	62.87%

Notes. The compositional effect reflects how much of the change observed over the 1997-1998 to 2016-2018 periods can be explained by compositional changes. Source: LFS master files.

Table 2.3: Transitions across business cycles (1997-1998 and 2016-2018)

	All tenures (1)	Tenure less than one year (2)
<i>Separations</i>		
EN	-.004	-.019
jtj	.000	-.002
<i>EN by destination</i>		
EU	-.004	-.013
EO	.000	-.006
<i>EN by type of separation</i>		
EN-lost	-.006	-.022
EN-left	.002	.004

Notes. The difference reflects the change between the average of the one-month (unadjusted) transition rates from 1997-1998 to 2016-2018. The EN rate is the employed to not-employed transition. The jtj rate is the job to job transition. The EU rate is the employed to unemployed transition. The EO rate is the employed to out of the labour force transition. EN-lost rate is the employed to not-employed due to a layoff transition. The EN-left rate is the employed to not-employed due to a quit transition. Source: LFS master files.

Chapter 3

Explaining the Canadian Job Stability Gender Gap Puzzle

3.1 Introduction

One has observed over the second half of the twentieth century, and across many countries, a long-running trend of gender convergence in labour market outcomes, such as labour force participation, hours of paid work and wages. Though women have made significant progress in narrowing the gaps, the convergence has in many cases stalled (Goldin, 2014).¹ For job stability it is a different story. The Canadian male-female job stability gap disappeared in the 1990s, and then turned negative as of the mid- to late 2000s.

In this paper, we address this puzzle. More precisely, we examine why female job stability, as measured by the female retention rate - the probability a job continues into the following period - did not just converge towards the male rate, but in fact caught up to it and then systematically surpassed it since the Great Recession. Convergence towards the male rate is well-documented (Heisz, 2005), and the source of this convergence (towards) has previously been explored (Brochu, 2013). However, the secular change of female rates now systematically surpassing those of their male counterparts is a newly minted stylized fact (Brochu and Li, 2024), and as such, its source has yet to be examined in the literature. This finding is particularly puzzling given that one has observed a systematic *negative* male-female job stability gap for low tenured jobs dating back to at least the mid-1970s.

For our empirical analysis we take advantage of the richness of the Canadian Labour Force Survey (LFS) data. Given that the LFS measures in-progress duration of an

¹Reasons given for the continued positive male-female wage gap, for example, (other than discrimination) have included difference in psychological attributes such as competitive behaviour (Morin, 2015b), risk aversion (Pekkarinen, 2015; Iriberry and Rey-Biel, 2019), and strategic behaviour in high versus low risk contexts (Iriberry and Rey-Biel, 2019; Borges et al., forthcoming). Blau et al. (2024), on the other hand, emphasize the role of self-selection.

employment relationship, i.e., job tenure, in a consistent and frequent manner since the mid-1970s, we can favour a retention rate approach. Such an approach has two main advantages. First, it is a direct measure of job stability. A job is stable if it has a high probability of persisting into the next period. Second, unlike in-progress measures (e.g., in-progress mean tenure), it is less sensitive to labour market inflows and outflows. Given the important inflow of women into the labour market over the 1970s to the early 1980s in Canada, this feature of retention rates is a key property when addressing gender differences in job stability.

Our cross-sectional counterfactual analysis, where we assign the other gender’s socio-demographic characteristics, reveals that gender differences in age structure are of second-order importance when explaining the retention rate puzzle. For education and industry, it is a different story. The role of education increases with time, reflecting the growing gender disparity in educational attainment. When assigning the other gender’s industry composition, its influence is present throughout the sample period. This finding is due to the persistent structural difference in industry composition across genders. Revisiting the effect of compositional changes through regression analysis (i.e., using panel data), where we can control for confounding factors, confirms our cross-sectional results. By controlling for all factors at the same time, we can conclude that as a group, age, education and industry can explain the gender gap puzzle and also explain the gender differences at the bottom of the tenure distribution.

This paper contributes to two literatures: first, it adds to the large literature regarding the gender convergence of labour market outcomes (wages: Baker and Drolet (2010); Goldin (2014); Schirle (2015); Blau and Kahn (2017); Blau et al. (2024); Olivetti et al. (2024), labour force participation: Blau (2024); Cardoso and Morin (forthcoming), unemployment rate: Albanesi and Şahin (2018); Cui (2024), hours of paid work: Blau and Kahn (2017); Cortés and Pan (2019)). The exploration of this additional dimension (i.e., job stability) can thus help paint a more complete picture of labour market outcomes of women in terms of how and why they differ from those of men. The second is the job stability literature (Heisz, 2005; Brochu, 2013; Brochu and Li, 2024; Molloy et al., 2024), and more generally, the literature that focuses on labour market transitions to better understand the workings of the labour market (Elsby et al., 2015; Jones and Riddell, 2019; Jones et al., 2023; Castro et al., 2024; Ferrer et al., forthcoming).² By capitalizing on the richness of the LFS tenure data we can address the job stability gender gap puzzle previously identified in the literature and thus sharpen our understanding of how job stability has evolved over time.

²Ferrer et al. (forthcoming) is of relevance to our paper because they also use LFS mini-panels to look at labour market transitions by gender. Their focus, however, is on how job loss within households influences labour market participation. They find that Canadian women are more likely to enter the workforce in response to a partner’s job loss, whereas men do not exhibit the same pattern. This effect appears stronger among those with higher education levels, households experiencing greater income disruption, and homeowners with ongoing mortgage commitments.

The rest of the paper is broken down as follows. In section 3.2 we present the data and empirical approach. Section 3.3 presents stylized facts. Section 3.4 explores the source of the gender gap puzzle using cross-sectional and panel approaches. Finally, section 3.5 concludes.

3.2 Data and Empirical Approach

We utilize master files data of the Canadian Labour Force Survey (LFS) covering the 1977-2022 period. The LFS is a household survey that collects labour market information of approximately 55,000 Canadian households every month.

A key feature of the LFS for our empirical work is the consistency of its tenure data. Since 1976, the LFS has asked employed respondents when they started working for their current employer, and the duration of their in-progress employment relationship (i.e., job tenure) is recorded in months. The richness of the tenure data allows us to construct cross-sectional retention rates (which we discuss below), and also enables us to condition on initial tenure when carrying out our retention rate analysis. A second key feature of the LFS is its rotating panel design. We take advantage of the fact that households are interviewed for six consecutive months to construct two-month mini-panels which we rely upon for our panel analysis.³

Given that we want to explain the gender puzzle identified by Brochu and Li (2024), we impose similar sample restrictions. More precisely, we limit our attention to individuals between the ages of 20 to 65 living in one of Canada's ten provinces, and exclude full-time member of the Canadian armed forces, full-time students, and returning students.

As in chapter 2, we use a retention rate approach for examining job stability. The retention rate is simply the probability a worker stays with the same employer one more period. More formally, the retention rate for workers with characteristics c and s periods of tenure as of time t can be expressed as

$$R_t^{s,c} = \frac{N_{t+1}^{s+1,c}}{N_t^{s,c}} \quad (3.1)$$

where the denominator $N_t^{s,c}$ is the number of workers with characteristics c and s periods of tenure as of time t , and the numerator represents how many of them continued to work for the same employer into the next period.

For the first part of our empirical analysis we treat the LFS as repeated cross-sections and estimate one-year retention rate using a cross-sectional estimator commonly used in the job stability literature (Neumark et al., 1999; Brochu, 2013; Brochu and Li, 2024).

³A detailed description of the construction of the mini-panels can be found in Appendix B.1.

The estimator takes advantage of the fact that the base weights of the LFS (and the same holds true for other households surveys like the CPS) represent the inverse probability of being selected, and thus sum up to their target population. One can therefore estimate the denominator of equation (3.1) by summing the base weights of individuals with characteristics c and s periods of tenure at time t . For the numerator one uses a similar approach. It should be noted that one can estimate the numerator and denominator using different cross-sections, and thus use a synthetic cohort approach, because for a worker to have, say, $s + 1$ periods of tenure at time $t + 1$, they had to have had s periods of tenure at time t .⁴

3.3 Stylized Facts

3.3.1 Job Stability Gender Gap Puzzle

Figure 3.1 shows the gender gap puzzle first identified by Brochu and Li (2024). It shows the one-year female retention rates not just converging towards the males rates, but catching up to them in the 1990s, and then systematically surpassing them since the Great Recession. The narrowing of the gender gap is well-documented in the literature (Heisz, 2005; Brochu, 2013), and the source of this change previously explored with the evidence pointing towards a cohort-based explanation (Brochu, 2013).⁵ The identification of the gender gap puzzle is, however, a new phenomenon. Only with the addition of more recent data could the opening of a *negative* male-female gap starting in the mid- to late 2000s be characterized as a secular change.

Equally puzzling is the gender gap at the bottom of the tenure distribution. When focusing on newly formed jobs (i.e., being with the same employer less than one year) one sees a long-standing negative male-female retention rate gap dating back to the mid-1970s, when LFS microdata was first made available (figure 3.2). However, the retention rates of workers with tenure of 12 months or more (figure 3.3) mirror the overall findings, and gender differences are much less apparent since the early 1990s. Having said this, for most of the post-Great Recession recovery period, the female rate does tend to exceed the male rate. This latter finding is not surprising given that longer-tenured workers make up the greater majority of the workforce. But the appearance of a negative gender gap in the second half of the sample for these longer tenured jobs, combined with the consistent negative gender gap for newly formed jobs is indicative of possible long-running structural differences across genders; that there is more to the story than just a cohort-based explanation.

⁴See Brochu (2011) for more details on the properties of this estimator.

⁵Where more recent cohorts of women are conducting themselves more like men along the job retention dimension.

3.3.2 Socio-demographic Composition

Age, education and industry are socio-demographic characteristics for which one observes important compositional changes over time, and above all, significant differences across genders. We document these changes/differences below. To do so, we rely on the public-use files of the LFS. Contrary to the retention rate analysis which requires the master files,⁶ examining group proportions can be carried out with the public-use version of the data.⁷

Age

Figures 3.4 to 3.7 present (five-year) age proportions by gender. One observes an ageing of the workforce (i.e., a baby-boom effect) for both genders. The strong presence of baby boomers as young adults can be seen in the early years of figure 3.4, and their impact is observed for older age groups moving forward in time (i.e., as the age). Although the overarching patterns are the same for both males and females, there are some noticeable gender differences, particularly in the 1970s and early 1980s due to the large inflow of women into the workforce. Having said this, some second-order differences nonetheless remain even in the later part of the sample period, with more women attending university explaining some but not all of these differences.⁸

Education

Figure 3.8 shows the proportion of workers that have a university degree (bachelor and up), by gender. Throughout the 1977-2022 sample period, one observes a steady rise for both genders, but the rate of increase is systematically larger for females. To put this slope differential into perspective, there is a 3.0 p.p. male-female gap in 1977, it turns negative in 1996, and by 2019 (the year prior to COVID-19), the proportion of women with a university degree was 8.2 p.p. higher than for males—an economically significant difference given that the male proportion stood at 29.8%. These findings, combined with the well-documented positive education profile of retention rates (Brochu and Li, 2024), i.e., more educated workers have more stable jobs, point to education playing a role in

⁶For the cross-sectional retention rate estimator we require age be recorded in years, and for its panel counterpart we need the person identifier variables to link observations across time. In both cases, the information is only available in the master files.

⁷We impose similar sample restriction when relying on the public-use files, i.e., we focus on workers 20 to 64 years of age, living in one of Canada's ten provinces, who are not full-time members of the armed forces, nor are full-time students. We cannot, however, drop returning students nor restrict our attention to the incoming rotation (as we did with the master files) as neither group can be identified in the public-use files. These differences do not materially affect the patterns discussed below.

⁸Recall we exclude full-time students from our sample. As such, one should observe relatively fewer young women than men in our sample, given that they are more likely to attend university.

explaining the gender gap puzzle. Yet, due to the concavity of the education profile,⁹ the significance of education in explaining the gender gap puzzle depends on which education grouping(s) saw a corresponding drop in their importance.

Figures 3.9 and 3.10 show how the proportions of workers that are dropouts, high school graduates, college graduates (certificate or diploma) and university graduates (bachelor and up) have evolved over the 1990-2022 period. We focus on 1990 onwards because of the important changes to the education question introduced as of January 1990, which makes any pre- and post-1990 comparison (other than for university degree) problematic. In particular, one cannot identify high school graduates in the data prior to 1990. Three observations drawn from these figures point to education playing an important role in explaining the gender gap puzzle. First, although one sees a similar decline in the importance of dropouts across genders (see figure 3.9), there is nonetheless a clear level effect; a dropout is significantly more likely to be male, and this holds true from the beginning to the end of our sample period. Second, the decline in the importance of the high school graduate category is more extensive for females (see figure 3.9). Finally, figure 3.10 shows a movement towards higher education (college and university) for both genders, but in the case of females it leans more heavily towards university.

Industry

Figures 3.11 and 3.12 show the male industry proportions by broadly defined industry classification (NAICS 1-digit), whereas figures 3.13 and 3.14 do the same but for females.¹⁰ For both genders, one observes an important decline over time in ‘manufacturing’ and a rise in the importance of ‘finance/insurance/real estate/rental and leasing services/professional, scientific and technical services/management, administration and other support’. The latter being mainly driven by the rise in ‘professional, scientific and technical services’. Although one sees ‘education, health and social assistance’ (driven by ‘health’) becoming more important for females (but not for males), the key gender differences are structural.¹¹ More precisely, there are significant level-effect differences across genders that persist throughout the whole 1977-2022 period. For example, there is, on average, a positive male-female industry proportion gap in ‘manufacturing’ (+13.0 p.p.), ‘utilities and construction’ (+9.0 p.p.), and trade, transport and warehousing’ (+4.1 p.p.), whereas it is negative in

⁹One sees, for example, a larger increase in job stability when going from dropouts to high school graduate than, say, from college to university.

¹⁰For the most part the public-use files of the LFS provide industry information at the 2-digit level, which we then aggregate to the 1-digit level. There are, however, a few instances where the LFS combines some 2-digit classifications, as to ensure that cell sizes are of sufficient sizes (for confidentiality reasons), which affects our aggregation. This holds true for ‘agriculture, forestry, fishing and hunting’ (2-digit code 11) which is combined with ‘mining, quarrying, and oil and gas extraction’ (2-digit code 21), and also for ‘information and cultural industries’ (2-digit code 51) which is combined with ‘arts, entertainment and recreation’ (2-digit code 71).

¹¹See appendix figures C.1 to C.6 for more details.

‘education, health and social assistance’ (-22.1 p.p.) and ‘finance/insurance/real estate/rental and leasing services/professional, scientific and technical services/management, administration and other support’ (-3.9 p.p.).

Comment

The role played by gender differentials in the slope (change over time) and the intercept (level effect) have important implications for the identification of the gender puzzle. For example, carrying-out counterfactuals for each gender where one holds their group composition constant over time, as in [Brochu and Li \(2024\)](#), cannot address systematic gender differences in socio-demographic compositions (level effects). We address these issues further below.

3.4 Source of Change

3.4.1 Cross-sectional Approach

Counterfactuals when conditioning on time-invariant characteristics

The retention rate that conditions on gender $g \in \{m, f\}$ - treated here as a time-invariant characteristic - can be expressed as

$$R_t^g = \sum_{k=1}^K \alpha_t^{k|g} R_t^{k,g} \quad (3.2)$$

where $\alpha_t^{k|g}$ is the proportion of workers of gender g that are in group k , and $R_t^{k,g}$ is the one-year retention rate of workers of gender g and group k .

One can create a counterfactual where one holds group composition constant at, say, 1997 levels by replacing $\alpha_t^{k|g}$ in equation (3.2) with $\alpha_{1997}^{k|g}$. This counterfactual can be expressed as

$$\widetilde{RC}_t^g = \sum_{k=1}^K \alpha_{1997}^{k|g} R_t^{k,g} \quad (3.3)$$

Such counterfactuals are useful for an overall understanding of the changing job stability patterns ([Brochu, 2013](#); [Brochu and Li, 2024](#)), but are less informative when dealing with the gender gap. To fully address differences in socio-demographics characteristics across genders (i.e., differences in starting points and evolutions over time), one must assign the

other gender's group proportions when carrying the decomposition exercise.¹² In such a case, the counterfactual takes the following form:

$$\widetilde{RC}_t^g = \sum_{k=1}^K \alpha_t^{k|g'} R_t^{k,g} \quad (3.4)$$

where g' is the other gender.¹³

Counterfactuals when conditioning on time-varying characteristics

Counterfactuals that condition on time-varying characteristics require a different approach. The retention rate of workers of gender $g \in \{m, f\}$ with s month of tenure (e.g., less than twelve months of tenure) can be expressed as

$$R_t^{s,g} = \sum_{k=1}^K \alpha_t^{k|s,g} R_t^{k,s,g} \quad (3.5)$$

where $\alpha_t^{k|s,g}$ is the proportion of workers of gender g with s months of tenure that are in group k .¹⁴ Again, this holds true only if the K groups are collectively exhaustive and mutually exclusive. Holding the α 's constant over time will hold the proportion of workers of gender g and tenure s (not of gender g) that are in group k constant over time. As shown in Brochu (2013), one can get around this issue by using Bayes' law. One can rewrite $\alpha_t^{k|s,g}$ as

$$\alpha_t^{k|s,g} = \frac{Prob_t(\text{tenure } s | \text{group } k, \text{gender } g) \cdot Prob_t(\text{group } k | \text{gender } g)}{\sum_{k=1}^K Prob_t(\text{tenure } s | \text{group } k, \text{gender } g) \cdot Prob_t(\text{group } k | \text{gender } g)} \quad (3.6)$$

One can therefore create a counterfactual where one holds group composition constant at, say, 1997 levels by replacing $Prob_t(\text{group } k | \text{gender } g)$ in equation (3.6) with $Prob_{1997}(\text{group } k | \text{gender } g)$. The counterfactual becomes

$$\widetilde{RC}_t^{s,g} = \sum_{k=1}^K \left(\frac{Prob_t(\text{tenure } s | \text{group } k, \text{gender } g) \cdot Prob_{1997}(\text{group } k | \text{gender } g)}{\sum_{k=1}^K Prob_t(\text{tenure } s | \text{group } k, \text{gender } g) \cdot Prob_{1997}(\text{group } k | \text{gender } g)} \right) R_t^{k,s,g} \quad (3.7)$$

¹²The assignment of the other gender's composition has been used in other settings, for example, when exploring for the source of the gender unemployment rate gap (Albanesi and Şahin, 2018).

¹³For example, if g represents males, g' , the other gender, is females.

¹⁴The group compositions can be carried out by age, education and industry. In fact, we measure all these dimensions.

3 Explaining the Canadian Job Stability Gender Gap Puzzle

As with the time-invariant characteristics case, to explain the changing gender differential one must assign the other gender's group composition. The counterfactual is therefore:

$$\widetilde{RC}_t^{s,g} = \sum_{k=1}^K \left(\frac{Prob_t(\text{tenure } s | \text{group } k, \text{gender } g) \cdot Prob_t(\text{group } k | \text{gender } g')}{\sum_{k=1}^K Prob_t(\text{tenure } s | \text{group } k, \text{gender } g) \cdot Prob_t(\text{group } k | \text{gender } g')} \right) R_t^{k,s,g} \quad (3.8)$$

i.e., one replaces $Prob_t(\text{group } k | \text{gender } g)$ with $Prob_t(\text{group } k | \text{gender } g')$ in equation (3.6).

Results

Figure 3.15 shows the male and female retention rate counterfactuals for all tenured workers where one assigns the other gender's age composition.¹⁵ Other than for the early years, which saw a substantive inflow of women into the workforce, gender differences in age structure are of second-order importance in explaining the gender gap. More precisely, assigning the male age composition to the female rate (and vice versa) reduces the gap but only slightly.¹⁶ This was to be expected as the most important changes to the age structure, i.e., the baby-boom effect, is common to both genders.

In figure 3.16, we show the retention rate counterfactuals where we assign the other gender's education structure. Even though there were important changes made to the education question as of 1990, our counterfactual exercise nonetheless covers the full sample period (1977-2021) because the education assignment is across gender, and not time.¹⁷ Furthermore, the fact that the gaps between the actual rates and their accompanying counterfactuals are similar in the years just prior and after 1989,¹⁸ and that any observed differences between the two tend to be gradual over time, suggests that one can nonetheless draw conclusions across the 1990 threshold. One can see education mattering more with time, i.e., explaining more of the gender gap, particularly since the Great Recession and

¹⁵The age counterfactuals are calculated using equation (3.4), where age is broken down into nine five-year bins, i.e., 20-24, 25-29, ..., 60-64. All subsequent counterfactuals that do not condition on initial tenure, as is the case here, also rely on the counterfactual approach shown in equation (3.4).

¹⁶Abstracting from age composition differences means that one compares the male rate to the female counterfactual rate (where one assigns the male age composition). Alternatively, it can be measured by comparing the male counterfactual rate (where one assigns the female age composition) to the female rate.

¹⁷Care must be taken, however, when comparing pre- and post-1990 periods because the education bins used to construct the education counterfactuals are not exactly the same across the two periods. For the 1990-2021 rates we use similar bins as in section 3.3.2, i.e., bin 1 (grade 8 or lower; grade 9-10; grade 11-13, non graduate), bin 2 (grade 11-13, graduate; some post-secondary education), bin 3 (trades certificate or diploma; community college, CEGEP; university certificate below bachelor's) and bin 4 (bachelor's degree; above bachelor's degree). For the 1977-1988 rates we rely on the following four bins: bin 1 (0 to 8 years of schooling; 9 to 10 years of schooling), bin 2 (11 to 13 years of schooling; some post-secondary education), bin 3 (post-secondary certificate or diploma) and bin 4 (university degree).

¹⁸No rates are shown for 1989 because one cannot consistently estimate one-year retention rates by education group, i.e., the synthetic cohort approach does not work.

this holds true whether one assigns the male education structure to the female rate, or vice versa. This reflects the growing disparity in educational attainment between men and women.

Finally, figure 3.17 presents the counterfactuals where we assign the other gender's industry structure.¹⁹ The impact is felt throughout the sample period, which is reflective of the persistent structural difference in industry composition across genders. Although a little noisy, the impact appears to be more heavily felt when assigning the female industry composition to the male retention rate. More specifically, this latter assignation substantially increases the male rate which means that the positive retention gap of the early years becomes much larger, whereas the negative male-female retention rate gap of the later years becomes much smaller.²⁰

If one focuses on the bottom of the tenure distribution, i.e., workers having less than 12 months of tenure with their current employer, one sees similar findings.²¹ The impact of age is still small in the second half of the sample period (see figure 3.18), education becomes increasingly important over time (see figure 3.19), and finally, industry appears to play the most important role, and this from the very beginning of the sample period (see figure 3.20).

3.4.2 Panel Approach

In this section, we revisit the effect of compositional changes using panel data. This allows us to carry-out regression analysis controlling for confounding factors. Given that one-year retention rates calculated using repeated cross-sections have very similar patterns over time as the one-month retention rates estimated using two-month mini-panels (Brochu and Li, 2024), means that one can treat the subsequent panels approach results as complementary evidence.

Econometric methodology

The econometric model takes the following form

$$retention_{it} = \beta_0 + \beta_1 female_{it} + X'_{it}\gamma + \epsilon_{it} \quad (3.9)$$

¹⁹Industry is broken down into nine (collectively exhaustive and mutually exclusive) bins (NAICS 1-digit).

²⁰It should be noted that the industry composition effect will vary with the approach used only if both the employment share and the retention rate of some key industries varies gender. Furthermore, for it to matter more when one assigns the female industry composition to the male rate one would also need the gender differential in the employment share and retention rate be of opposite sign. A more thorough exploration of why this is the case, however, is left to future work.

²¹This requires the use of the counterfactual approach shown in equation (3.8).

where the dependent variable $retention_{it}$ is a binary variable that equals one if worker i at time t continues with the same employer into the next month (and zero otherwise). The main explanatory variable $female_{it}$ is a binary variable equaling one if the worker is a female (and zero otherwise). Finally, vector X represents a vector of controls which we add sequentially. For the base specification we only control for time using a full set of month-year time dummies. In the second specification we add five-year age dummies, whereas in the third specification we also include indicator variables for highest educational attainment.²² Finally, in the fourth and most complete specification, we further add industry controls (NAICS 1-digit level).

Results

Table 3.1 shows the Linear Probability Model regression results of equation (3.9) for different subperiods.²³ Column (1) shows the female coefficient findings when only month-year time dummies are including, whereas column (2) adds age dummies and column (3) further includes education controls. Finally, column (4) shows the results for the full specification, i.e., when also accounting for industry.

The findings in column (1), where one only accounts for time, are in line with those of figure 3.1.²⁴ Female jobs are relatively less stable in the early periods, and the difference dissipates over time only to reverse sign in later periods. For 2014-2018, for example, the female rate is 0.13 p.p. higher than the male rate, a difference that is both economically and statistically significant.²⁵ As with the cross-sectional counterfactual evidence, controlling for age (column (2)) only really matters in the late 1970s, whereas education plays a gradually more important role with time. In fact, controlling for education switches the sign of the gender coefficient during the strong post-Great Recession expansionary period. Finally, controlling for industry matters in all periods. This confirms what was observed in the stylized facts of section 3.3.2 (and the counterfactual analysis of section 3.4.1); that there are important industry differences present from very early on. What the regression analysis further reveals is that accounting for industry reinforces what was observed when

²²For the regressions that cover post-1990 years, we focus on 1) dropouts, 2) high school graduates (and some post-secondary education), 3) college (which includes community college, CEGEP, trade certificate or diploma and university certificate below bachelor's), and 4) bachelor and up. For the regressions that involve pre-1990 periods the education categories are slightly different, accounting for the changes to the education question discussed earlier. More precisely, the categories are 1) 10 years of education or less, 2) 11 to 13 years of education (including some post-secondary education), 3) post-secondary certificate or diploma and 4) university degree.

²³All regressions in this table and subsequent tables are weighted and heteroskedasticity-robust standard errors are shown in parenthesis.

²⁴One gets essentially the same results if one were to not include time dummies.

²⁵We show findings for 2014–2018 and not just 2017–2018 because the regression findings for column (1) are somewhat sensitive to the inclusion of 2018. Having said this, the patterns that one observes moving from columns (1) through (4) are the same.

education controls were added: the male-female job stability gap becomes systematically more negative.

Table 3.2 shows regression results when focusing on workers with less than one year of tenure. One observes in column (1) the same large positive male-female job stability gap seen in both the cross-sectional and panel retention rates. The main point to be taken from this table, however, is that this gap dissipates with the addition of the full set of controls. This is in line with the previous findings that differences at the bottom of the tenure distribution play an important role in explaining the gender job stability gap.²⁶

3.5 Conclusion

The long-running trend of gender convergence in labour market outcomes is well-documented. That it has stalled in many cases is also well-known. For Canadian job stability, however, it is a different narrative. Female job stability, as measured by the retention rate, caught up to the male rate and then systematically surpassed it since the mid- to late 2000s. This finding is particularly puzzling given that for new jobs the retention rate is systematically higher for females than for males, and this holds true going back to at least the mid-1970s.

Relying on the LFS, a rich source of tenure data, we explore this gender gap puzzle. We carry-out a cross-sectional counterfactual analysis where we assign the other gender's socio-demographic characteristics, and find that education and industry, but not age, play important roles. We complement this cross-sectional analysis with a panel one, taking advantage of the panel features of our data. Our regression analysis confirms our cross-sectional findings that education and industry are the driving forces. Given that the regression approach allows us to control for all factors at the same time, we can further conclude that, industry, education and to a much less extent age grouped together can explain the gender gap puzzle (including the gender differences at the bottom of the tenure distribution). As part of our future work, we plan on further exploring the industry findings. We want to examine whether one can attach a positive (or negative) connotation to the fact that women tend to be more prevalent in industries that have more job stability. More precisely, we want to see if job stability means a different thing for men and women.

²⁶In the (cross-sectional) counterfactuals of section 3.4.1, one controls for group composition. For example, when one looks at the importance of education, a education counterfactual can answer the following question: If one were to assign the male education structure to females, how would this affect the female retention rate (and thus the gender differential). When going to panel data, the regression analysis done in this section answers a related question: holding other factors constant (like education) does one observe a gender difference in the retention rate. Given that the large gender gap disappears for low tenured jobs, and also for all tenure in the latter periods, means that composition seems to really matter as for the counter-cyclical approach. This is why we restrict our attention to a regression where gender is just a level effect. As part of future work, we plan do pursuing an Oaxaca-type decomposition.

3.6 Figures and Tables



Figure 3.1: One-year retention rate, by gender. Source: LFS master files.

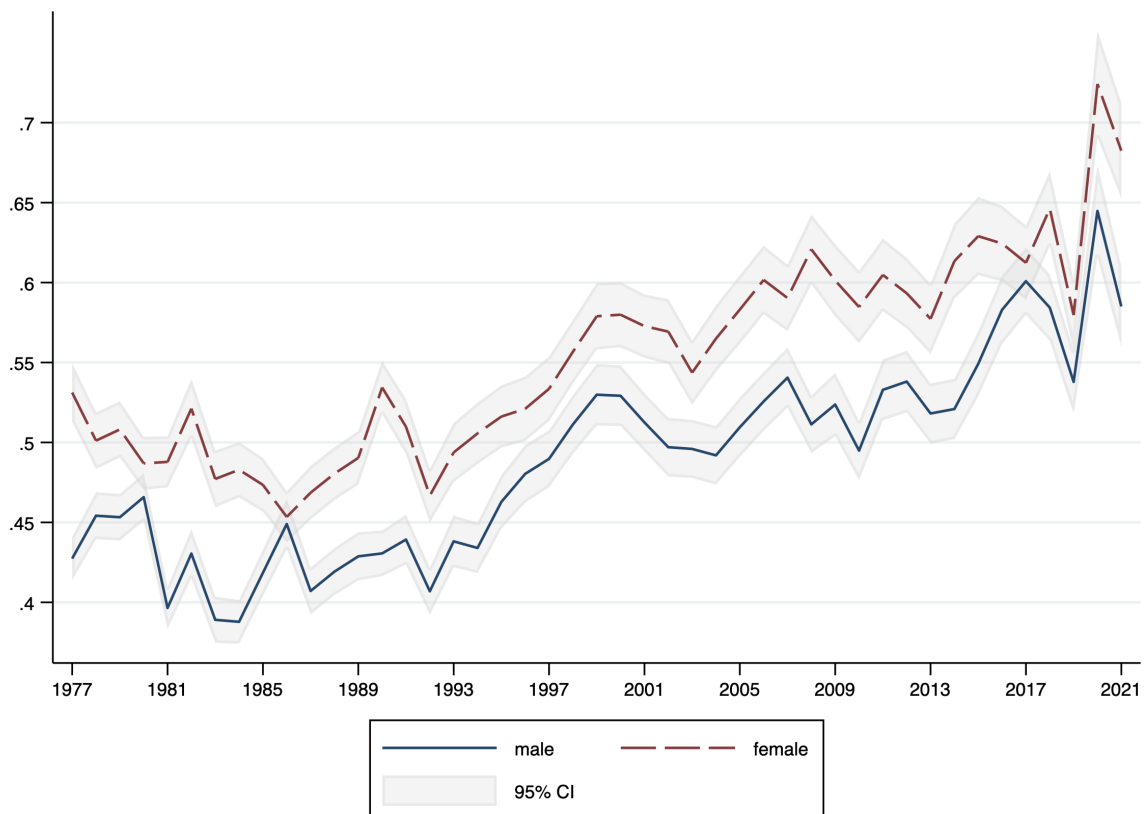


Figure 3.2: One-year retention rate, initial tenure less than one year, by gender. Source: LFS master files.

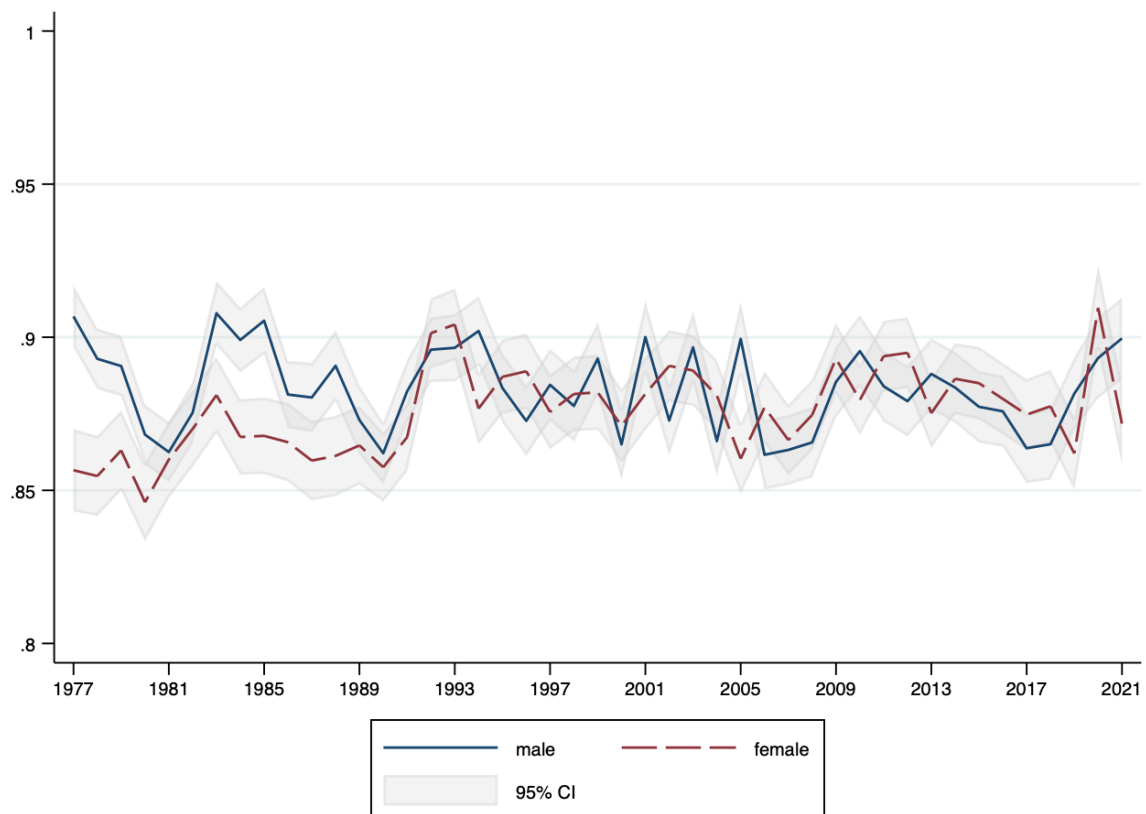


Figure 3.3: One-year retention rate, initial tenure of twelve or more months, by gender. Source: LFS master files.

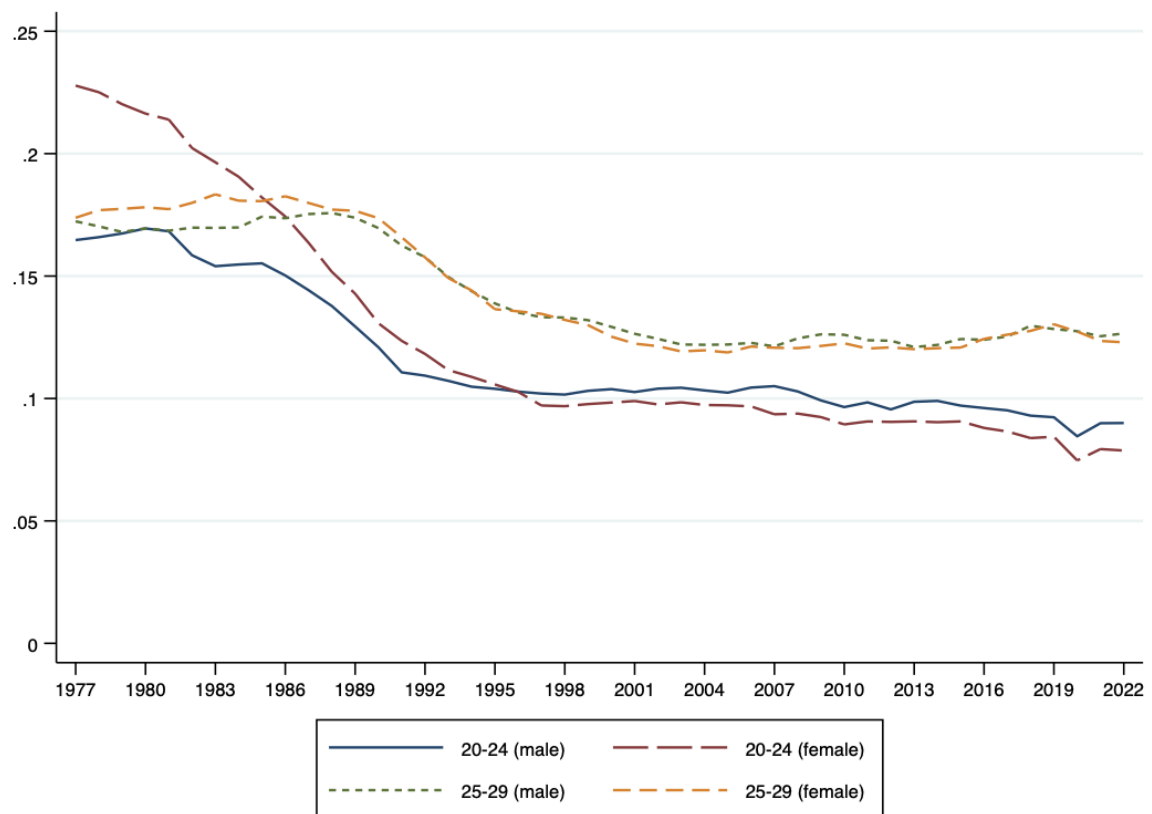


Figure 3.4: Proportion by age categories, 20-24 and 25-29, by gender. Source: LFS public-use files.

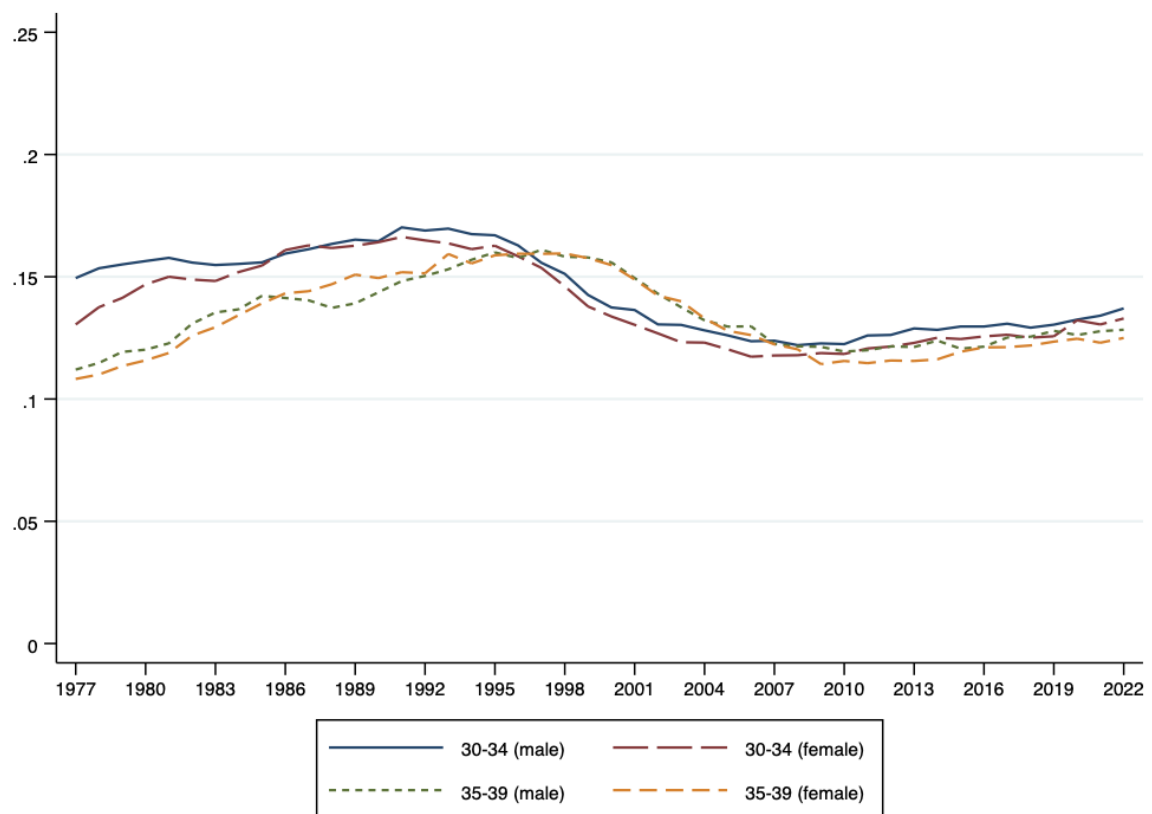


Figure 3.5: Proportion by age categories, 30-34 and 35-39, by gender. Source: LFS public-use files.

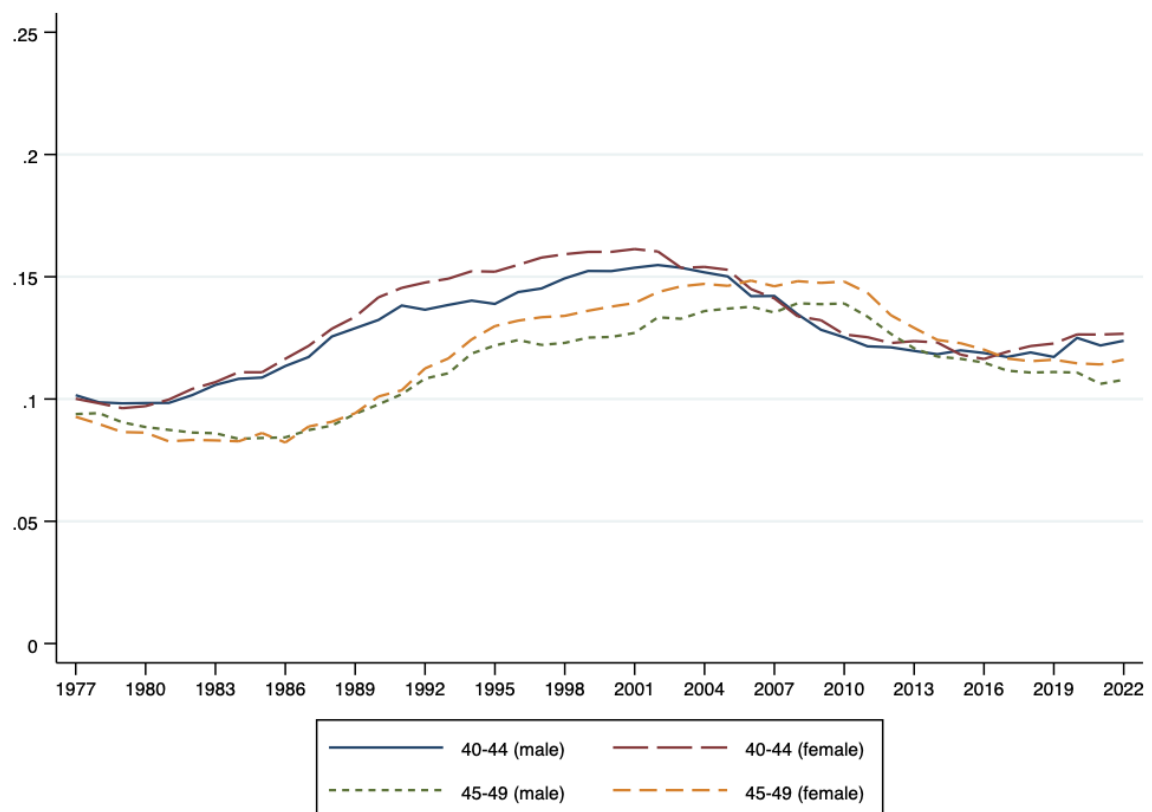


Figure 3.6: Proportion by age categories, 40-44 and 45-49, by gender. Source: LFS public-use files.

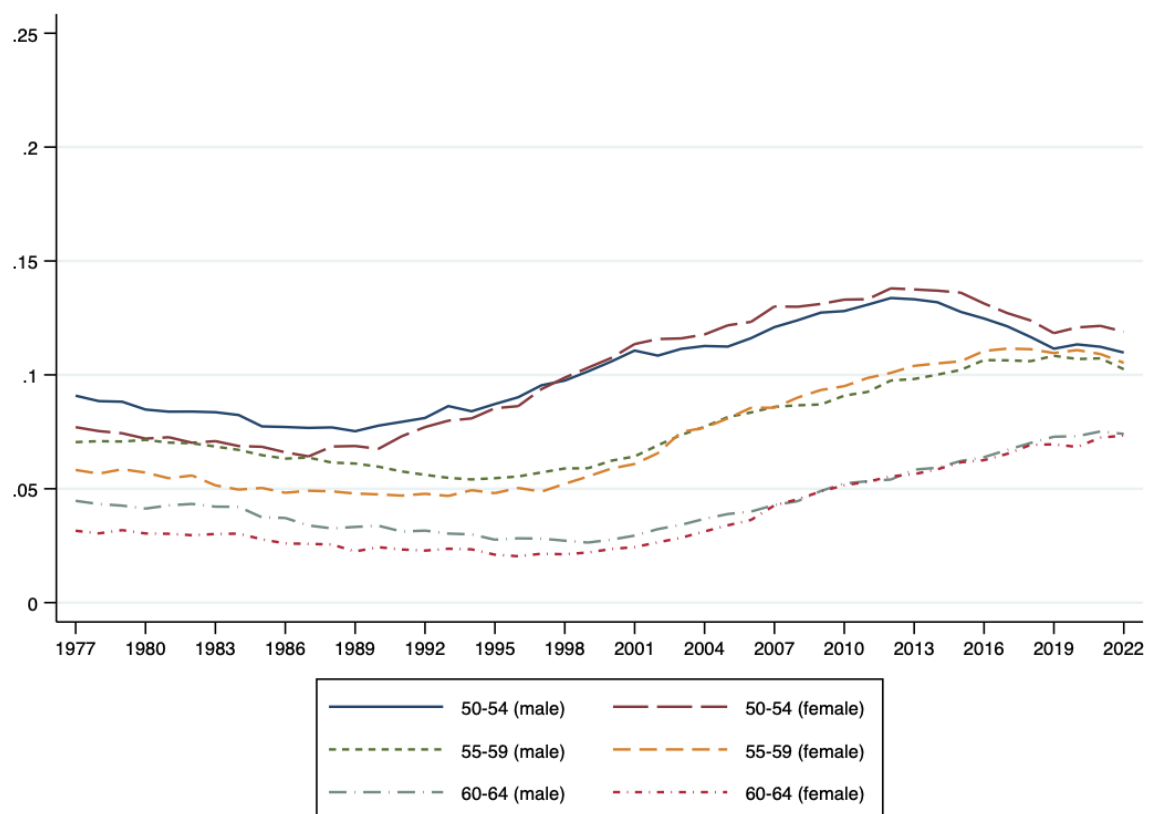


Figure 3.7: Proportion by age categories, 50-54, 55-59 and 60-64, by gender. Source: LFS public-use files.

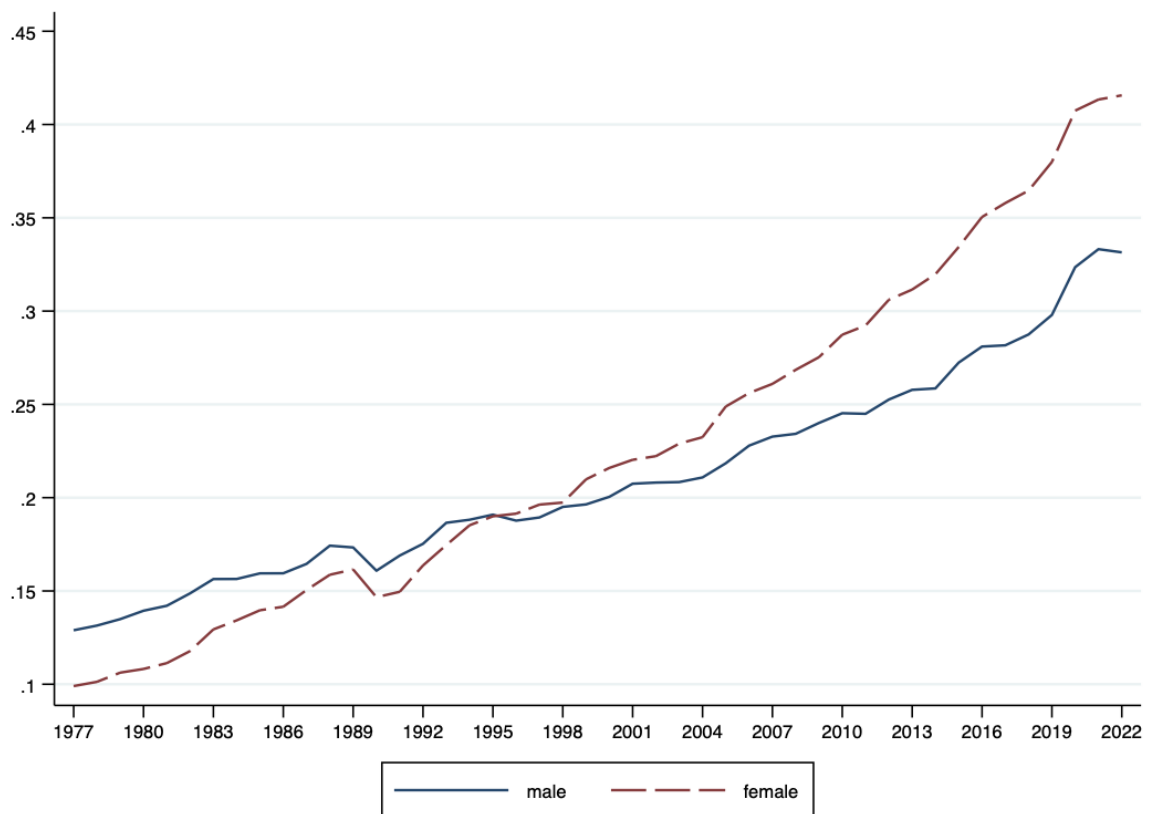


Figure 3.8: Proportion with a university degree, by gender. Highest educational attainment. Source: LFS public-use files.

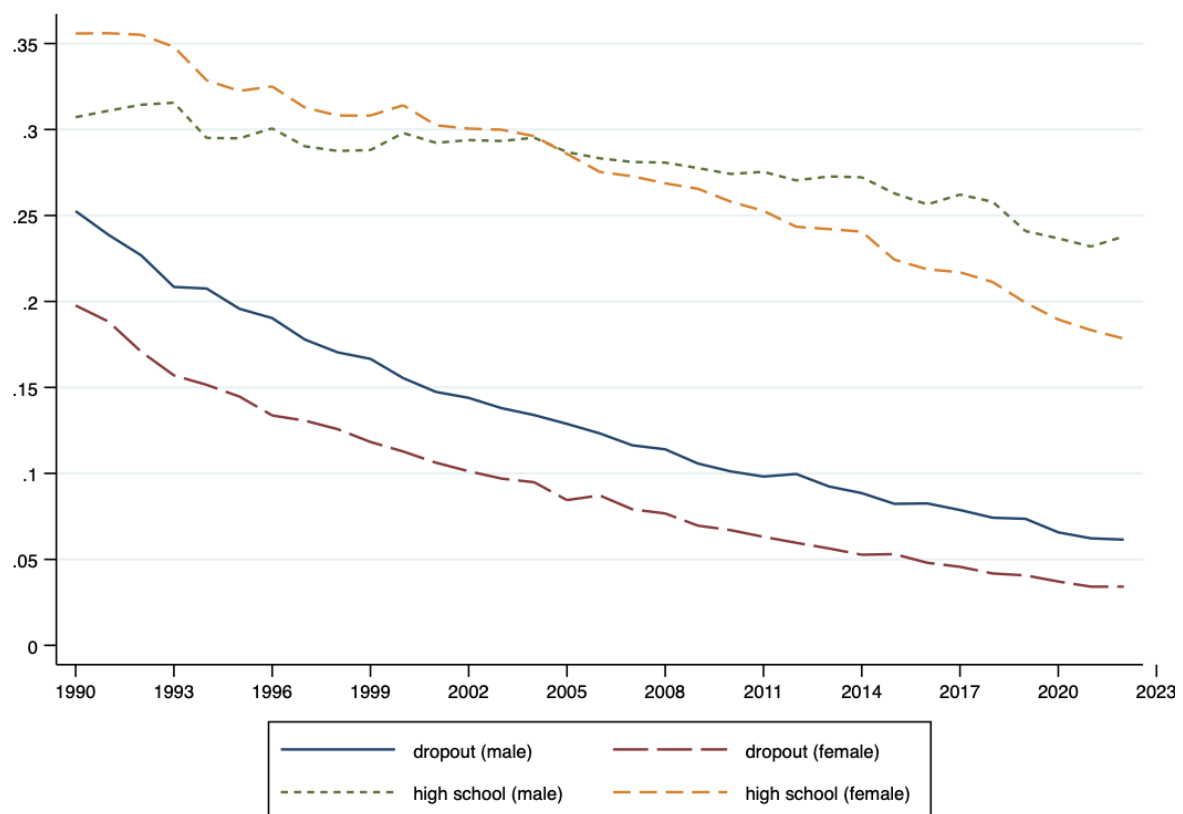


Figure 3.9: Proportion who are dropouts and with a high school degree (and some post-secondary), by gender. Highest educational attainment. Source: LFS public-use files.

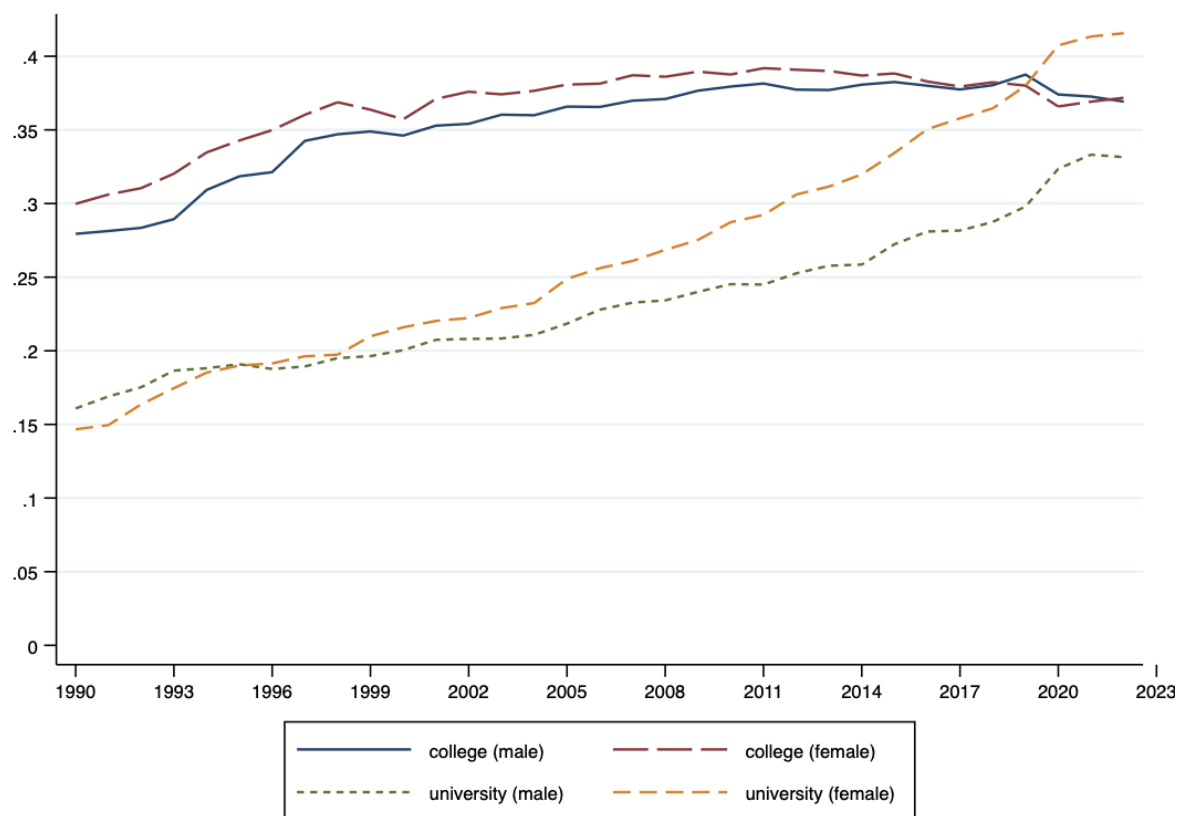


Figure 3.10: Proportion with a college diploma or certificate and university degree, by gender. Highest educational attainment. Source: LFS public-use files.

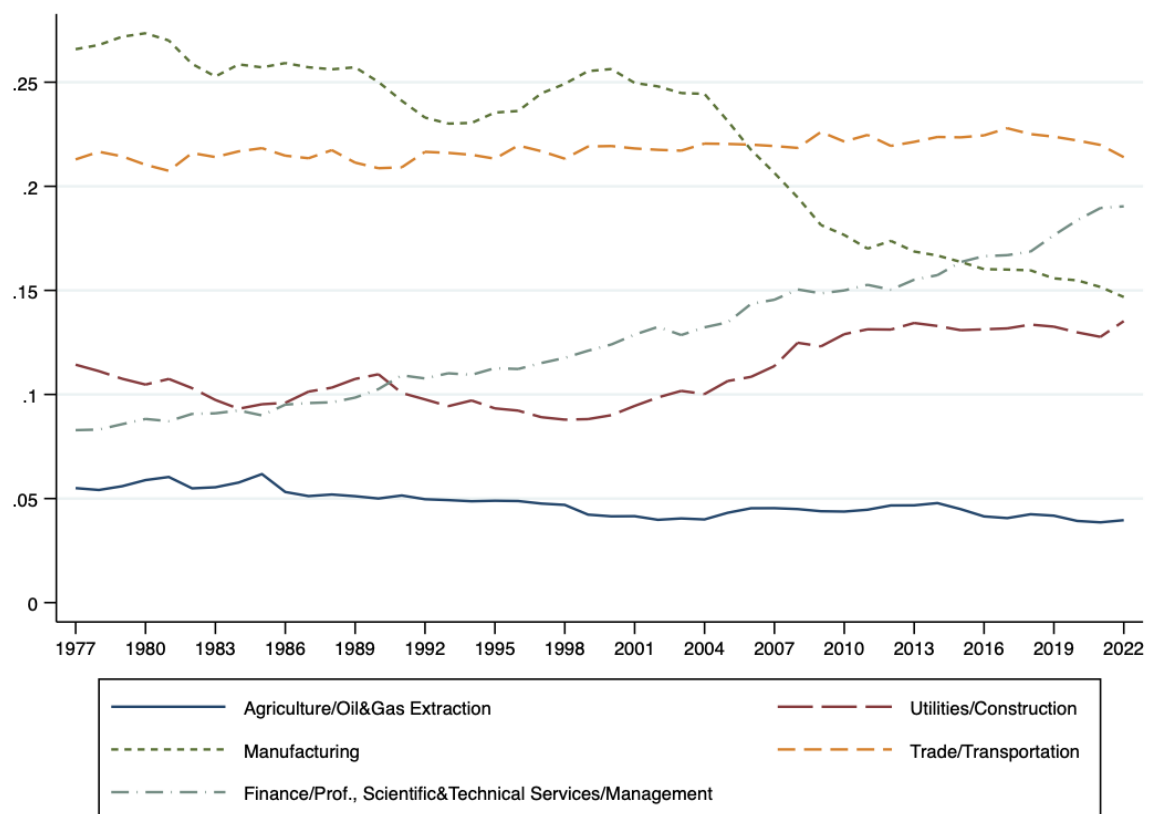


Figure 3.11: Proportion by broad industry classification, NAICS 1-digit codes 1 through 5, male. Source: LFS public-use files.

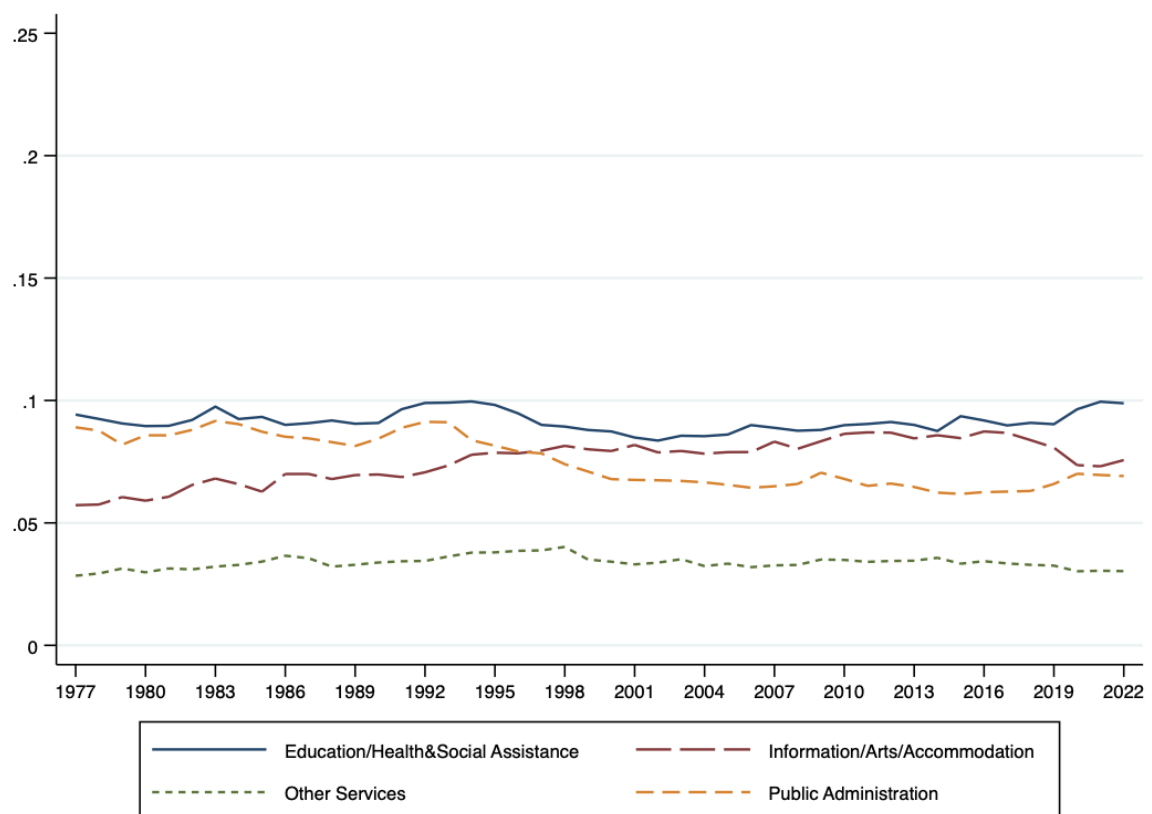


Figure 3.12: Proportion by broad industry classification, NAICS 1-digit codes 6 through 9, male.
Source: LFS public-use files.

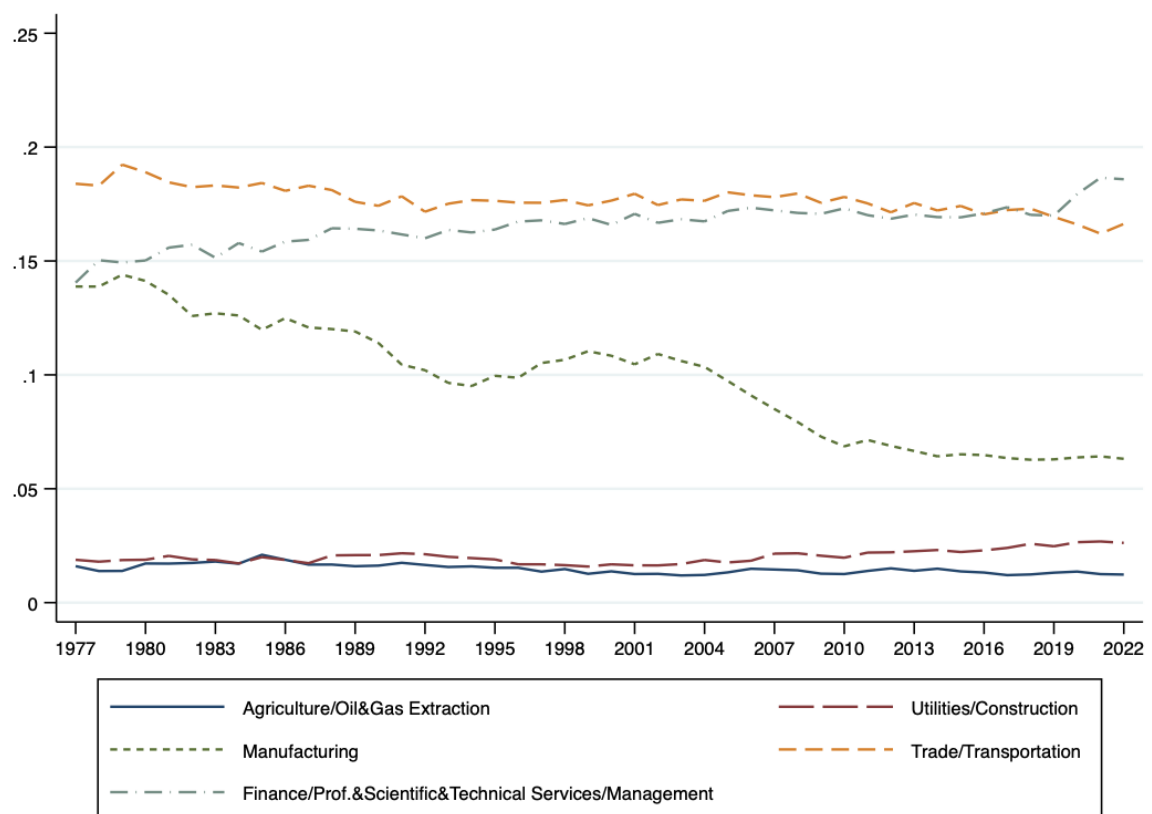


Figure 3.13: Proportion by broad industry classification, NAICS 1-digit codes 1 through 5, female. Source: LFS public-use files.

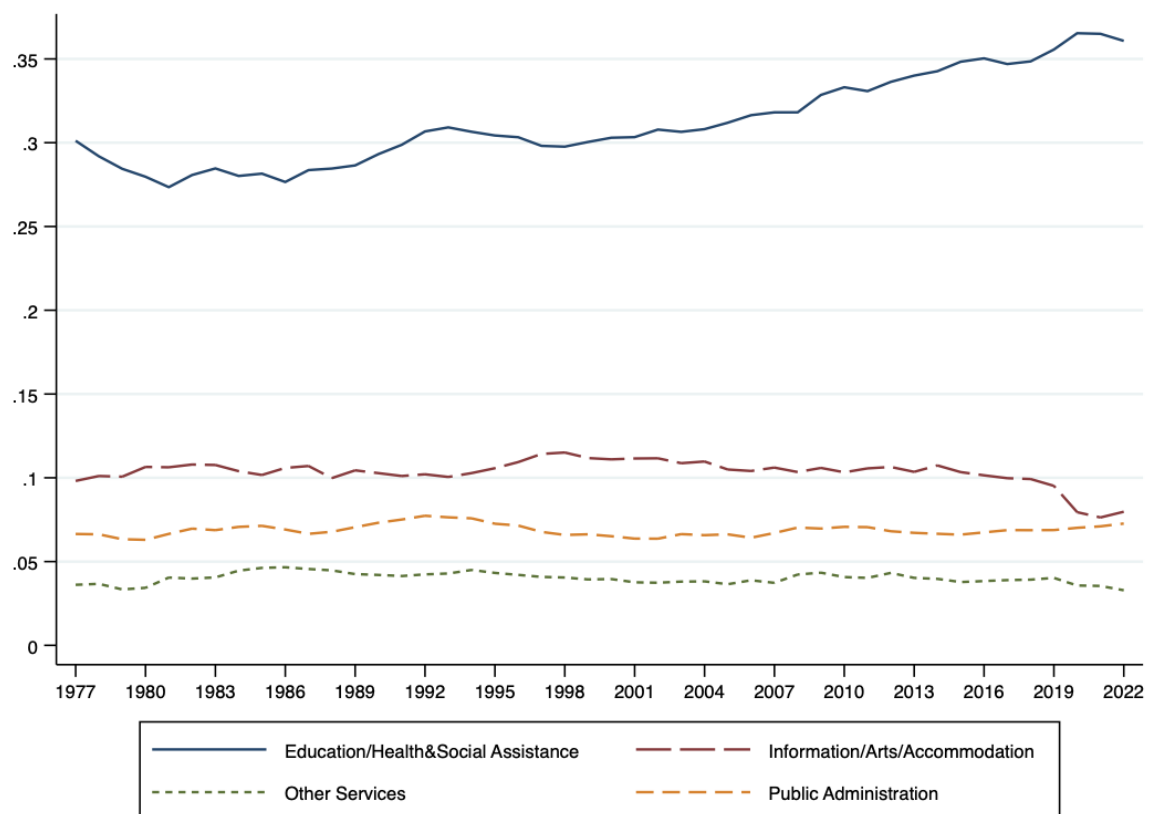


Figure 3.14: Proportion by broad industry classification, NAICS 1-digit codes 6 through 9, female. Source: LFS public-use files.

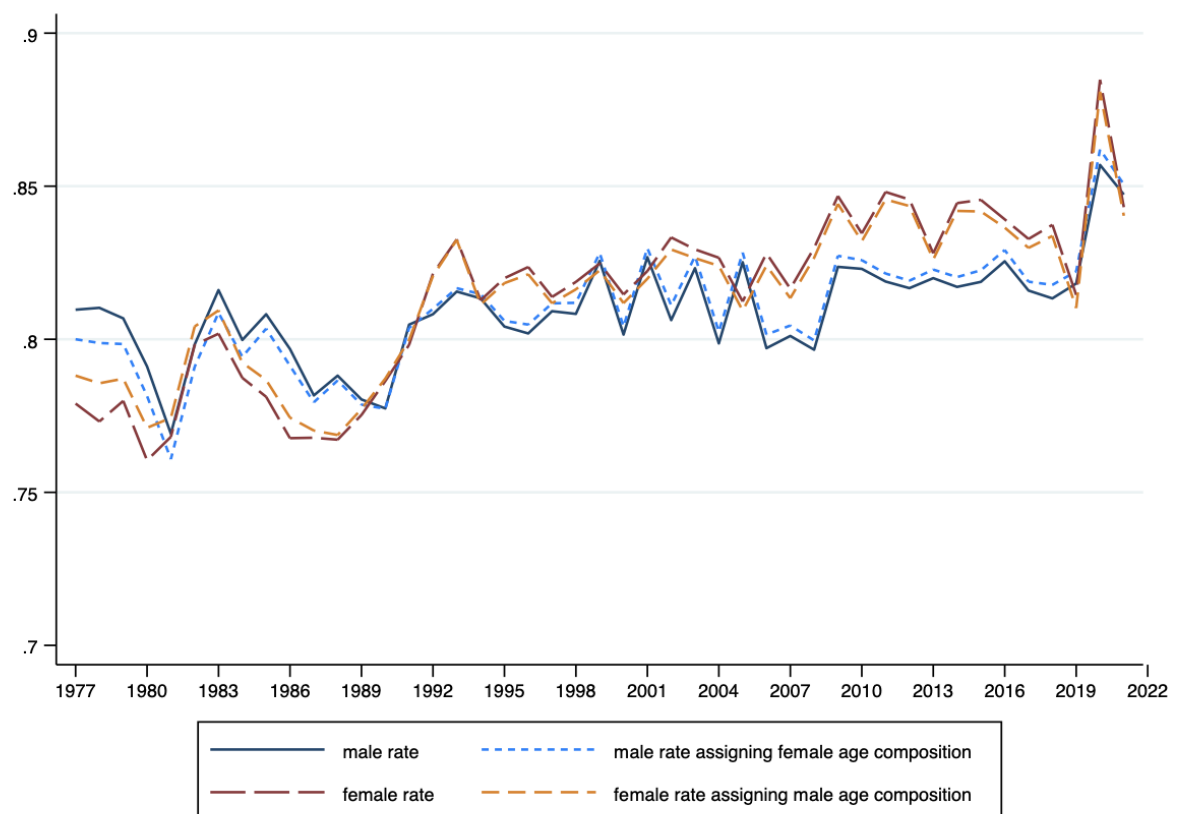


Figure 3.15: One-year retention rate counterfactual, by gender - assigning other gender's age composition. Source: LFS master files.

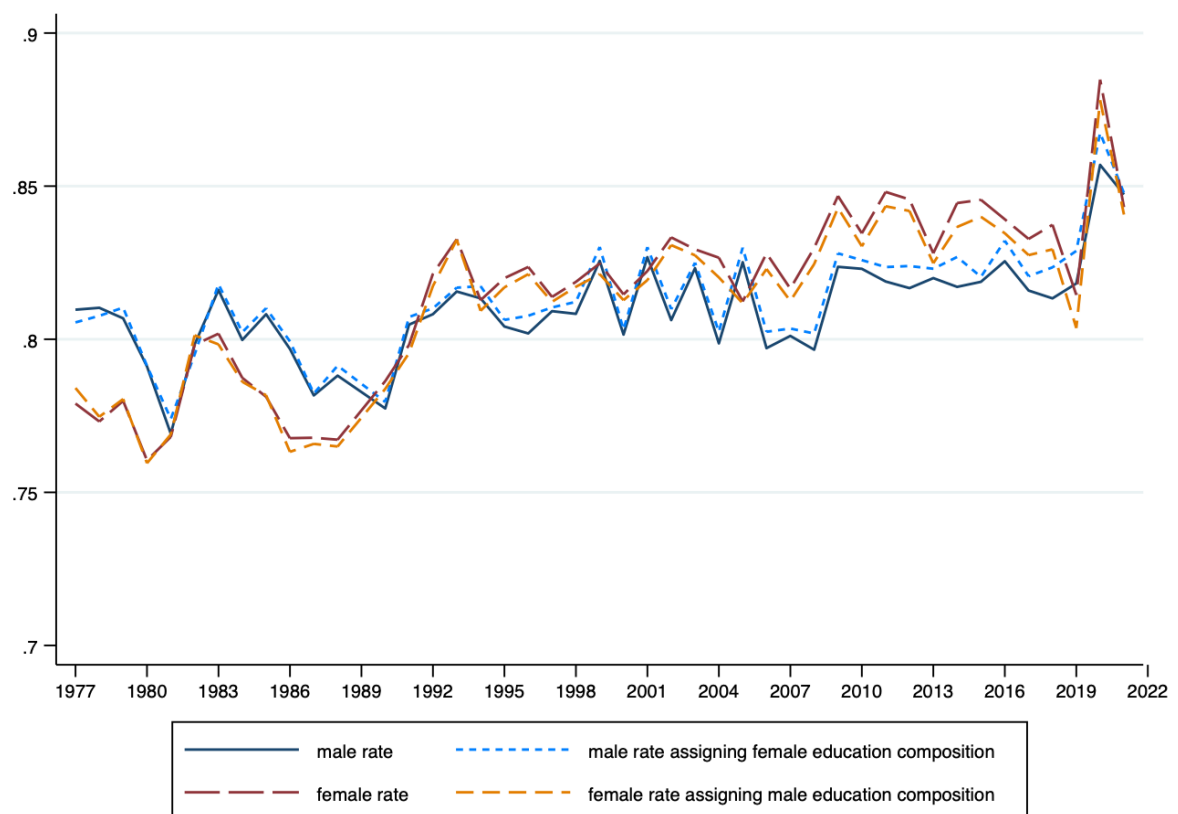


Figure 3.16: One-year retention rate counterfactual, by gender - assigning other gender's education composition. Source: LFS master files.

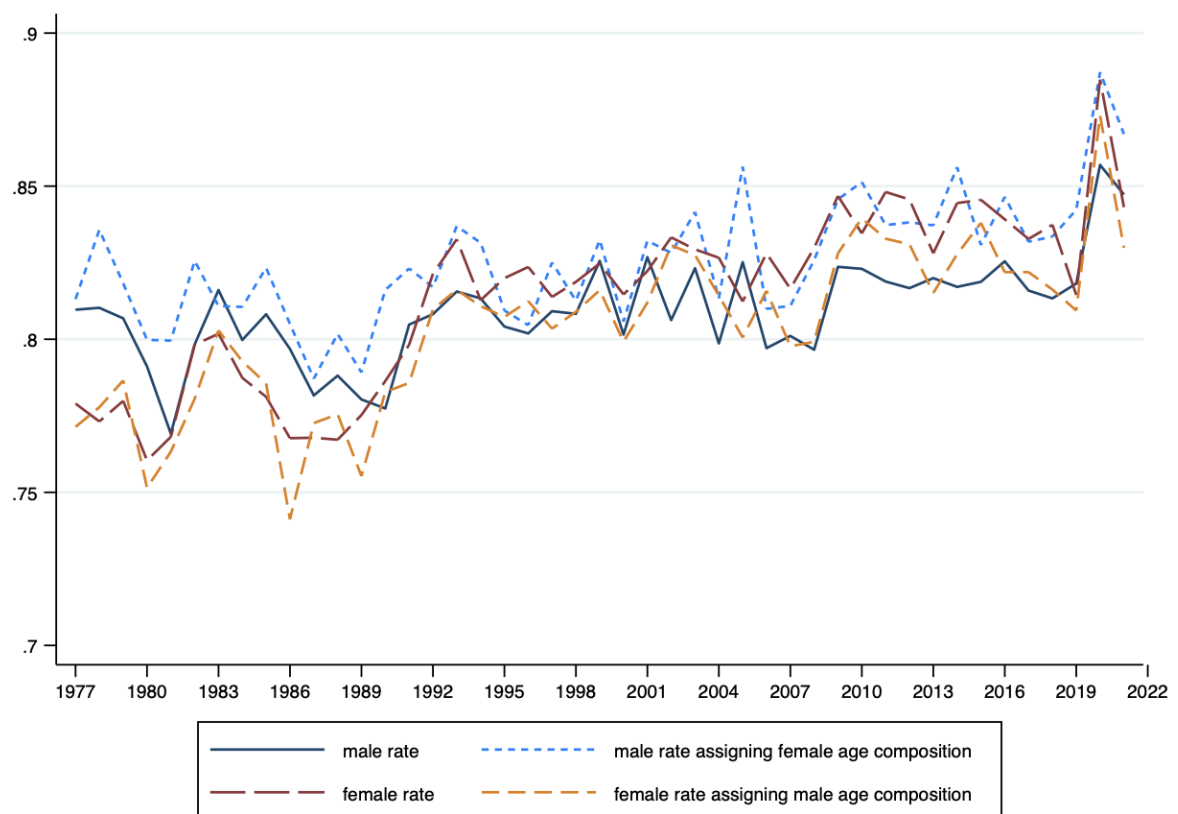


Figure 3.17: One-year retention rate counterfactual, by gender - assigning other gender's industry composition. Source: LFS master files.

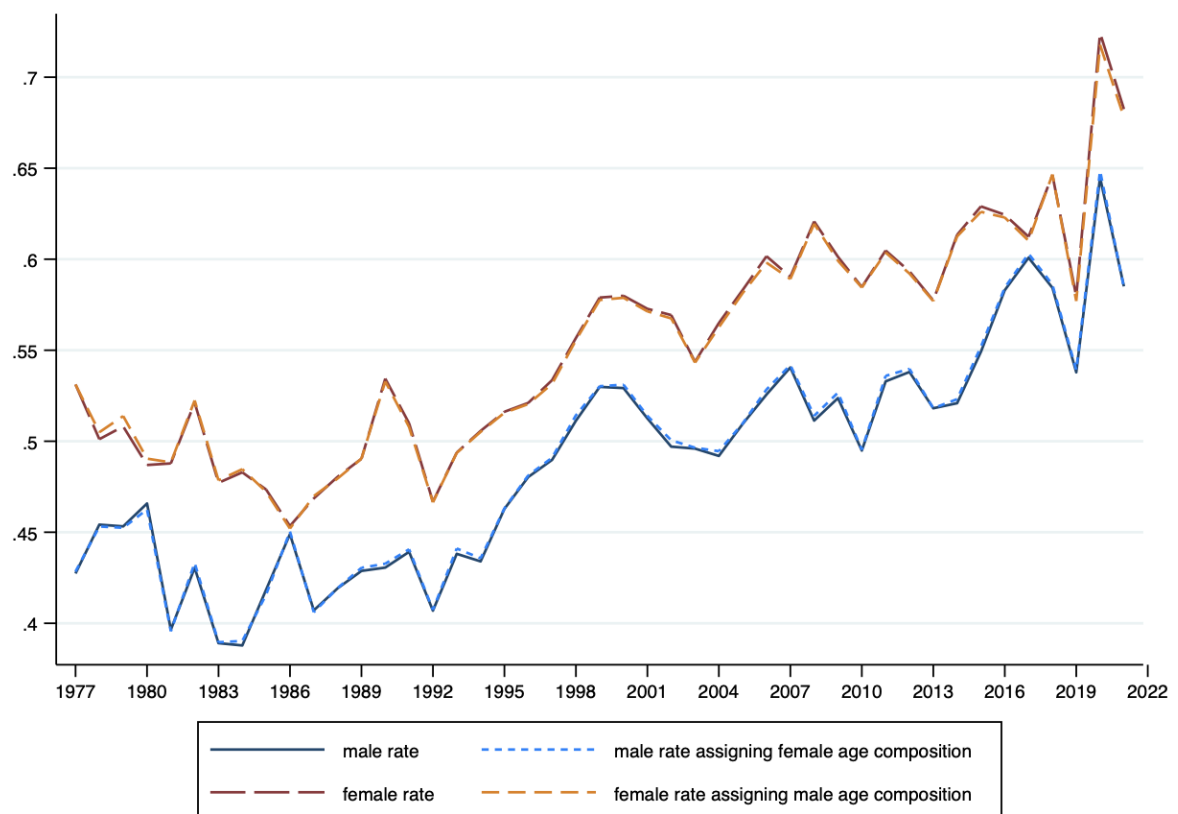


Figure 3.18: One-year retention rate counterfactual, by gender and initial tenure less than one year - assigning other gender's age composition. Source: LFS master files.



Figure 3.19: One-year retention rate counterfactual, by gender and initial tenure less than one year - assigning other gender's education composition. Source: LFS master files.

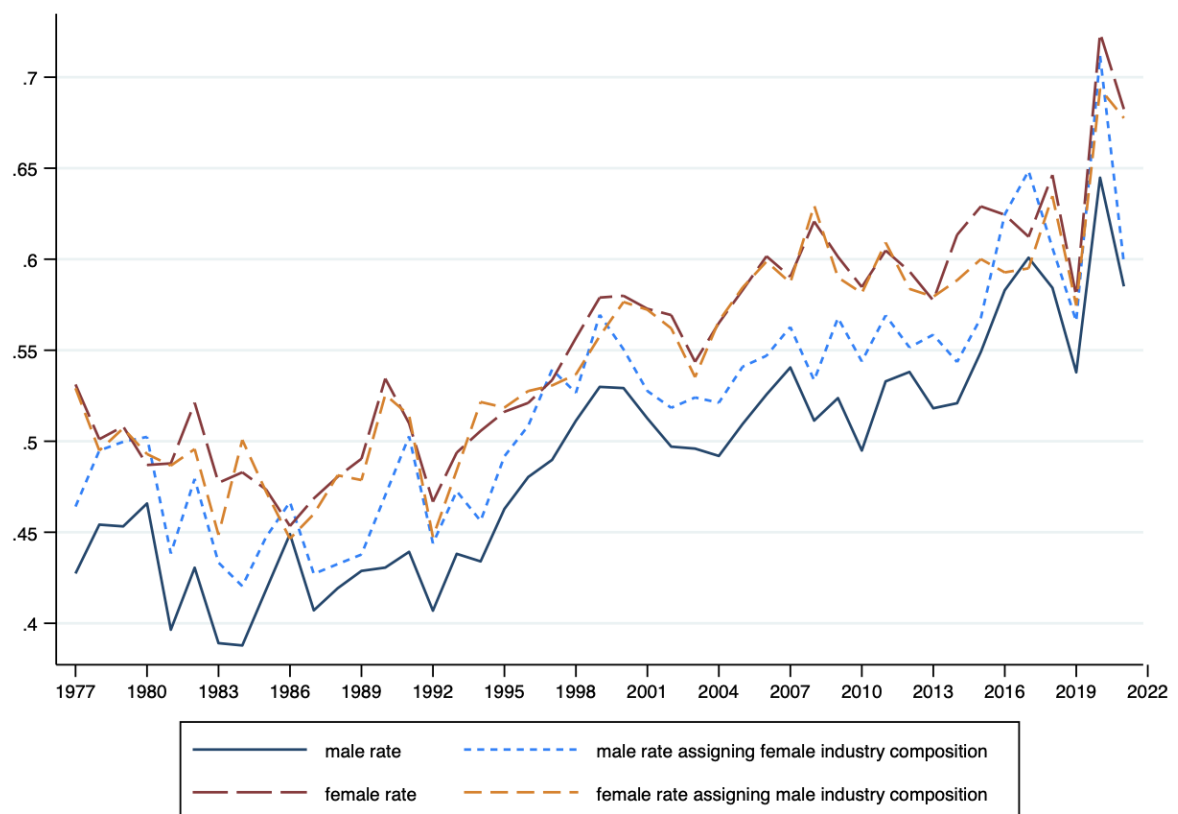


Figure 3.20: One-year retention rate counterfactual, by gender and initial tenure less than one year - assigning other gender's industry composition. Source: LFS master files.

3 Explaining the Canadian Job Stability Gender Gap Puzzle

Table 3.1: Retention results, all tenures

	(1)	(2)	(3)	(4)
<i>1979-1980</i>				
female	-.0121*** (.0005)	-.0107*** (.0005)	-.0122*** (.0005)	-.0160*** (.0006)
N	880,925	880,925	880,925	880,925
<i>1987-1988</i>				
female	-.0048*** (.0006)	-.0044*** (.0006)	-.0061*** (.0006)	-.0095*** (.0007)
N	735,700	735,700	735,700	735,700
<i>1998-1999</i>				
female	.0008 (.0005)	.0003 (.0005)	-.0007 (.0005)	-.0042*** (.0005)
N	782,410	782,410	782,410	782,410
<i>2005-2006</i>				
female	.0002 (.0006)	-.0004 (.0006)	-.0016*** (.0006)	-.0042*** (.0006)
N	733,430	733,430	733,430	733,430
<i>2017-2018</i>				
female	.0007 (.0005)	.0003 (.0005)	-.0012** (.0005)	-.0023*** (.0006)
N	733,235	733,235	733,235	733,235
<i>2014-2018</i>				
female	.0013*** (.0003)	.0008** (.0003)	-.0006* (.0003)	-.0021*** (.0004)
N	1,828,880	1,828,880	1,828,880	1,828,880

Notes. Dependent variable: A binary variable equal to one if the the employed individual stays with the same employer into the next month (and zero otherwise). The full sample consists of individuals who in the first month of the mini-panel are employed individuals between the ages of 20 to 64 living in one of Canada's ten provinces, and exclude full-time member of the Canadian armed forces, full-time students, and returning students over different time periods (i.e., 1979-1980, 1987-1988, 1998-1999, 2005-2006, 2017-2018 and 2014-2018). The same regression is estimated in all cases, but for different control variables. Main independent variable: A binary variable equal to one if the individual is female (and zero otherwise). The control variables in column (1) have a full set of time (month-year) dummies. Column (2) adds five-year age group dummy variables. Column (3) includes four education attainment dummy variables including dropouts, high school (and some post-secondary), post secondary diploma/certificate and university degree, and column (4) continues elaborating North American Industry Classification System (NAICS) 1-digit classification group dummy variables. All regressions are weighted and include a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

Table 3.2: Retention results, tenure less than one year

	(1)	(2)	(3)	(4)
<i>1979-1980</i>				
female	-.0014 (.0018)	-.0020 (.0018)	-.0055*** (.0018)	-.0172*** (.0019)
N	191,690	191,690	191,690	191,690
<i>1987-1988</i>				
female	.0088*** (.0020)	.0085*** (.0020)	.0039** (.0020)	-.0068*** (.0021)
N	176,900	176,900	176,900	176,900
<i>1998-1999</i>				
female	.0120*** (0.0018)	.0111*** (0.0018)	.0079*** (0.0018)	-.0004 (0.0019)
N	149,415	149,415	149,415	149,415
<i>2005-2006</i>				
female	.0081*** (0.0019)	.0076*** (0.0019)	.0048** (0.0019)	-.0012 (0.0021)
N	131,520	131,520	131,520	131,520
<i>2017-2018</i>				
female	.0086*** (.0020)	.0083*** (.0020)	.0041** (.0020)	.0005 (.0021)
N	115,565	115,565	115,565	115,565
<i>2014-2018</i>				
female	.0121*** (.0013)	.0116*** (.0013)	.0078*** (.0013)	.0029** (.0014)
N	287,815	287,815	287,815	287,815

Notes. Dependent variable: A binary variable equal to one if the employed individual with initial tenure less than one year stays with the same employer into the next month (and zero otherwise). The full sample consists of individuals who in the first month of the mini-panel are employed individuals with initial tenure less than one year between the ages of 20 to 64 living in one of Canada's ten provinces, and exclude full-time member of the Canadian armed forces, full-time students, and returning students over different time periods (i.e., 1979-1980, 1987-1988, 1998-1999, 2005-2006, 2017-2018 and 2014-2018). The same regression is estimated in all cases, but for different control variables. Main independent variable: A binary variable equal to one if the individual is female (and zero otherwise). The control variables in column (1) have a full set of time (month-year) dummies. Column (2) adds five-year age group dummy variables. Column (3) includes four education attainment dummy variables including dropouts, high school (and some post-secondary), post secondary diploma/certificate and university degree, and column (4) continues elaborating North American Industry Classification System (NAICS) 1-digit classification group dummy variables. All regressions are weighted and include a constant. Each estimate and the associated standard error is for a different regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%. Source: LFS master files.

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Appendix A

Chapter One Appendices

A.1 Human Capital Model - Card (2001)'s Representation

Within Card (2001)'s representation of the human capital, there are some basic assumptions for the model: First, it assumes a continuous time environment, where individuals are infinitely lived. Second, all individuals are identical. Third, human capital takes the form of schooling and labour market experience. Fourth, there are cost to going to school, which take the form of tuition fee $T(\cdot)$ and a psychic cost of going to school $\phi(\cdot)$ which increases with each additional year of schooling. Fifth, individual makes a once-for-all decision on when to leave school. Sixth, while in school, individuals can work part-time. Individuals can only work full-time when they are done schooling; seventh, part-time income $p(\cdot)$ depends on years of schooling, whereas full-time income $y(\cdot)$ depends both of years of schooling and labour market experience since having left school. Finally, individuals maximize the present discounted value of utility. The utility at time t depends on consumption $c(t)$ in period t and on whether they are in school (and working part time) or out of school and working full time.

The individual's lifecycle utility conditional on schooling S and consumption c profile, is

$$V(S, c(t)) = \int_0^S e^{-\rho t} [u(c(t)) - \phi(t)] dt + \int_S^\infty e^{-\rho t} u(c(t)) dt \quad (\text{A.1})$$

where ρ is the subjective discount factor.

The intertemporal budget constraint is

$$\int_0^\infty e^{-Rt} c(t) dt = \int_0^S e^{-Rt} [p(t) - T(t)] dt + \int_S^\infty e^{-Rt} y(S, t) dt \quad (\text{A.2})$$

where R is the borrowing/lending rate.

The individual maximizes the present discounted value of life time utility, by choosing the schooling level and their consumption profile, subject to the intertemporal budget

constraint. As such, the lagrangian function takes the form

$$\begin{aligned}\Omega(S, c(t), \lambda) = & V(S, c(t)) \\ & - \lambda \left\{ \int_0^\infty e^{-Rt} c(t) dt - \int_0^S e^{-Rt} [p(t) - T(t)] dt \right. \\ & \left. - \int_S^\infty e^{-Rt} y(S, t) dt \right\}\end{aligned}\tag{A.3}$$

The first order condition of this expression with respect to S is

$$\begin{aligned}\Omega_S = & e^{-\rho S} [u(c(S)) - \phi(S) - u(c(S))] \\ & - \lambda e^{-RS} [-p(S) + T(S) + y(S, S)] \\ & + \lambda \int_S^\infty e^{-Rt} \cdot \frac{\partial y(S, t)}{\partial S} dt \\ = & \lambda e^{-RS} [MB(S) - MC(S)]\end{aligned}\tag{A.4}$$

The optimal level of schooling will satisfy

$$MB(S) = MC(S)\tag{A.5}$$

where

$$MB(S) = \int_0^\infty e^{-R\tau} \cdot \frac{\partial y(S, S + \tau)}{\partial S} d\tau \quad \text{and}\tag{A.6}$$

$$MC(S) = y(S, S) - p(S) + T(S) + \frac{1}{\lambda} e^{-(\rho-R)S} \phi(S)\tag{A.7}$$

and where $\tau = t - S$ is labour market experience.

In the human capital model, schooling (i.e., $S(\cdot)$) is one endogenous variable, and individuals decide the optimal $S(\cdot)$. schooling and working experience together decides the full time wage (i.e., $Y(\cdot)$). In another word $Y(\cdot)$ is an intermediate variable. After the first order derivation, it will find the optimal schooling. There are several exogenous variable which can change the marginal benefit or the marginal cost and change the optimal schooling time. The exogenous variables include the cost of going to school which is explicit cost $T(\cdot)$ (such as tuition fee, renting and commuting cost), no matter for that, from the economic point of view, the cost of going to school also need to consider the implicit cost of going to school which can be treated as a part of the opportunity cost, such as the potential benefit of not going to school, that is the potential working income in the labour market. In addition, another exogenous variable is a psychic cost of going to school (i.e., $\phi(\cdot)$), it measures the disutility of going to school versus work.

Now, it can be found how the exogenous variables $T(\cdot)$ and $\phi(\cdot)$ change will influence the endogenous variable of schooling. First, if $T(\cdot)$ increases, the marginal cost MC will increase, and in order to reach the necessary optimal condition, the MB will also increase, and it will lead the optimal schooling to be decreased. Second, if $\phi(\cdot)$ increases, it will lead the marginal cost MC to increase, and in order to reach the necessary optimal condition, the MB will also increase, and it will lead the optimal schooling choice to be decreased.

A.2 Appendix Figures and Tables

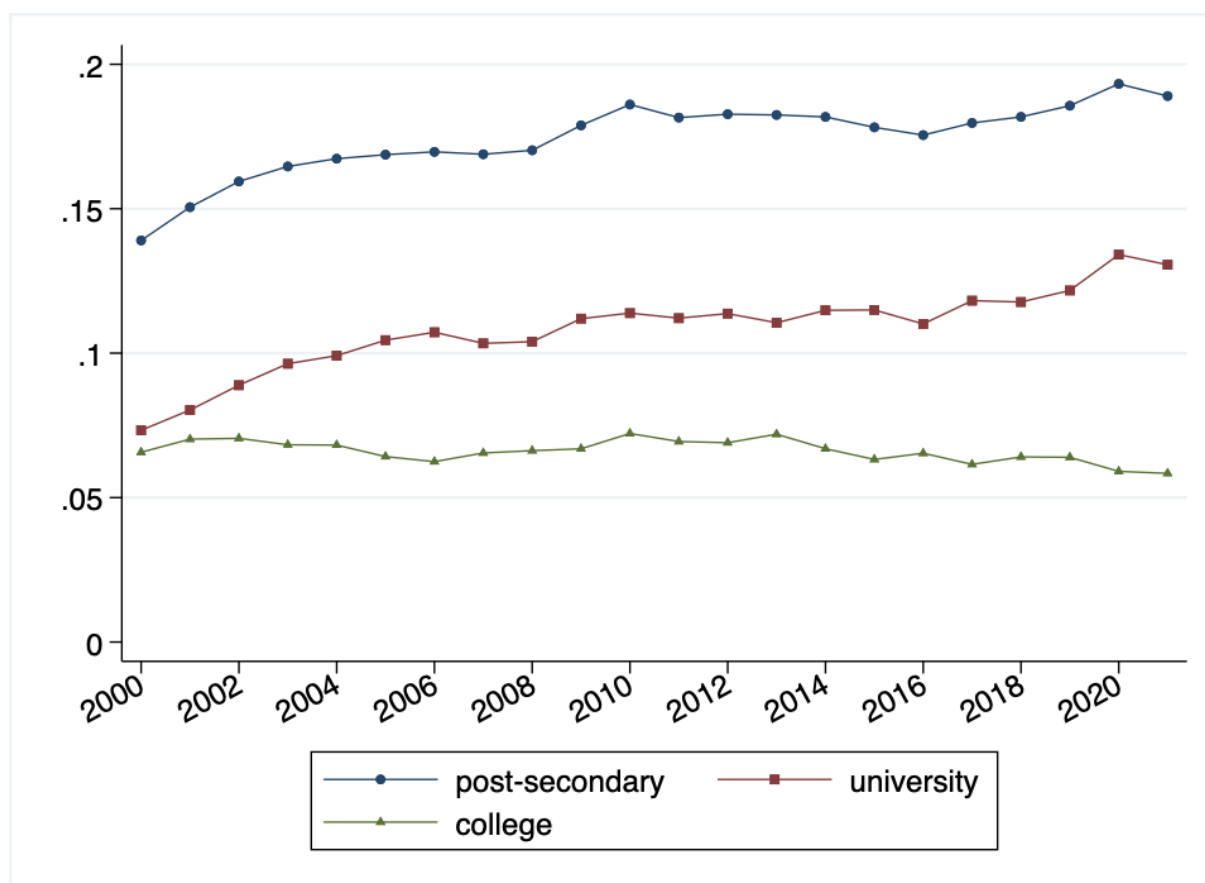


Figure A.1: Post-secondary enrolment rate, 17-39, 2000-2021 (Sep. only), by institution type.
Source: LFS master files.

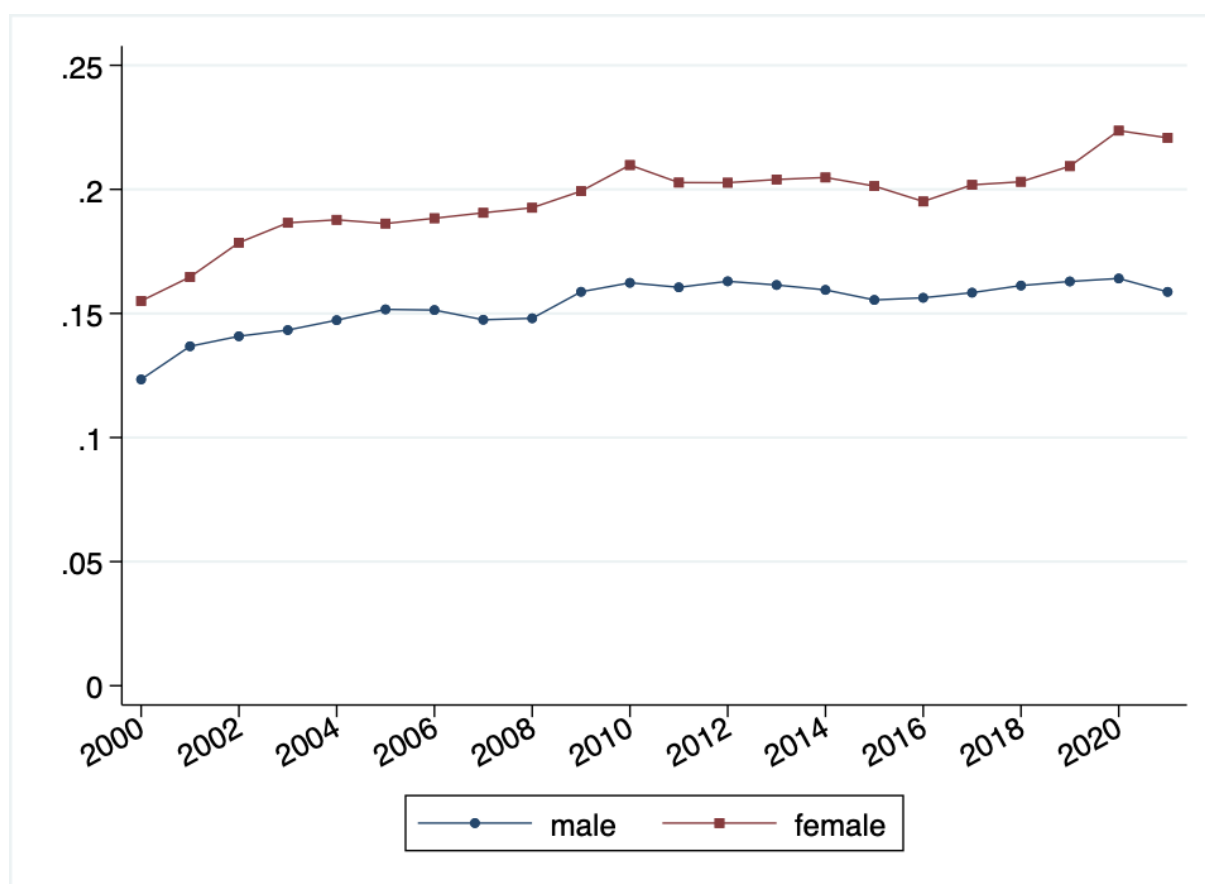


Figure A.2: Post-secondary enrolment rate, 17-39, 2000-2021 (Sep. only), by gender. Source: LFS master files.

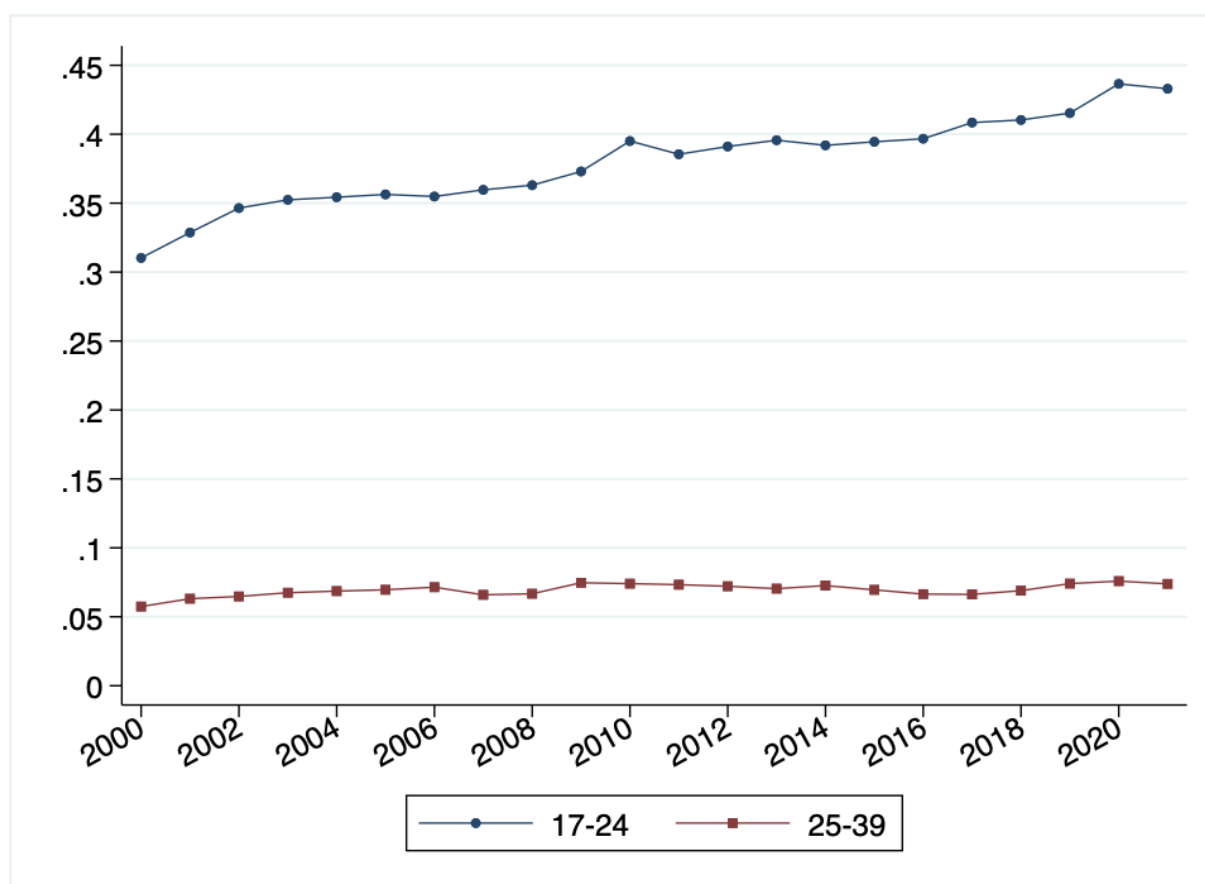


Figure A.3: Post-secondary enrolment rate, 17-39, 2000-2021 (Sep. only), by age group. Source: LFS master files.

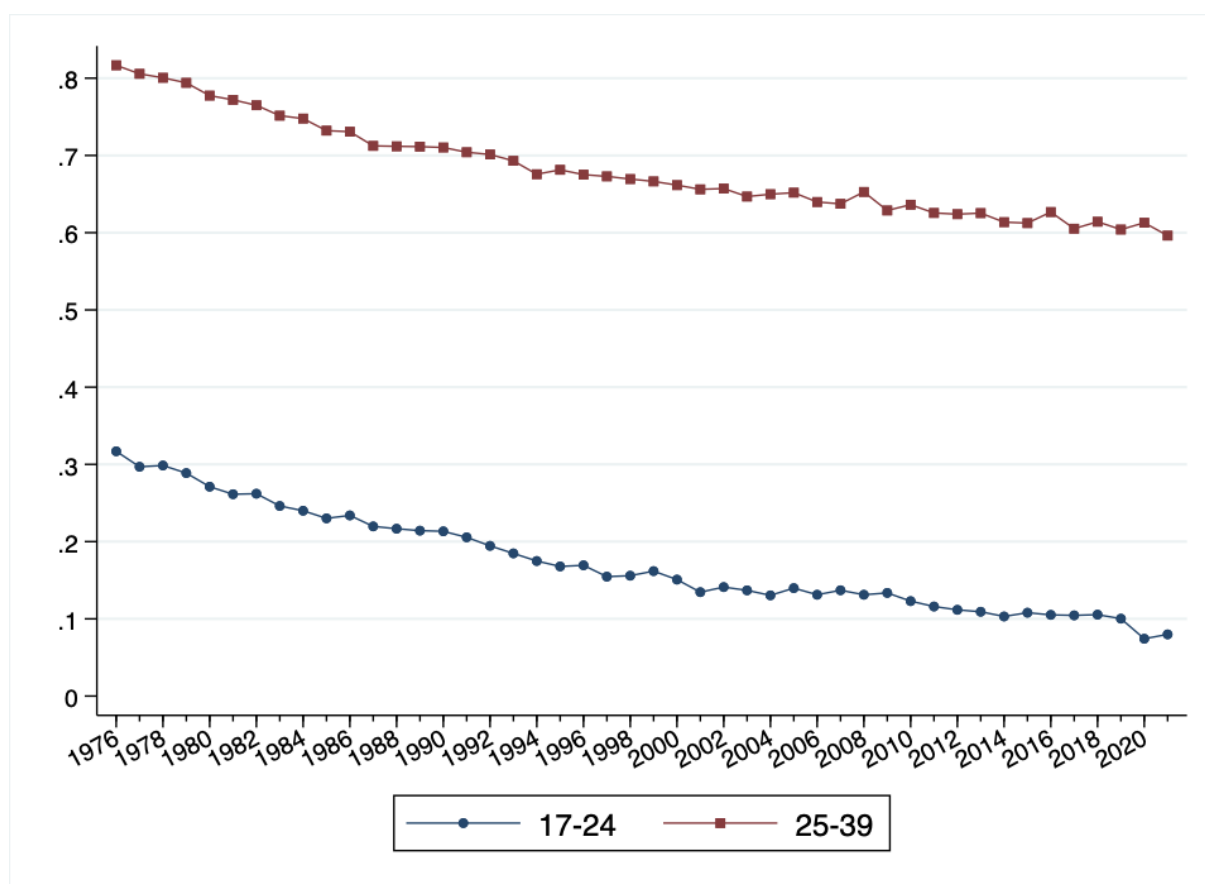


Figure A.4: Marriage rate, 17-39, 1976-2021 (Sep. only), by age group. Notes: Married and common-law relationships are both considered married. Source: LFS public-use files.

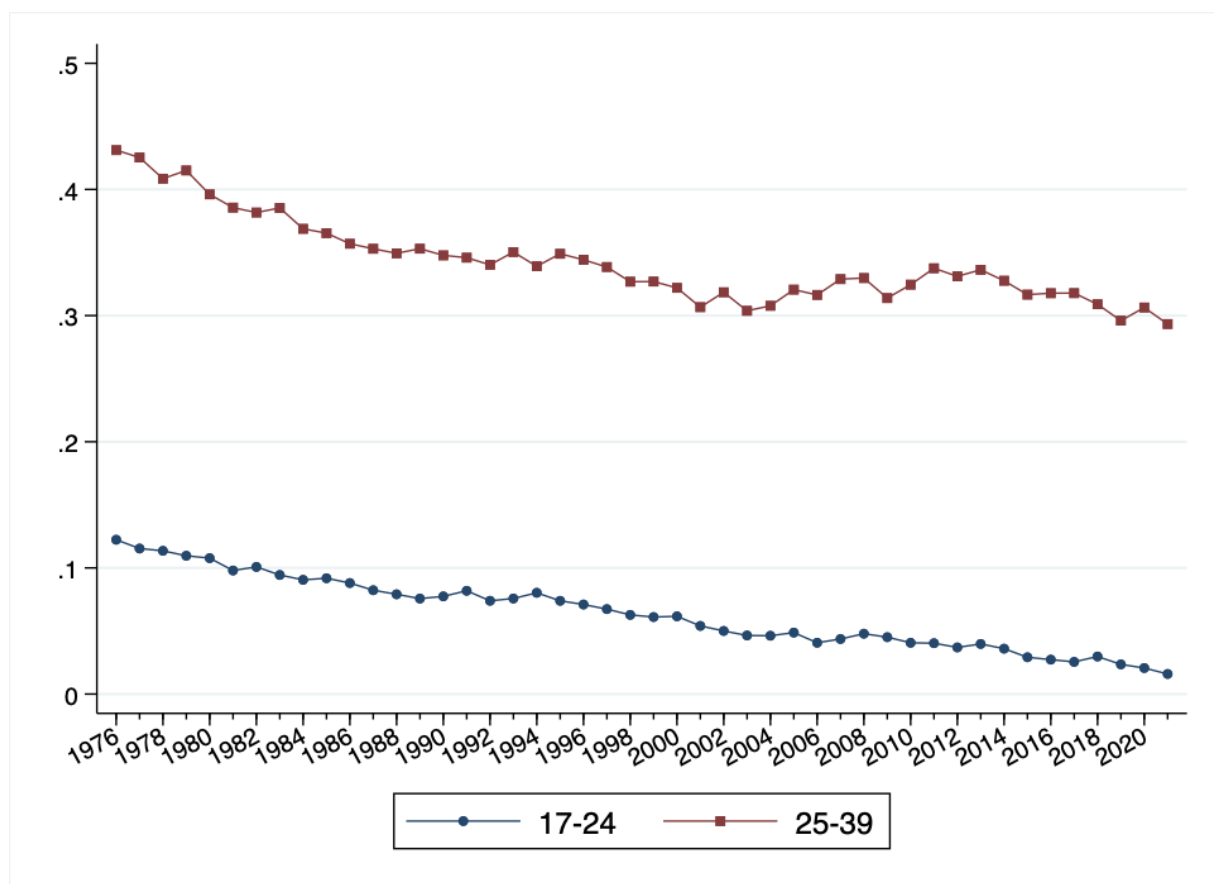


Figure A.5: Proportion with a young child (0-5) at home, 17-39, 1976-2021 (Sep. only), by age group. Source: LFS public-use files.

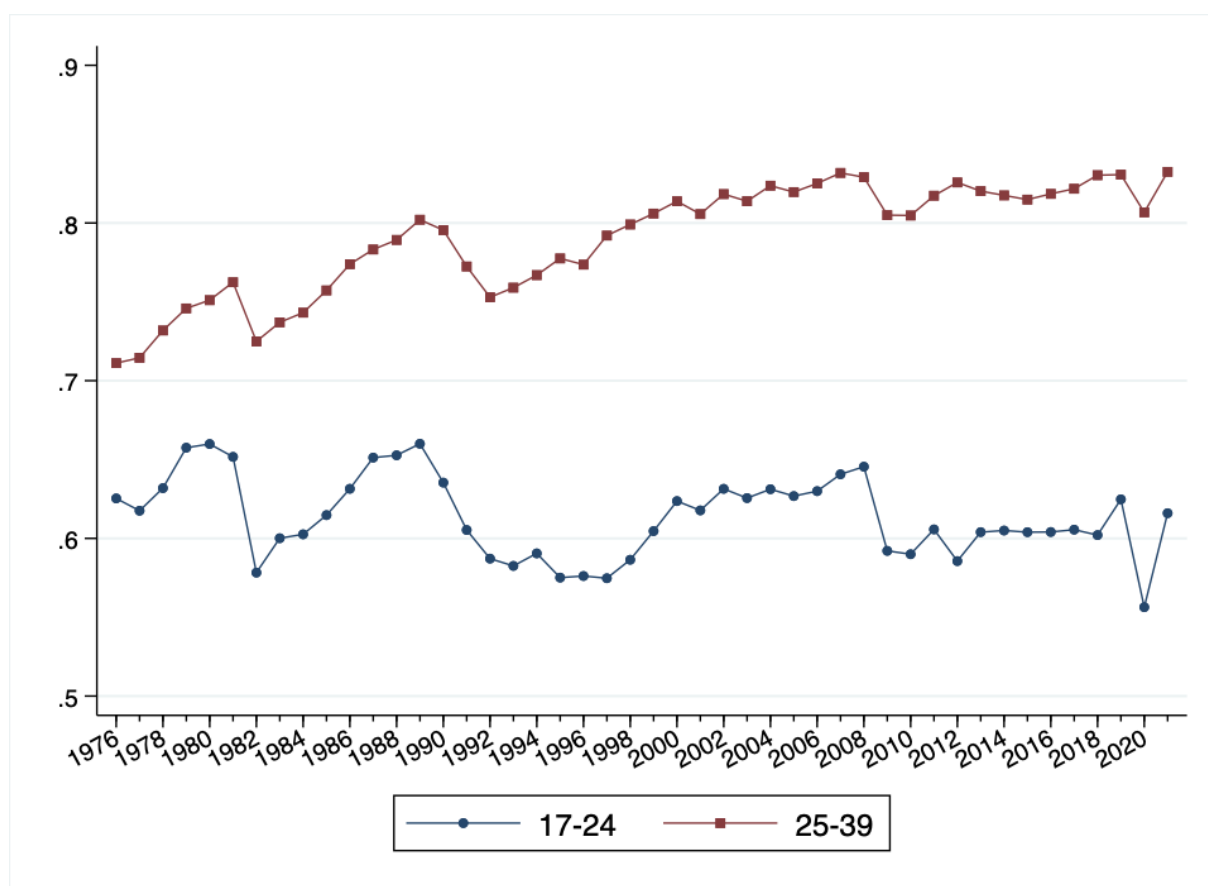


Figure A.6: Employment rate, 17-39, 1976-2021 (Sep. only), by age group. Source: LFS public-use files.

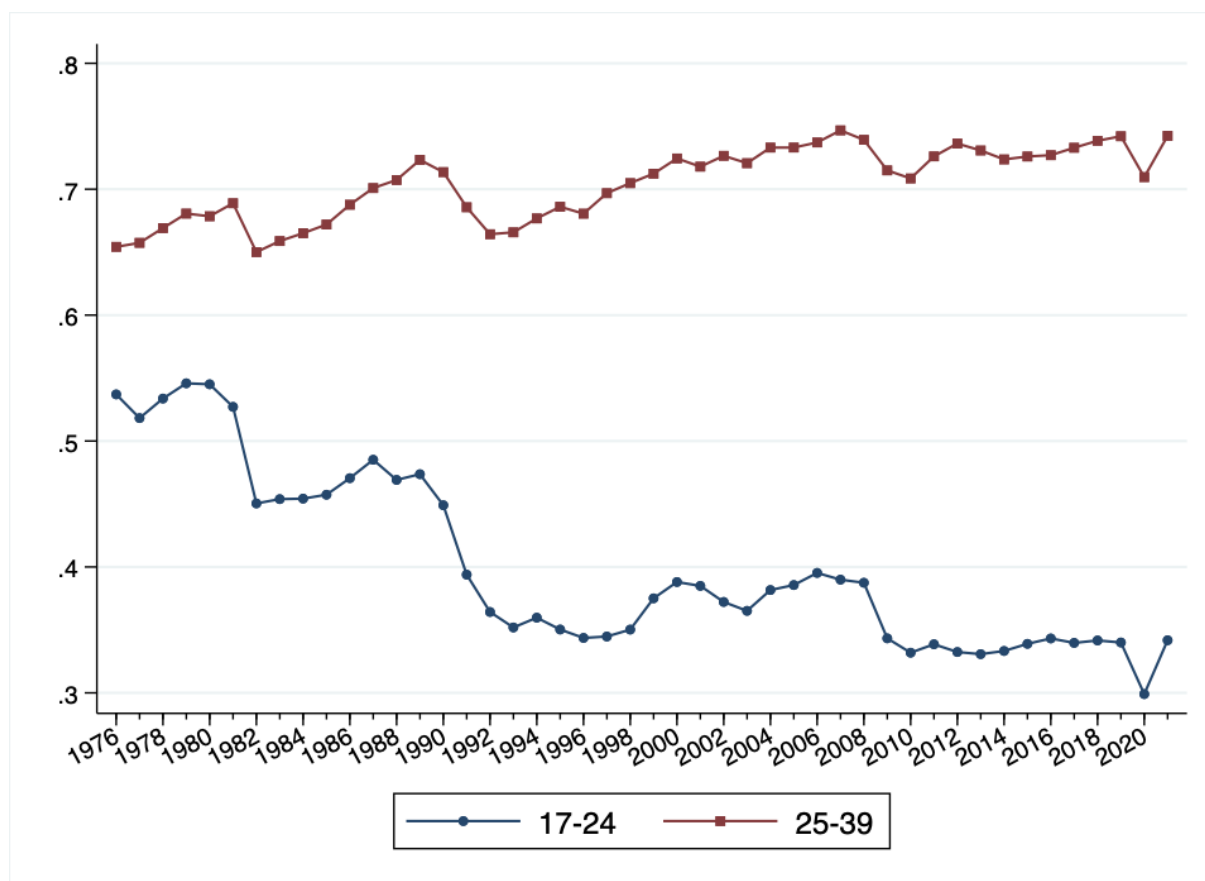


Figure A.7: Full-time employment rate, 17-39, 1976-2021 (Sep. only), by age group. Notes: Employment is considered full-time if the individual's usual hours at all jobs is 30 hours or more. Source: LFS public-use files.

Table A.1: Probit model: Post-secondary enrolment results

	17-39		17-24		25-39	
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	.011*** (.004)	.003 (.005)	.019*** (.006)	.022** (.009)	.015 (.013)	.031** (.014)
N	145,818	72,522	73,296	45,686	23,612	22,074
				100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a post-secondary institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and associated standard error is for a different probit regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.2: Probit model: College enrolment results

	17-39			17-24			25-39		
	All	Male	Female	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
COVID	.001 (.002)	.000 (.003)	.003 (.004)	.001 (.006)	.001 (.009)	.001 (.009)	.002 (.002)	.000 (.002)	.004 (.003)
N	145,818	72,522	73,296	45,686	23,612	22,074	100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a college institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and associated standard error is for a different probit regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.3: Probit model: University enrolment results

	17-39		17-24		25-39	
	All	Male	Female	All	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
	(7)	(8)	(9)	(10)	(11)	(12)
COVID	.010** (.004)	.003 (.005)	.017*** (.005)	.023** (.009)	.014 (.012)	.033** (.014)
N	145,818	72,522	73,296	45,686	23,612	22,074
				100,132	48,910	51,222

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 39 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and associated standard error is for a different probit regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.4: Probit model: University enrolment results, female, 25-39, by labour market characteristics

	All	Not Employed	Employed		Employed		Employed		Other	Post-sec. Educ.	Other
			All	Full-time	Part-time	High Skilled Occup.	Other	Other			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
COVID	.011** (.004)	.016 (.011)	.010** (.004)	.008* (.004)	.026* (.015)	.015** (.007)	.004 (.005)	.009 (.005)	.008 (.006)		
N	51,222	10,741	40,481	32,991	7,490	19,137	21,344	29,673	10,808		

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of females born in Canada or is (or ever was) a landed immigrant, 25 to 39 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). High skilled occupations (i.e., column (6)) are the broad occupational categories where there is a high prevalence of graduate degrees. Post-secondary education (i.e., column (8)) refers to those that have attained a post-secondary certificate, diploma or degree. All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and associated standard error is for a different probit regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.5: Probit model: University enrolment results, female, 25-39, by type of work and presence of young children at home

	Employed		All		Employed	
	Remote Work	Other	Young Child	Other	Young Child	Other
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	.014* (.008)	.008 (.005)	.004 (.005)	.012** (.006)	.006 (.005)	.011* (.006)
N	13,558	26,923	18,864	32,358	13,746	26,735

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of females born in Canada or is (or ever was) a landed immigrant, 25 to 39 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). Remote work occupations (i.e., column (1)) are the occupations that are carried out remotely, and young children (i.e., columns (3) and (5)) refers to those individuals who have a young child under the age of six at home. All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and the associated standard error is for a different probit regression. Heteroskedasticity-robust standard errors are in parentheses. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.6: Probit model: University enrolment results, 17-24, by age group and labour market characteristics

	Female					Male				
	All	Not Emp.	Emp.	Emp. Full-time	Emp. Part-time	All	Not Emp.	Emp.	Emp. Full-time	Emp. Part-time
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Panel A: Teenagers</i>										
COVID	.069*** (.020)	.055* (.030)	.085*** (.025)	.131** (.051)	.088*** (.028)	.011 (.017)	-.022 (.025)	.046** (.021)	-.001 (.015)	.088*** (.029)
N	8,604	4,099	4,505	974	3,480	9,125	4,647	4,478	1,774	2,704
<i>Panel B: Young adults</i>										
COVID	.018 (.017)	.033 (.032)	.017 (.019)	.021 (.018)	.045 (.035)	.016 (.016)	-.005 (.031)	.023 (.016)	-.002 (.011)	.036 (.041)
N	13,470	4,444	9,026	5,452	3,574	14,487	4,629	9,858	7,536	2,322

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 24 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and the associated standard error is for a different probit regression. The number of observations may be dropped because some provinces or marriage status predict failure perfectly. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.7: Probit model: Full- and part-time university enrolment results, 17-19, by gender and labour market characteristics

Female						Male				
All	Not Emp.	Emp.	Emp.	Emp.		All	Not Emp.	Emp.	Emp.	Emp.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
<i>Panel A: Full-time enrolment</i>										
COVID	.059***	.045	.074***	.114**	.082***	.009	-.021	.041*	.000	.080**
	(.020)	(.030)	(.025)	(.048)	(.028)	(.017)	(.025)	(.021)	(.013)	(.028)
N	8,604	4,099	4,505	836	3,480	9,125	4,647	4,478	1,774	2,704
<i>Panel B: Part-time enrolment</i>										
COVID	.010**	.015	.010*	.054	.005	.002	-.001	.006	-.002	.010
	(.005)	(.011)	(.006)	(.049)	(.004)	(.004)	(.003)	(.007)	(.010)	(.011)
N	8,381	2,623	4,395	650	3,402	7,682	3,868	3,462	1,104	2,011

Notes. Dependent variable: In panel A, a binary variable equal to one if the individual is enrolled in a full-time university institution (and zero otherwise). In panel B, a binary variable equal to one if the individual is enrolled in a part-time university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 19 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). All regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and the associated standard error is for a different probit regression. The number of observations may be dropped because some provinces or marriage status predict failure perfectly. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.8: Probit model: University enrolment results, 17-18, by economic family earnings

	Women			Female			Male			Member of the Parents' Dwelling			Male				
	Member of the Parents' Dwelling			Female			Male			Member of the Parents' Dwelling			Male				
	All	p75	p50	p25	All	p75	p50	p25	All	p75	p50	p25	All	p75	p50	p25	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)							
COVID	.081*** (.023)	.066** (.024)	.063** (.028)	.077** (.033)	.116** (.052)	.027 (.018)	.012 (.019)	-.013 (.024)	-.002 (.031)	-.035 (.038)							
N	5,819	5,284	3,395	2,197	1,128	6,230	5,706	3,588	2,245	1,116							

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a university institution (and zero otherwise). The full sample consists of individuals born in Canada or is (or ever was) a landed immigrant, 17 to 18 years of age, over the 2017-2021 period (Sep. data only). The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). Living at home means the respondent's relationship to the reference person is son or daughter, grandchild, son/daughter-in-law, or foster child. p75, p50 and p25 indicate subsamples of teenagers whose economic family earnings are below the 75th percentile, 50th percentile, and 25th percentile. All probit regressions include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and the associated standard error is for a different probit regression. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Table A.9: Probit model: University enrolment results, 17-18, by geographical area

	All		All		CMA*/CA*		CMA*		CMA*	
	Urban (1)	Rural (2)	CMA*/CA* (3)	Other (4)	Core (5)	Other (6)	Core (7)	Other (8)		Sec. Core (9)
<i>Panel A: Female</i>										
COVID	.087*** (.027)	.043 (.035)	.085*** (.028)	.041 (.032)	.086** (.030)	.077 (.064)	.090*** (.031)	.082 (.073)	.335** (.157)	
N	4,287	1,532	3,780	2,039	3,016	764	2,790	625	54	
<i>Panel B: Female, bottom 75th percentile of family income</i>										
COVID	.069** (.031)	.058 (.040)	.069** (.032)	.052 (.039)	.048 (.036)	.168** (.071)				
N	2,739	1,011	2,355	1,395	1,906	445				
<i>Panel C: Male</i>										
COVID	.031 (.022)	.012 (.025)	.041* (.024)	-.002 (.023)	.043 (.027)	.038 (.045)	.045 (.028)	.022 (.049)	.026 (.139)	
N	4,652	1,578	4,055	1,808	3,232	821	2,923	695	94	
<i>Panel D: Male, bottom 75th percentile of family income</i>										
COVID	.004 (.036)	.016 (.027)	.018 (.031)	-.014 (.024)	.014 (.047)	.046 (.049)				
N	2,407	1,027	2,490	1,159	1,663	502				

Notes. Dependent variable: A binary variable equal to one if the individual is enrolled in a full-time university institution (and zero otherwise). The sample in Panel A consists of female individuals born in Canada or is (or ever was) a landed immigrant, 17 to 18 years of age, over the 2017-2021 period (Sep. data only). The samples in Panel B is restricted to female respondents whose family income is in the bottom 75th percentile. Panels C and D are similarly defined, but for males. The same probit regression is estimated in all cases, but for different subsamples (as identified in the column heading). CMA and CA are census metropolitan area and census agglomeration, respectively. The LFS uses the 2016 Census of Population geographical definitions where the core is defined as the population centre with the largest population around which a CMA or CA is delineated. The core of CMA must have a population of at least 40,000, whereas for a CA it must be in the 10,000-39,999 range. A secondary core is a population centre with 10,000 or more individuals within a CMA (and in many cases has much more), that is not situated in the core. CMAs and CAs can only have one (primary) core, but given their sizes CMAs can have multiple secondary cores. The CMA* and CA* notations designate CMAs and CAs that have a university within their boundaries. All probit regressions are weighted and include a married binary variable, age and age squared, the unemployment rate, province fixed effects and a constant. Each marginal effect estimate of COVID and the associated standard error is for a different probit regression. The number of observations may be dropped because some provinces or marriage status predict failure perfectly. Some results are empty because of the confidential requirements from the ORDC centre. Heteroskedasticity-robust standard errors are in parenthesis. * significant at 10%; ** significant at 5%; ***significant at 1%. Source: LFS master files.

Appendix B

Chapter Two Appendices

B.1 Two Month Mini-panels

Although the LFS consists of rolling panels where households remain in the survey for six-consecutive months and one-sixth of the households are replaced every month, it is not a panel per se. In fact, the LFS follows dwellings. The LFS will only follow a household as long as it remains within the selected dwelling. If a household moves out partway through the six-month window, it is beyond the scope of the survey. The LFS will then focus on the new household that replaces it for the remaining months the dwelling is part of the survey.¹ Having said this, one can nonetheless follow individuals that remain in the survey for two months or more using the unique household identifier (HHLDID) and the identifier that uniquely identifies a person within a household (LINE).² One needs to make an adjustment to the household identifier before merging the data. The household identifier is actually made up of 10 variables, and the way the LFS records one of these variables, i.e., MULT which identifies structures that have more than one dwelling, has changed starting in January 2006. As such, the LFS states that one must replace blanks in the MULT variable with '0' when matching dwellings from before 2006 to after 2006.³

For the two-months mini-panels, we impose the following sample restrictions:

First, we drop individuals that do not have information for both periods 1 and 2 of the mini-panels. The main culprit is the survey's rolling panel design; one does not have two periods of data for households that rotates-in or out of the survey partway through the panel. As such, when constructing two consecutive month mini-panels we must drop one rotation out of six, which represents approximately one-sixth of the sample.⁴ Other reasons

¹The same holds true if some, but not all, individuals in the household leave the selected dwelling. In this case the LFS will continue interviewing those that stayed, but not those that left the dwelling.

²The panel structure of the LFS has been relied upon to look at a wide variety of topics. See [Brochu \(2021\)](#) for examples.

³This modification, however, generates non-uniqueness in the person identifier for some (not many) month-year. These observations are dropped.

⁴An example will better illustrate this point. Households in rotation group 1 enter the survey in January of each year, and have their sixth and last interview in June of that same year. A new batch of households (also referred to as rotation 1) will be part of the survey from July to December. As such, one will need to drop rotation group 1 households when constructing the December-January and June-July mini-panels as it is not the same household in both periods of the mini-panels. For mini-panels where the periods are three month apart, which we rely upon in our robustness checks, one would lose three rotations out of six.

(of second-order importance) include: individuals moving out or in partway through the panel, the matching across periods was poor due to difficulties with the matching variables, or there were ‘unusual circumstances’ which meant that no information could be collected in one of the two periods.

Second, we remove individuals for which there is household or person non-response where whole record imputation or complete carrying forward of labour market information is performed. We do so because the tenure information in such a case will not reflect the actual tenure status of the individual. In the case of complete carrying forward (carried out prior to 2005), tenure is automatically increased by one month if the individual was employed (and answered the survey) in the previous month. In the case of full-record imputation (carried out since 2005) he/she is given the tenure of a ‘donor’, again only if the person answered the survey in the previous month. This issue is also of second-order importance. Person/household non-response was very low prior to the advent of COVID-19, and even when it did go up during COVID-19 full-record imputation is only performed in a minority of non-response cases (i.e., the household had to have answered in the previous month).

Third, following [Brochu and Green \(2013\)](#), We drop individuals who have incompatible tenure spells across the two periods of the mini-panel. In the case of the two consecutive months mini-panels it means the following: an individual that worked in period 1, he/she must have one more month of tenure in period 2 (i.e., continued with the same employer), no job tenure in period 2 (i.e., is out of work), or one month of tenure in period 2 (i.e., started a new job). As with [Madrian and Lefgren \(1999\)](#), we also remove individuals that have inconsistencies along the gender and age dimensions. Socio-demographic information is only asked of the birth/initial interview. As such, one should not observe a gender change across the two periods. For age, it is a little more complicated as the LFS asks the birth date (day, month and year) in the initial interview. One can therefore observe an increase of one year in the respondent’s age from period 1 to period 2, but one should not observe a drop in age, or an increase of two or more years. These incompatibilities/inconsistencies are of minor importance.

Finally, the minimum conditioning characteristics for all transitions that rely on the mini-panels are that individuals in period 1 of the mini-panel be an employee 20 to 64 years of age. Finally we drop individuals that are full-time students or returning students in either period of the panel.

B.2 Construction of Counterfactuals for Low-tenure Workers

Care must be taken when constructing the counterfactual of a retention rate that conditions on characteristics that are not time-invariant, such as tenure. The retention rate of workers with less than twelve months of tenure is

$$R_t^{1-11} = \sum_{g=1}^G \alpha_t^{g|1-11} R_t^{g,1-11} \quad (\text{B.1})$$

where $\alpha_t^{g|1-11}$ is the proportion of workers with less than twelve months of tenure that are in group g . As such, holding the α 's constant over time will hold the proportion of low-tenure workers (not of the working population) in group g constant. One can get around this issue by using Bayes's Law. One can rewrite $\alpha_t^{g|1-11}$ as

$$\alpha_t^{g|1-11} = \frac{Prob_t(1 \text{ to } 11 \text{ months of tenure} | \text{group } g) \cdot Prob_t(\text{group } g)}{\sum_{g=1}^G Prob_t(1 \text{ to } 11 \text{ months of tenure} | \text{group } g) \cdot Prob_t(\text{group } g)}. \quad (\text{B.2})$$

As such, the counterfactual retention for worker with less than twelve months of tenure where one holds the group proportions of the working population constant at, say, 1997 levels is

$$RC_t^{1-11} = \sum_{g=1}^G \left(\frac{Prob_t(1 \text{ to } 11 \text{ months of tenure} | \text{group } g) \cdot Prob_{1997}(\text{group } g)}{\sum_{g=1}^G Prob_t(1 \text{ to } 11 \text{ months of tenure} | \text{group } g) \cdot Prob_{1997}(\text{group } g)} \right) R_t^{g,1-11}. \quad (\text{B.3})$$

B.3 Appendix Figures and Tables



Figure B.1: Three-month retention rate, initial tenure less than one year. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.



Figure B.2: Three-month retention rate, initial tenure less than one year, by gender. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

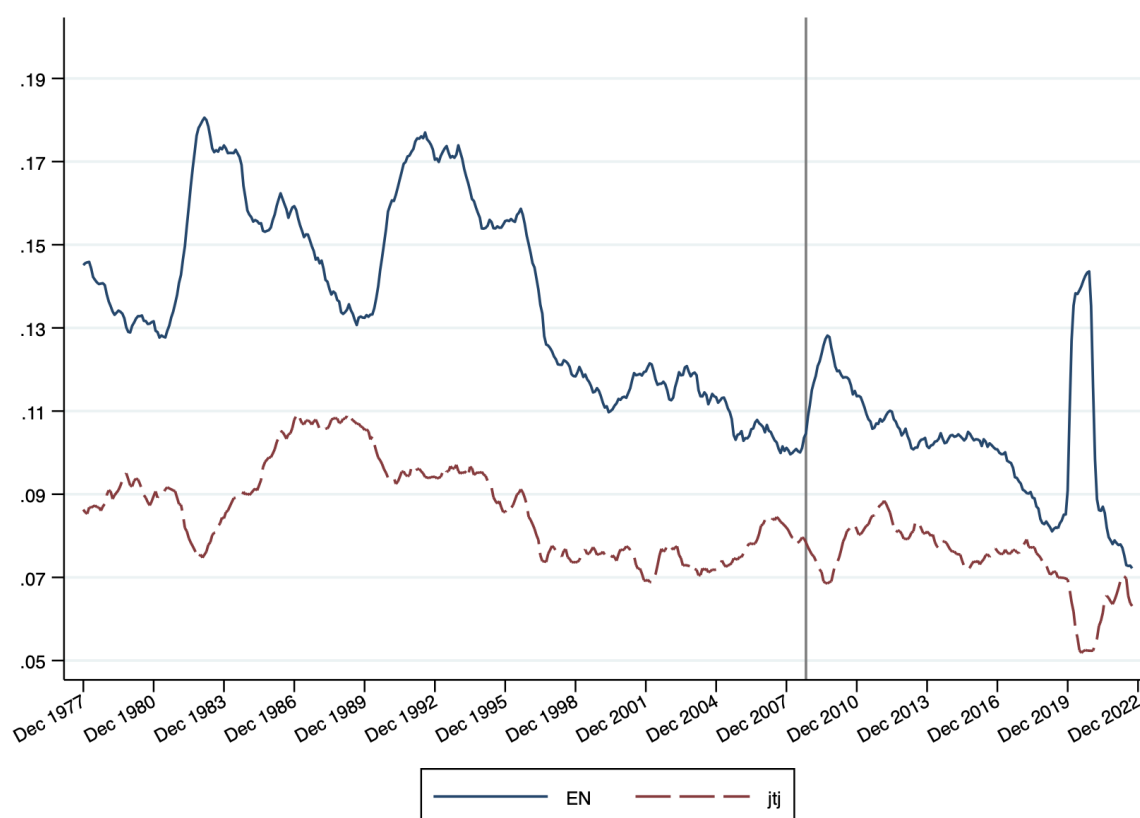


Figure B.3: Three-month EN and jtj rates, initial tenure less than one year. The EN rate is the employed to not-employed transition. The jtj rate is the job-to-job transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

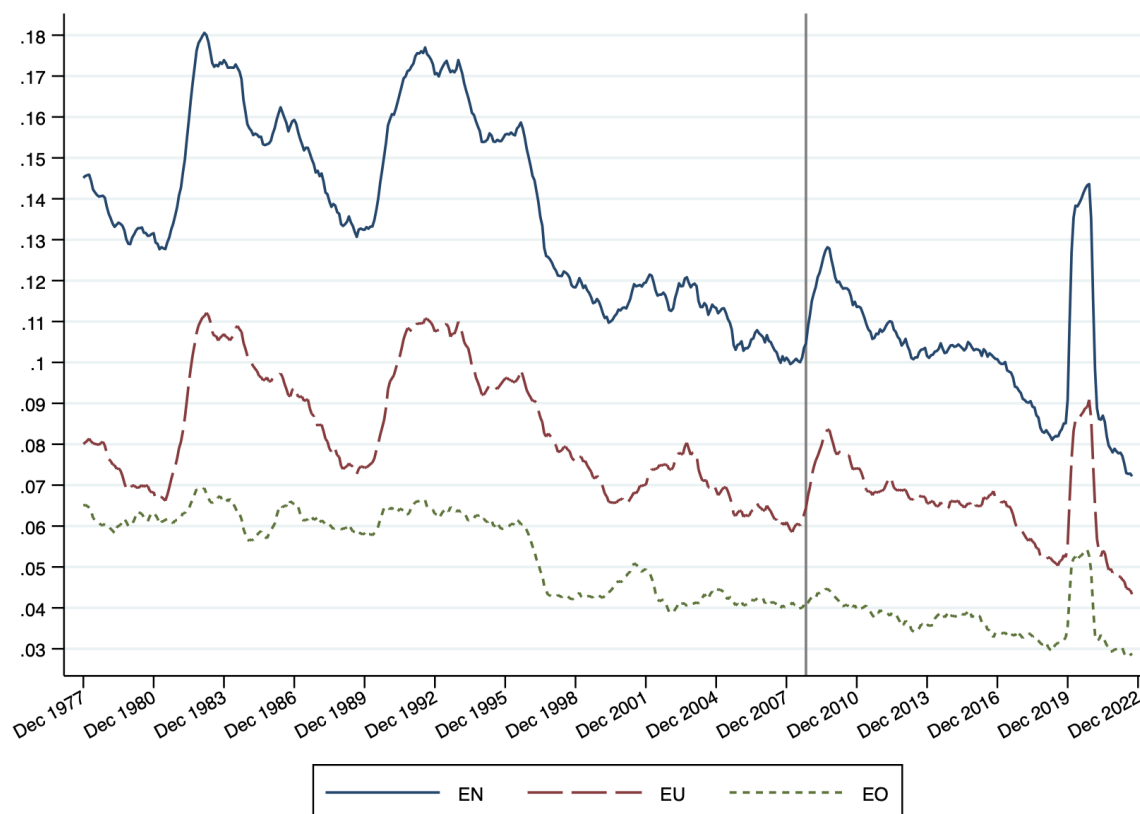


Figure B.4: Three-month EN, EU and EO rates, initial tenure less than one year. The EN rate is the employed to not-employed transition. The EU rate is the employed to unemployed transition. The EO rate is the employed to out of the labour force transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

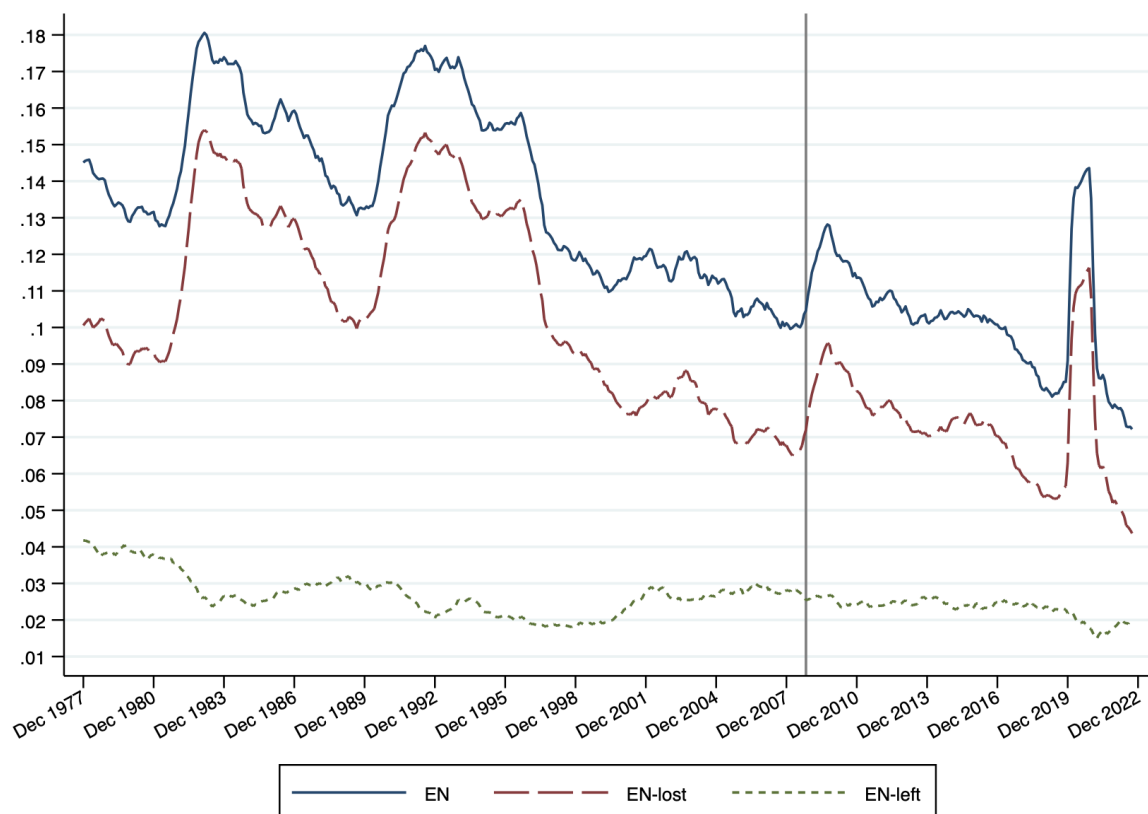


Figure B.5: Three-month EN, EN-lost, EN-left rates, initial tenure less than one year. The EN rate is the employed to not-employed transition. The EN-lost rate is the employed to not-employed due to a layoff transition. The EN-left rate is the employed to not-employed due to a quit transition. The figure shows 12-month moving averages. The vertical line indicates the start month of the Great Recession (October 2008). Source: LFS master files.

Appendix C

Chapter Three Appendices

C.1 Appendix Figures and Tables

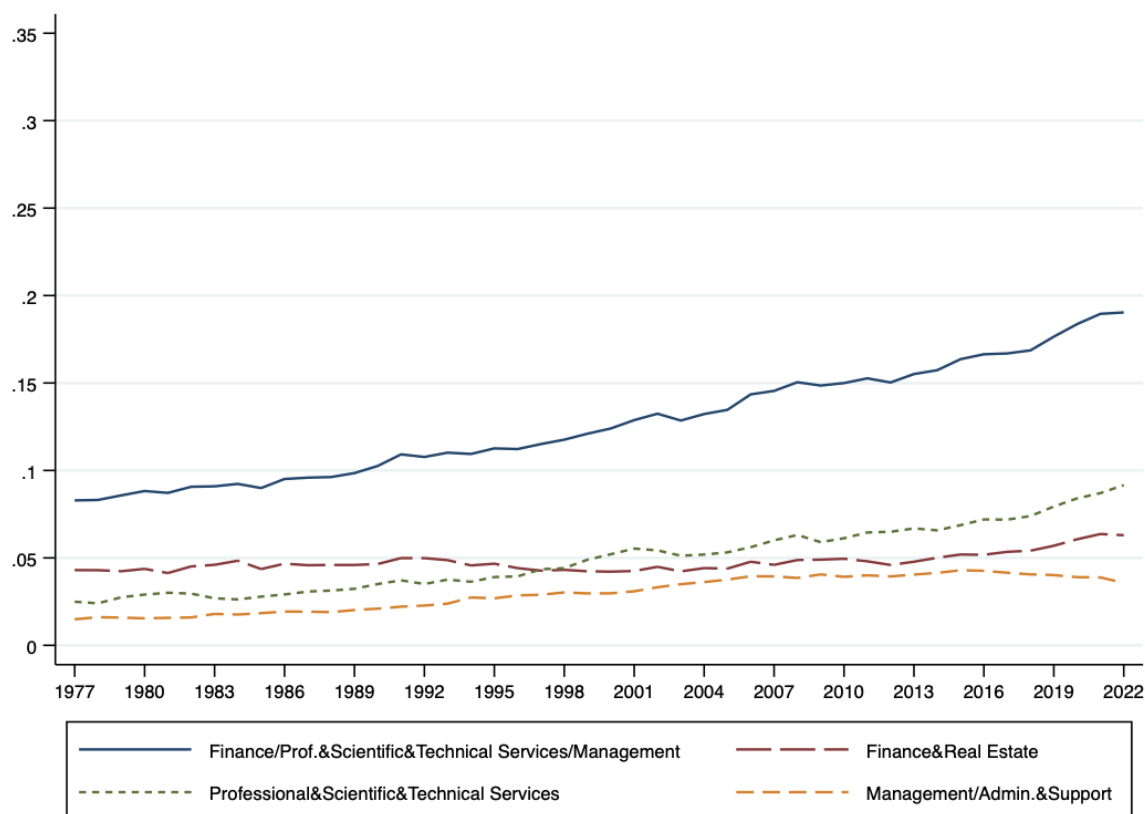


Figure C.1: Proportion by broad industry classification, NAICS 2-digit codes 5.2-5.3, 5.4 and 5.5-5.6, male. Source: LFS public-use files.

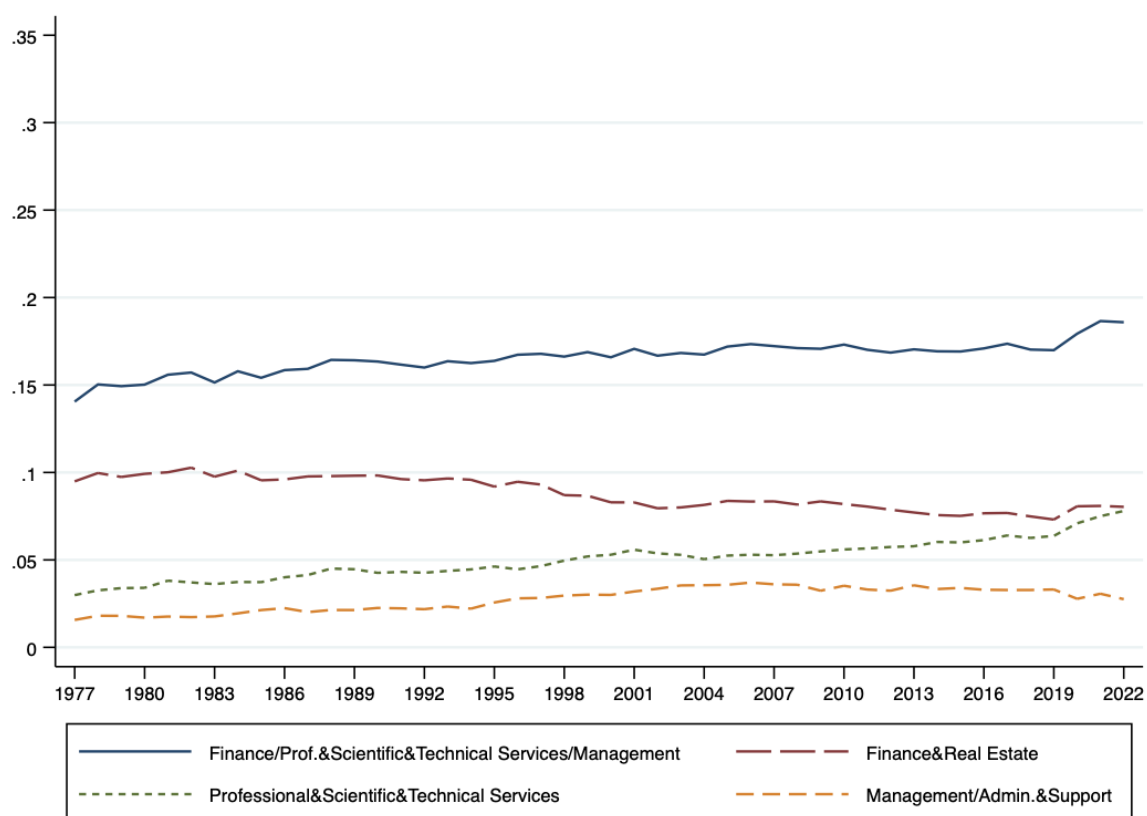


Figure C.2: Proportion by broad industry classification, NAICS 2-digit codes 5.2-5.3, 5.4 and 5.5-5.6, female. Source: LFS public-use files.

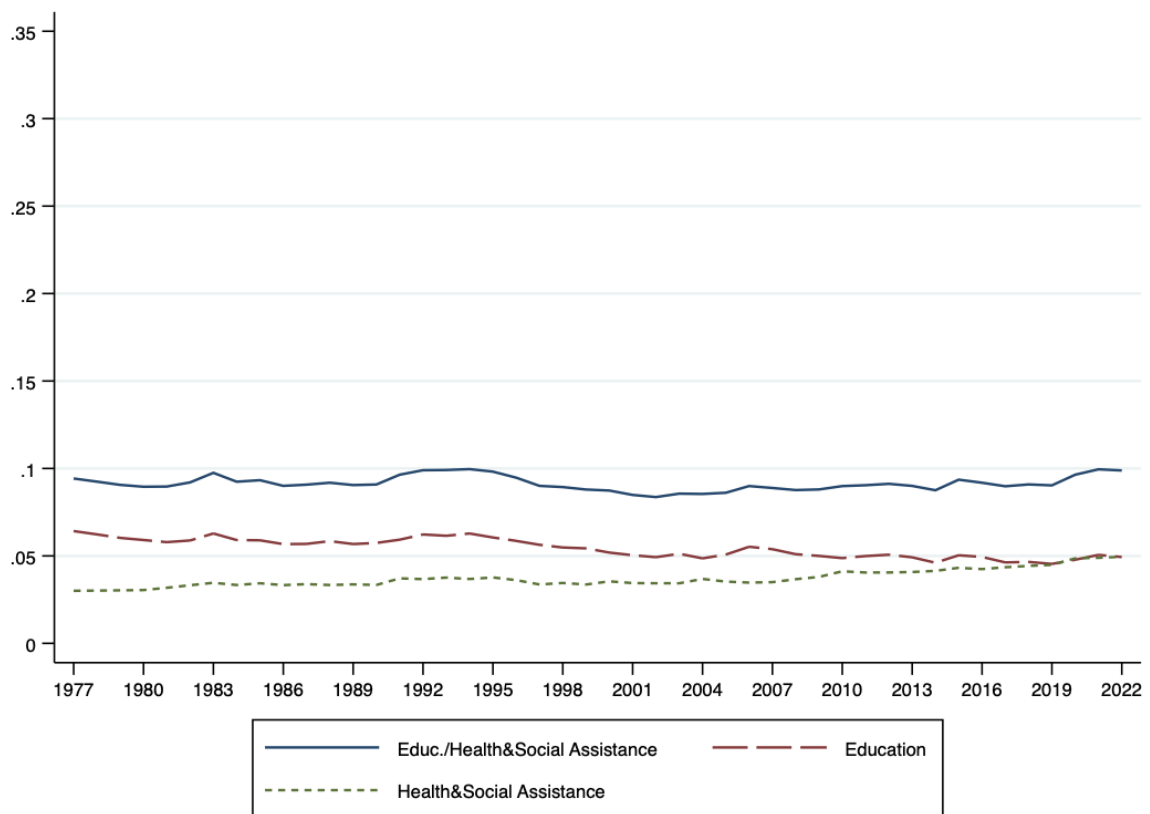


Figure C.3: Proportion by broad industry classification, NAICS 2-digit codes 6.1 and 6.2, male.
Source: LFS public-use files.

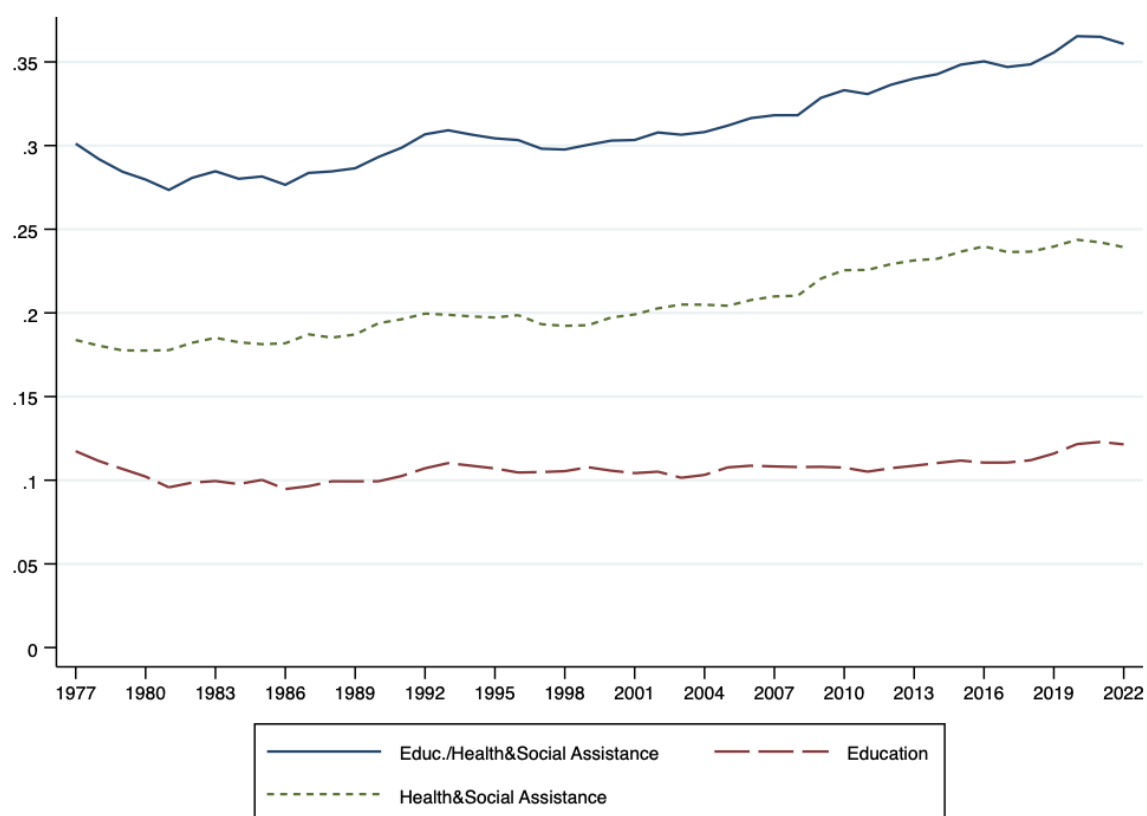


Figure C.4: Proportion by broad industry classification, NAICS 2-digit codes 6.1 and 6.2, female. Source: LFS public-use files.



Figure C.5: Proportion by broad industry classification, NAICS 2-digit codes 2.2 and 2.3, male. Source: LFS public-use files.

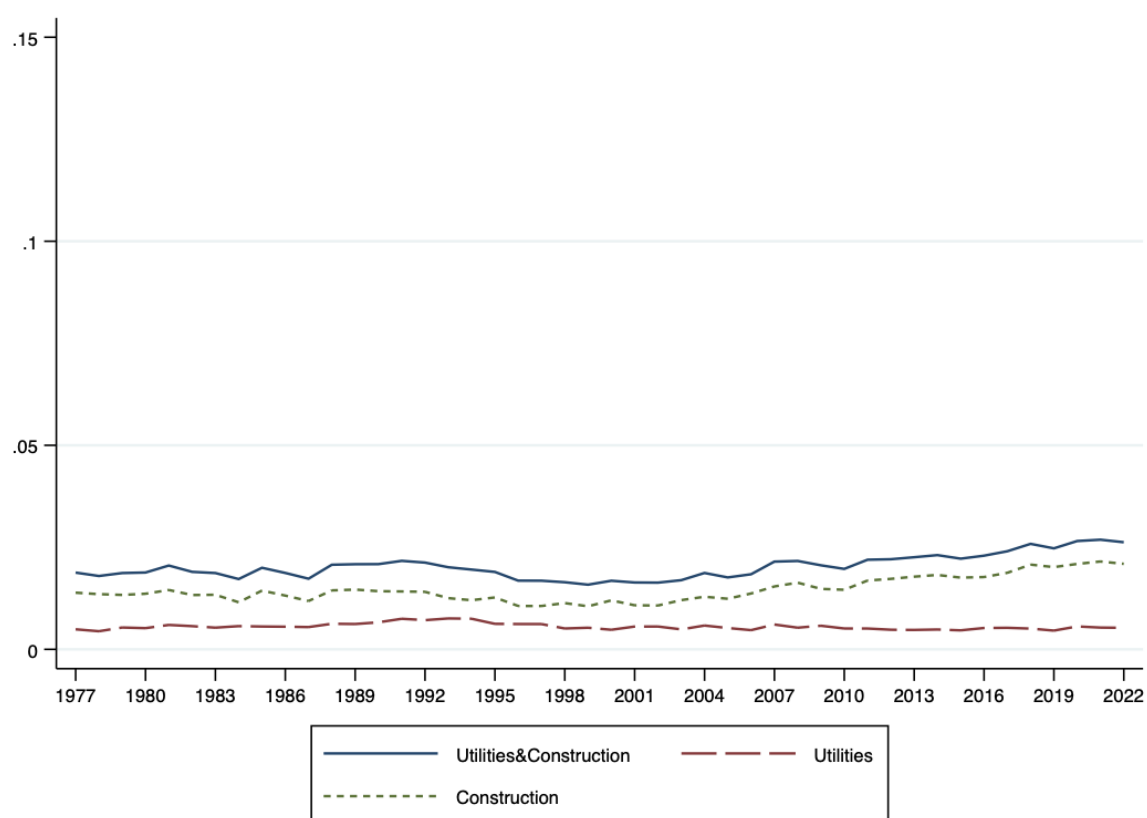


Figure C.6: Proportion by broad industry classification, NAICS 2-digit codes 2.2 and 2.3, female. Source: LFS public-use files.