Long-Term Effects of Labor Market Entry Conditions: The Case of Korea

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Abstract

This study investigates the effects of labor market conditions at the time of graduation, proxied by the local unemployment rate, on long-term family and labor market outcomes in Korea. The examination yields four main findings. Labor market entry conditions have strong and persistent effects among high school graduates. Male college graduates have a persistently lower probability of working at large firms if the demand for local labor shrinks at the time of graduation. Self-employment can also be persistently hampered by adverse economic conditions at graduation, which implies another type of career mismatch. Family formation and childbearing are temporarily affected by labor market entry conditions, especially for less educated women. The first three findings highlight the notable segmentation of the Korean labor market into protected jobs in large firms—mostly part of business groups (*chaebol*s)—and unprotected jobs.

Keywords: Recession, Graduation, Long-Term Effects, Labor Market Institutions, Instrumental Variable.

JEL Classification Numbers: E32, J23, J31.

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1 Introduction

Macroeconomic conditions on labor market entry have long-lasting effects on individual earnings, according to recent empirical studies. For example, in the US and Canada, a typical recession reduces initial earnings of fresh college graduates by 9–10 percent, and the negative effect persists until 7–10 years after graduation (Oreopoulos, Von Wachter, and Heisz, 2012; Altonji, Kahn, and Speer, 2016). These findings show that recessions, including the recent Great Recession, create a job crisis, particularly for youth, giving the government another important reason to intervene actively in the labor market and smoothen the business cycle.

It is unclear in the literature, however, why temporary economic conditions have persistent effects on individual earnings. While some studies explain the long-term effects by lost opportunities for accumulating skills (Kahn, 2010; Altonji et al., 2016), other studies emphasize less productive job search (Oreopoulos et al., 2012), increased mismatch between majors and occupations (Liu, Salvanes, and Sørensen, 2016), or sluggish promotion (Kwon, Milgrom, and Hwang, 2010).

A growing body of literature notes on the role of labor market institutions. The realized patterns of the long-term effects are widely different across countries. For example, in Japan, the negative effects of a recession at graduation are the most salient among high school graduates, rather than college graduates (Genda, Kondo, and Ohta, 2010). In another case, in Belgium(Flanders) and Spain, the effects of labor market entry conditions on employment are more noticeable than those on labor earnings (Cockx and Ghirelli, 2016; Fernández-Kranz and Rodríguez-Planas, 2017). It is natural to explain the cross-country differences in relation to distinctive labor market institutions—the school-based hiring system in Japan, high minimum wages in Flanders, and strict employment protection laws in Spain. Still, it requires more empirical evidence to ascertain the possibility and understand each mechanism.[1]

[1]For literature survey on the role of labor market institutions, see Nickell and Layard (1999), Ryan (2001), and Boeri (2010). Kawaguchi and Murao (2014) present a cross-country analysis of the relationship between employment protection legislature and the long-term effect of labor market entry conditions.

Besides, the effects of labor market entry conditions can be seen beyond the labor market outcomes. Particularly, family formation and childbearing can also be affected by economic conditions on labor market entry (e.g., Hashimoto and Kondo, 2012; Hofmann and Hohmeyer, 2016; Schaller, 2016). While negative income effects will unambiguously discourage family formation and childbearing, positive substitution effects—via cheaper leisure—may encourage those decisions. Family-related decisions may mask the real impacts of a recession at graduation on labor market outcomes, by buffering the negative impact of a recession at graduation.[2] Nevertheless, existing literature has rarely investigated the effects of local demand on the labor market in conjunction with family outcomes.

In this study, I investigate the long-term effects of labor market entry conditions by using a panel data set from Korea. Besides providing useful information on young people's choices in the Korean labor market by using local demand shock as a source of identification, this study may be of interest to the general readers in two ways. First, while Korea's K-12 education system and labor market have many things in common with those in other East Asian countries, especially Japan, the school-to-work transition in Korea distinguishes Korea from other East Asian countries. Korea's K-12 system is highly centralized like the other East Asian countries—with similarly high PISA test scores. Additionally, large firms in Korea, which are mostly part of business groups (called *chaebol*s), have maintained a hiring strategy characterized by large-scale open recruitment of new graduates, a practice also followed by their counterparts in Japan (*keiretsu*). Despite these similarities, the school-to-work transition in Korea is quite different. The links connecting the vocational education and training system with industry and business are rather weak (Kis and Park, 2012), while the attainment of tertiary education among people aged 25–34 years in Korea is the highest among the Organisation for Economic Co-operation and Development (OECD) countries

[2]That is, although a recession at graduation makes the graduates' current *time in the labor market* less productive, they can still minimize their loss in lifetime productivity by adjusting family-related decisions. For example, by utilizing their current time for family formation and childbearing, they can mitigate the negative impacts of a recession at graduation—for example, investing in unnecessary human capital (that will depreciate quickly due to career/job mismatches), wasted job search efforts, or less job offers arising from duration dependence (e.g., Kroft et al., 2013, 2016).

(accounting for 70 percent in 2016).

Second, the Korean labor market shares many characteristics with Southern European labor markets. The large share of self-employed workers (accounting for 25.5 percent of the total workers in 2016) and temporary contracts (accounting for 21.9 percent of dependent employment in 2016) in the Korean labor market is comparable to those in the Italian and Spanish labor markets. Particularly, the Korean labor market has been severely segmented into protected and unprotected jobs since the 1998–1999 Asian financial crisis, which also brought about a job crisis in the country (e.g., Cho, Freeman, Keum, and Kim, 2013). While regular workers, especially those in large firms who had been highly unionized, remained protected, non-regular workers[3] became more vulnerable to economic shocks after the introduction of a series of labor flexibility policies. Moreover, workers in large firms are relatively more shielded from firm-level volatility, owing to risk-sharing at the business group level. Due to these double layers of protection on regular workers in large firms, the effects of a recession are likely to be more persistent and concentrated among the less protected in the Korean labor market.

In order to better understand the outcomes experienced by those who graduate during a recession, I examined various labor market outcomes, other than individual earnings and employment, such as firm size, educational mismatch, contractual stability, job change, and self-employment. I also kept track of family outcomes, such as marital status and number of children, because they are simultaneously determined with labor market outcomes. Since college graduates might postpone graduation to prevent graduating during a recession, I constructed the local unemployment rate at the 'predicted' date of graduation by setting the year of middle school graduation as the reference period and used the rate as an instrument for the local unemployment rate at the time of actual graduation—this approach is similar in spirit to Kahn (2010)'s identification strategy.

The estimation results show that adverse labor market entry conditions are particularly

[3]Non-regular workers include fixed-term, temporary-help, and indirect-hire workers.

harsh for high school graduates. A typical recession[4] in Korea reduces the initial earnings of high school graduates by about 3.9 percent, and the negative impact persists for more than 10 years after graduation. The probability of working full-time decreases by about 4.7 percent initially and persist over 7 years. For college graduates, neither their earnings nor their employment is affected by the local demand shock at graduation. However, recent college graduates who are impacted by a recession are more likely to start their career at a small firm (for men) or change their job (for women), both of which indicate that their job quality has been deteriorated. Particularly, the negative effect on firm size persists in most groups for more than 10 years after graduation, suggesting that the career/job ladder does not work effectively in the Korean labor market. Additionally, self-employment among low-skilled men is persistently hampered by a local demand shock at graduation, explaining most of the negative long-term effect at the extensive margin.

Finally, conditional on completing their education, female graduates from high school or 2–3 year college graduation program are temporarily *more* likely to be married and give birth to a child if they face adverse labor market conditions at graduation, as per the theory of cheaper leisure. This effect disappears several years after graduation, without affecting the total fertility rate of women aged 35 years.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 presents the econometric framework. Section 4 shows the estimation results. Section 5 presents the conclusion.

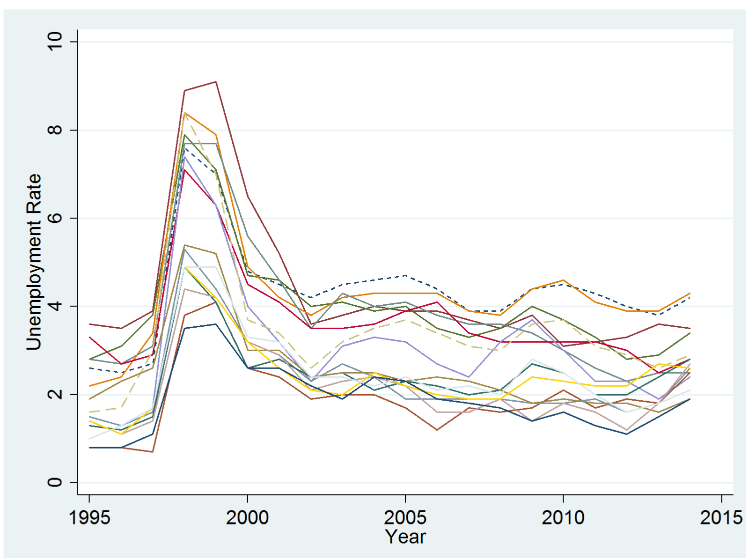
[4]There have been 10 official recessions since 1970, according to Statistics Korea, the national agency of official statistics in the country. The average unemployment rate at the trough is approximately 0.5 percent lower than the all-time average unemployment rate between 1970–2014.

2 Data

2.1 Data sources

The main data source in this study is the Youth Panel Survey 2007 (YPS07); the survey data was provided by the Korea Employment Information Service (KEIS). The YPS07 annually surveys a nationally representative sample of 10,206 men and women aged 15–29 years in 2007. This survey is benchmarked against the National Longitudinal Survey of Youth (NLSY) of the US. The questionnaire asks detailed questions about personal characteristics and family backgrounds on or before the labor market entry. Additionally, it is designed to construct event histories of each respondent's education and job. Complemented by event histories, this nine-year-long survey provides useful information for understanding the youth labor market in Korea.

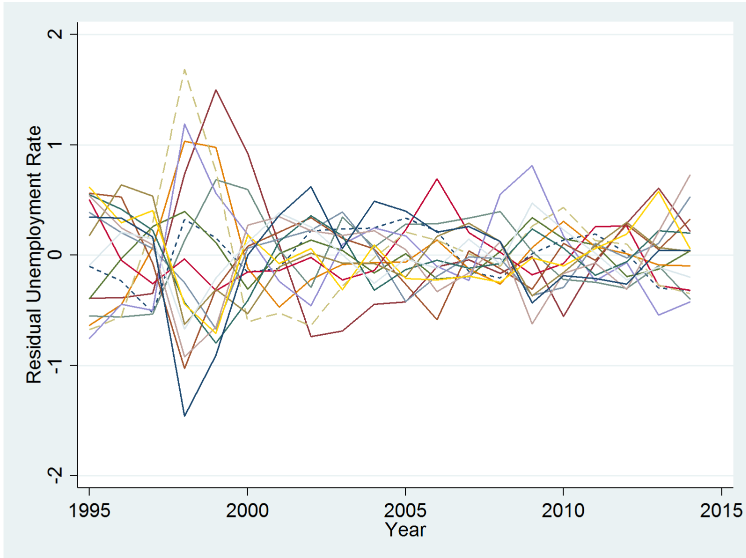
Figure 1: Local Unemployment Rate



The unemployment rates (old definition) of 16 provinces (*sido*). The dotted line represents Seoul—the capital and the largest city, and the dashed line represents the Kyungki province—the most populated province. The unemployment rate in Korea soared during the Asian financial crisis (1997–1998) but quickly declined (to a new equilibrium level), owing to rapid economic recovery.

I combine two other data sources with the panel data. First, the Korean Statistical

Figure 2: Residual Unemployment Rate



The residual unemployment rates of 16 provinces (*sido*) after controlling for year and region fixed effects and region-specific linear time trends. The dotted line represents Seoul—the capital and the largest city, and the dashed line represents Kyungki province—the most populated province.

Information Service (KOSIS) provides local unemployment rates from 1989 to 2014 at the province level, based on the Economically Active Population Survey.[5] By matching this information with the graduating school location and year, I construct the local unemployment rate at graduation. Second, I extract information on the official length of a undergraduate study program for each college-by-major-by-cohort combination, ranging from 2 to 5 years, from the Higher Education Statistics in Korea. This information is used to construct the local unemployment rate at the predicted date of graduation by setting the year of middle school graduation as the reference period.

Figure 1 shows that the local unemployment rate shows a similar pattern across all regions—especially during the Asian financial crisis from 1997 to 1999—and region-specific

[5] While another local unemployment rate generated by the current definition of unemployment is available from 2000 to present date, I use the local unemployment rates generated by the previous definition of unemployment—people who are jobless, available to take up work, and who actively looked for job during the prior *one week* (instead of four weeks in the current definition)—to include all graduation cohorts in the sample. In the overlapped period, 2000–2014, the estimation results remain almost the same, regardless of the choice of the unemployment rate.

components. However, after eliminating year- and region-fixed effects and region-specific linear trends, the residual unemployment rate changes year by year almost randomly (Figure 2). This study focuses on this year-by-year change in the residual unemployment rates. The identification strategy that uses this variation is explained in detail in the next section.

Additionally, I use the wage structure survey (1980–2015) (WSS hereafter) to construct the wage profile of each entry cohort over the life cycle, which is shown in Section 4 (Figure 3, 4 and 5). This annual survey, conducted by the Ministry of Labor and Employment, contains accurate payroll information with a few individual characteristics such as sex, age, education, job tenure, experience, and contract type. Although the WSS is not nationally representative—its population has only wage workers in private-sector establishments that employed 10 permanent workers or more[6]—its sample size (300,000–700,000 workers each year) is large enough to estimate the effects of a recession on individual earnings very precisely.

The subsections below focus on the main data set, the YPS07, and explain variable definitions and the sample selection criterion.

2.2 Variables

I define several important variables used in the regression analysis as well as explain a few distinct institutional settings in Korea, in the next section.

First, I defined labor market entry based on the 'first graduation.' The first graduation year in this study is the year when the respondent is not enrolled at any educational institution for the first time in the data. This empirical definition is similar to the definition used in previous studies using the NLSY data (e.g., Lange, 2007; Arcidiacono et al., 2010). However, complexities in defining the first graduation year arise due to the distinct institutional settings in Korea. For example, a non-negligible fraction of high school graduates

[6]The survey from 1997 included establishments that employed 5 permanent workers or more, but the survey before 1997 had only establishments that employed 10 permanent workers or more. I maintained the same criterion of sample selection in all the surveys.

prepare for an annual national college entrance exam called the college scholastic ability test (CSAT), without any official enrollment or employment.[7] I considered the respondent as being enrolled if the respondent's answer to the question on the main activity undertaken in the prior week was 'preparation for the CSAT.' Similarly, for the same question, a small number of young men were considered as being enrolled if they answered 'waiting for entering into the armed forces.'[8]

Subsequently, I use a graduate's potential experience—the length of time (months) from the date of the first graduation to the date of actual interview, which are recorded in the year and month—in all the regressions. I do not use actual experience because it is a highly endogenous variable, as noted in previous literature (e.g., Altonji and Pierret, 2001; Altonji et al., 2016).

Subsequently, I focus on the main job at interview date and its characteristics. Observations with less than 30 hours per week are considered as not working. For labor income, I used (log) real monthly average earnings, instead of hourly wages, because employees usually receive a monthly salary in Korea. The average monthly earnings are deflated by using the (annual) consumer price index (CPI). Additionally, real monthly earnings less than the bottom 1 percent and more than the top 1 percent are considered as missing, to eliminate influential observations.

Additionally, I consider the following three measures of match quality: firm size, educational (mis)match, and job (in)stability. For firm size, I use a dummy for firm that is larger than 500 workers.[9] For educational mismatch, I construct a measure of overeducation for the job—a dummy for the education level required at the respondent's current job being

[7]About 30 percent college freshmen are 'old graduates'—the time between high school graduation and joining college spanned over a year to several years.

[8]With very few exceptions, Korean men aged 18–35 years are required to serve in the armed forces. The length of the mandatory military service may vary by entry position and branch, but most men serve for 21–24 months. While, to a certain extent, the timing of entry into the military service is a choice, most men begin their mandatory military service right after their high school graduation. This is because the completion of mandatory military service serves as a key qualification for (eligible) men.

[9]Each worker answers one of the nine categories—1–4, 5–9, 10–29, 30–49, 50–99, 100–299, 300–499, 500–999, and 1000+.

lower than the respondent's education level. While this measure might still be affected by subjective assessment, among available measures of overeducation, this measure is closest to the approaches developed for avoiding the problem of self-measurement (e.g., Leuven and Oosterbeek, 2011). For job instability, I use a dummy for a temporary or fixed-term job with a contracted period that is lesser than two years.[10] For job change, I use a dummy for a job tenure that is lesser than 12 months while conducting the survey interview.

Finally, I also investigate the marital status and the number of children of young men and women. Family formation is another important goal of young people, which is closely connected with labor market outcomes. Based on the respondent's answer, I construct a dummy for having ever been in a married relationship until the date of interview. The information contained in YPS07 is limited because it only considers the legal marital status; however, this should not pose a problem, as cohabitation or *de facto* marriage is not very common for this age group in Korea. While other forms of family are certainly increasing, the traditional family set up that is established through legal marriage is still dominant in Korea, as in other East Asian countries.

The number of children in YPS07 is not very precisely defined—the questionnaire does not distinguish between the number of children conceived, born, or alive. As a result, this variable frequently decreases within an individual. Moreover, this variable has too many zero values in wave 2 and 3, which may be coding errors. Owing to this problem, I do not use the number of children variable in those two waves—I consider them as missing throughout all regression analyses. Nonetheless, using the recorded values in those two waves does not significantly change the final results.

[10]For wave 1, the YPS07 does not distinguish between a regular contract and a fixed-term contract that is longer than a year, but this is not likely to change the results significantly. Even if I use a dummy for a temporary job (lesser than a year), the estimation results will largely remain the same.

2.3 Sample selection

From the YPS07 sample, I discard all individuals who did not graduate during the sample period or whose first graduation year could not be specified (-2363). Additionally, some individuals whose school region could not be correctly identified are dropped from the sample (-116). The individuals whose local unemployment rate at graduation is constructed from the KOSIS data, mostly the 2015 graduation cohort, are also not included in the sample (-360).

While those graduating from graduate schools can also form the focus of this study, I do not consider them because of the difficulty in predicting the year of graduation (-186). I focus only on graduates because a decision to drop out from school is often related to job opportunities that are directly linked to the business cycle condition at that time (-810). In addition, since additional education after labor market entry is highly correlated with ability measures and possibly endogenously chosen in relation to the labor market conditions at graduation, I limit the sample to those whose education level at the first graduation (edu_0) matches with the education level observed in the last interview (edu_T) (-290). The main results presented in this paper, however, are robust to the inclusion of those who dropped out from their last school and those who attained further education after first graduation—this is mainly because the portion of this group is relatively small. Finally, I consider only the observations after labor market entry.

The final sample consists of 6,078 individuals who (first) graduated between 1995 and 2014 and interviewed from 2007 to 2015. The descriptive statistics of the final sample are presented in Table 1.

Table 1: Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
Birth year	6,078	1984.2	4.13	1978	1994
Gender	6,078	1.59	0.49	1	2
Father's schooling	6,078	12.1	2.89	6	21
Mother's schooling	6,078	11.2	2.53	6	21
Birth order	6,078	1.69	0.90	1	7
Number of siblings	6,078	2.44	0.90	1	11
Education at first grad.	6,078	14.6	1.57	12	16
Sch. region at first grad.	6,078	6.32	4.55	1	16
Year of first grad.	6,078	2006.9	4.58	1995	2014
Predicted year of first grad.	6,076	2006.2	4.47	1995	2016
Unemp. rate at first grad.	6,078	3.44	1.21	0.7	9.1
Predicted unemp. rate at first grad.	6,054	3.48	1.23	0.7	9.1
Potential exper.	33,848	6.11	4.19	0	20.7
Predicted potential exper.	33,841	6.83	4.06	-2.42	20.7
Working	33,848	0.69	0.46	0	1
Monthly earnings (in 2015 Won)	22,120	216.0	77.7	70	507.9
Log real monthly earnings	22,120	5.31	0.36	4.2	6.2
Firm size	22,056	299.2	411.5	1	1000
Overeducated	22,120	0.35	0.48	0	1
Weekly hours	22,109	46.6	8.60	30	112
Temporary contract[a]	20,846	0.11	0.31	0	1
Self-employed	23,329	0.06	0.24	0	1
Ever Married[b]	33,807	0.29	0.45	0	1
Number of children[c]	27,467	0.36	0.74	0	5

a. Conditional on wage workers.
b. Including Married, Separated, Divorced, and Widowed.
c. Inaccurately defined but close to the number of children alive.

3 Econometric Model

The period t and labor market outcome y of individual i, who graduated in the year c from her/his school located in region r, is expressed as follows:

$$y_{icrt} = \sum_{e} \alpha_e u_{cr} + X_i'\gamma + f(e) + \phi_c + \nu_r + \nu_r \times t + \mu_t(+\beta u_{r(t),t}) + \epsilon_{icrt} \tag{1}$$

First, labor market entry conditions can persistently affect labor market outcomes. In this study, labor market entry conditions are defined by the local unemployment rate at graduation (u_{cr}). It must be noted that the effects of labor market entry conditions (α) may vary depending on the time spent in the labor market (e). That is, the focus of this study is the persistence of those effects, as well as their magnitude.

Subsequently, individual characteristics (X_i) also affect labor market outcomes. I control for parents' schooling levels, birth order, and the number of siblings for all education groups. I additionally control for the CSAT scores and university rankings for college graduates.

Subsequently, a function of potential experience ($=f(e)$) captures the average life-cycle profile of each labor market outcome.[11] An unrestricted cubic is used, which is a popular choice of functional form in the literature.

Finally, I control for the fixed effects of graduating year (c), graduating region (r), and current year (t). Region-specific linear trends ($\nu_r \times t$) are also controlled. These fixed effects summarize many endogenous factors that affect both the local unemployment rate and labor market outcomes. For example, cohort fixed effects absorb any changes in the average cohort quality; additionally, region-specific linear trends with regional fixed effects eliminate the possible correlation between predicted changes in regional characteristics and the local unemployment rate at graduation.

[11] It is also possible to control for cohort-specific profiles, owing to the regional variation within a cohort. This can be crucial if the shape of the lifecycle profile does not remain constant over time. For example, female labor participation ratio has risen rapidly, changing their work experience over the life cycle across cohorts. Introducing cohort-specific profiles to the above equation, however, does not significantly affect the estimation results for both men and women.

The estimation results presented in the next section do not control for current unemployment rate ($u_{r(t),t}$) as the region-specific linear trends are controlled for. However, the results remain largely the same even if I additionally control for the current unemployment rate.

As is well known in the literature, it is impossible to separately identify cohort, year, and potential experience effects from Eq. (1) if potential experience ($e = t - c$) is a linear combination of current year and entry year. However, the typical linear dependency is broken because potential experience is measured at a monthly frequency in this study.[12] More importantly, this cohort-age-time non-identification issue does not affect the identification of α_e, the main parameter of interest, which is identified from the variation in the local unemployment rate across regions within a graduation cohort.

Although individual decisions can hardly affect labor market conditions, individuals can alter the year of graduation—by discontinuing their school or delaying their graduation. These endogenous choices about the timing of entry into the labor market will positively bias the ordinary least squares (OLS) estimates of the above equation. Therefore, I calculated the predicted unemployment rate at graduation by setting the year of middle school graduation as the reference period and by adding the typical length of study in high school (3 years) and the standard length of study in the college-by-major-by-cohort cell (2–4 years), which is obtained from an external data source. Concerning men, who actually completed their mandatory military service during college education, I add the typical length of military service (3 years including the waiting period).[13] From the predicted graduation year, I get the predicted unemployment rate at graduation. Additionally, I construct the 'predicted potential experience,' which is the amount of time spent in the labor market from the time of predicted labor market entry.

These instruments based on the predicted graduation year are highly correlated with

[12] That is, potential experience is defined by the length of time (months) from graduation to the interview date.

[13] The length of military service and the timing of entry into military service are choice variables. However, most men choose the shortest length and the earliest timing possible to minimize their loss in human capital, in accordance with the economic theory.

the explanatory variables that are potentially endogenous. Although the predicted variables are not exogenous, *per se*, they are less likely correlated with the error term in the above equation—that is, the potential upward bias from the decision of delaying graduation can be eliminated by using the instruments. In the two stage least squares (2SLS) estimation, I control for the fixed effects of the predicted graduation year, instead of the actual graduation year.

4 Estimation Results

4.1 A national-level analysis

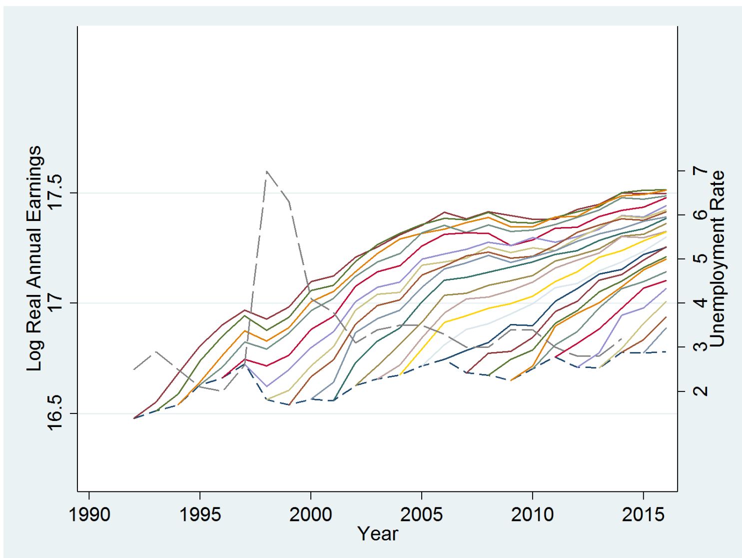
Before reporting the main results using local-level variation, I show some evidence of the negative effects of a recession at graduation at the national level. The data set used in this subsection is the Wage Structure Survey (WSS, hereafter), as is explained in the data section. While the scope of the WSS is limited, it provides reliable information on individual earnings with large sample size.

Figure 3 shows that the initial earnings of male high school graduates are clearly pro-cyclical. It is apparent that the two large recessions—the Asian Financial Crisis (AFC) in 1998–1999 and the Global Financial Crisis (GFC) in 2008–2009—suppressed the initial earnings during those periods. Moreover, the negative effects are likely long-lasting—cohorts that entered into the labor market during a recession consistently have lower average earnings than the earlier cohorts. Figure 4 shows that the initial earnings of college graduates from a 2–3 year study program are also pro-cyclical, but the cyclical pattern is less clear.

Figure 5 shows that the initial earnings of college graduates from a 4–5 year study program are almost uncorrelated with the national unemployment rate, except for the period of the AFC (1998–1999). Their earning stability arises from the legal protection of regular contracts. Most male college graduates (about 90%) are regular workers, whose employment and earnings are strongly protected by the Labor Standard Act. Moreover, male college graduates are more likely at large firms, which are mostly part of business groups. They are additionally protected against firm-level volatility owing to risk sharing at the business group level.

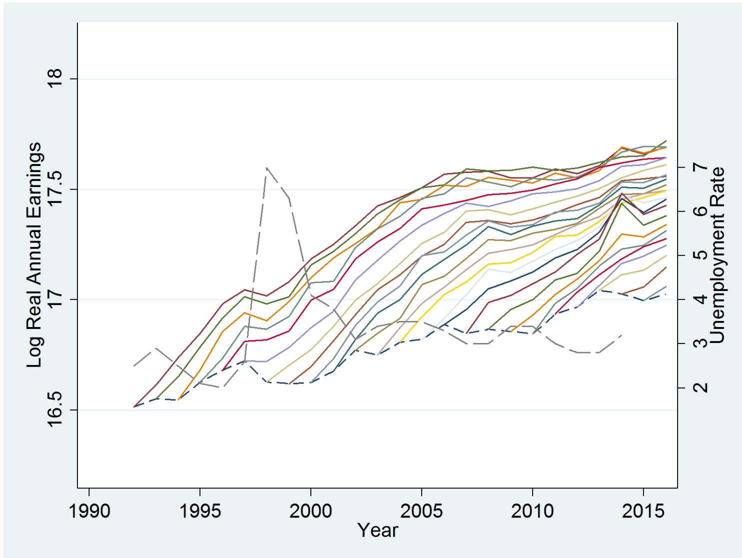
In the following subsections, I report the OLS and 2SLS estimates extracted from the YPS07 data; the estimates reveal why the negative effects on individual earnings are more pronounced among high school graduates when compared to the college graduates.

Figure 3: Earnings profile by birth cohort: Men, high school graduates



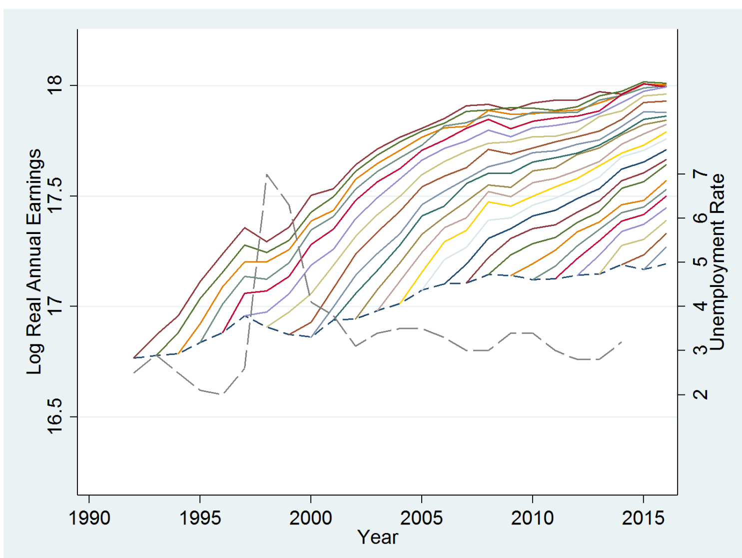
Men, aged 22 years or above, who were born in and between 1970–1994 in the ESS sample. The dotted line shows the average earnings at 22 years(on the left y-axis). The dashed line shows the national unemployment rate (on the right y-axis).

Figure 4: Earnings profile by birth cohort: Men, graduates from a 2–3 year graduation study programme



Men, aged 24 years or above, who were born in and between 1968–1992 in the ESS sample. The dotted line shows the average earnings at 24 years (on the left y-axis). The dashed line shows the national unemployment rate (on the right y-axis).

Figure 5: Earnings profile by birth cohort: Men, graduates from a 4–5 year graduation study programme



Men, aged 26 years or more, who were born in and between 1966–1990 in the ESS sample. The dotted line shows the average earnings at 26 years(on the left y-axis). The dashed line shows the national unemployment rate (on the right y-axis).

4.2 Main results: OLS estimation using local-level variation

The OLS estimation results of Eq. 1 are presented in Table 2–7. The estimated coefficients on the unemployment rate at graduation (interacted with potential experience) show that the negative effects of graduating during a recession are indeed strong and persistent among high school graduates for both men and women (Table 2 and 3). A typical recession at graduation (approximately a 0.5 percent increase in the local unemployment rate) reduces initial earnings by 3.6 (for female) or 4.7 (for male) percent[14], and the negative effect persists over at least 7–10 years. In the case of men, besides individual earnings, this negative effect also becomes evident in the form of lower self-employment and higher job change probabilities. In the case of women, the negative effect on earnings is highly likely linked to smaller firm size, downgraded match quality, and less contractual stability. On the contrary, for college graduates, the estimated effects of a recession at graduation on individual earnings or employment are not statistically different from zero, and some of the estimated coefficients have unexpected signs (Table 4–7). These results are robust to the inclusion of additional control variables, such as the college entrance exam scores and university rankings.

However, the OLS results may be biased, especially for college graduates. Particularly, the estimates may be biased toward zero because college students can delay graduation after they observe adverse labor market conditions. Owing to this possibility, I use the local unemployment rate at predicted graduation as an instrument for the local unemployment rate at actual graduation, which is constructed by setting the year of middle school graduation as the reference period and adding the official length of study for each educational group—3 years for high school graduates and specified length of study for each college-major-cohort combination. Concerning men who completed military service before their actual graduation, the typical length of the military service—3 years including the waiting period—is added to construct the predicted graduation year.

[14] $3.6(\%) = 0.5 \times 0.071 \times 100, 4.7(\%) = 0.5 \times 0.094 \times 100.$

Table 2: Effects of labor market entry conditions (OLS): Men, high school graduates

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.094*	-0.059	0.096*	0.080	-0.064+	0.052	-0.094*	0.032	0.160+
	(0.039)	(0.066)	(0.047)	(0.059)	(0.035)	(0.061)	(0.040)	(0.041)	(0.086)
× Exper.(2–3)	-0.055+	-0.033	0.011	0.021	-0.070*	0.028	-0.075*	0.015	0.126
	(0.030)	(0.048)	(0.033)	(0.040)	(0.032)	(0.046)	(0.033)	(0.040)	(0.083)
× Exper.(4–5)	-0.058*	-0.031	-0.007	0.027	-0.059+	0.078*	-0.044	-0.004	0.094
	(0.024)	(0.041)	(0.023)	(0.034)	(0.033)	(0.036)	(0.028)	(0.039)	(0.080)
× Exper.(6–7)	-0.055*	-0.021	-0.012	0.014	-0.068*	0.063+	-0.046+	-0.033	0.043
	(0.022)	(0.037)	(0.020)	(0.031)	(0.032)	(0.034)	(0.025)	(0.039)	(0.077)
× Exper.(8–9)	-0.058**	-0.012	-0.012	0.004	-0.064+	0.059*	-0.037	-0.052	-0.008
	(0.021)	(0.036)	(0.015)	(0.030)	(0.034)	(0.030)	(0.024)	(0.038)	(0.074)
× Exper.(10+)	-0.054**	-0.015	-0.008	-0.001	-0.066+	0.070*	-0.021	-0.058	-0.027
	(0.020)	(0.034)	(0.014)	(0.032)	(0.035)	(0.028)	(0.024)	(0.039)	(0.077)
N	2077	2072	2077	1826	2200	2200	2960	2959	2343

Table 3: Effects of labor market entry conditions (OLS): Women, high school graduates

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.071*	-0.078+	0.021	0.087*	0.026	-0.014	-0.071*	0.064*	0.124+
	(0.032)	(0.047)	(0.026)	(0.035)	(0.023)	(0.031)	(0.034)	(0.028)	(0.066)
× Exper.(2–3)	-0.067*	-0.079*	0.046*	0.125**	0.019	0.010	-0.006	0.046+	0.111+
	(0.028)	(0.038)	(0.021)	(0.030)	(0.022)	(0.027)	(0.031)	(0.027)	(0.058)
× Exper.(4–5)	-0.057*	-0.074*	0.064**	0.133**	0.012	0.023	0.021	0.013	0.068
	(0.025)	(0.033)	(0.018)	(0.028)	(0.022)	(0.028)	(0.027)	(0.025)	(0.053)
× Exper.(6–7)	-0.032	-0.059+	0.060**	0.098**	0.006	0.045+	0.025	0.001	0.023
	(0.024)	(0.032)	(0.017)	(0.028)	(0.022)	(0.026)	(0.026)	(0.023)	(0.052)
× Exper.(8–9)	-0.023	-0.074*	0.057**	0.083**	0.002	0.038	0.031	0.003	-0.005
	(0.023)	(0.030)	(0.014)	(0.027)	(0.022)	(0.023)	(0.024)	(0.021)	(0.051)
× Exper.(10+)	-0.020	-0.068*	0.046**	0.070*	-0.001	0.023	0.029	0.004	-0.015
	(0.024)	(0.031)	(0.013)	(0.028)	(0.023)	(0.020)	(0.023)	(0.020)	(0.052)
N	1993	1986	1993	1843	2117	2117	4344	4342	3357

Standard errors in parentheses are clustered at the school region-by-cohort level.

$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

All specifications control for parents' education, birth order, number of siblings, a cubic in potential experience, graduating year and region fixed effects, linear trends by school regions, and current year fixed effects. The dependent variables comprise the log real monthly earnings, a dummy for firm size larger than or equal to 500 workers, a dummy for overeducation (being more qualified than what is required by the current job), a dummy for temporary contract that is conditional on wage worker, a dummy for self-employment, a dummy for job change (current job tenure being less than a year), a dummy for working full-time (more than 30 hours per week), a dummy for having ever been in a married relationship, and the number of children on the date of survey interview.

Table 4: Effects of labor market entry conditions (OLS): Men, graduates from a 2–3 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	0.019	-0.073	0.098*	0.050	0.049	-0.030	-0.036	0.057	0.134
	(0.033)	(0.059)	(0.050)	(0.032)	(0.039)	(0.034)	(0.035)	(0.054)	(0.085)
× Exper.(2–3)	0.013	-0.065	0.091^{+}	0.052^{+}	0.047	-0.010	-0.020	0.046	0.103
	(0.032)	(0.055)	(0.047)	(0.028)	(0.037)	(0.032)	(0.034)	(0.054)	(0.086)
× Exper.(4–5)	0.001	-0.064	0.079^{+}	0.052*	0.032	0.025	-0.007	0.038	0.077
	(0.031)	(0.052)	(0.047)	(0.026)	(0.034)	(0.032)	(0.031)	(0.054)	(0.087)
× Exper.(6–7)	-0.008	-0.063	0.062	0.053*	0.032	0.020	0.000	0.029	0.042
	(0.030)	(0.051)	(0.045)	(0.025)	(0.032)	(0.030)	(0.030)	(0.054)	(0.089)
× Exper.(8–9)	-0.006	-0.069	0.064	0.044^{+}	0.022	0.010	0.005	0.026	0.023
	(0.030)	(0.051)	(0.047)	(0.024)	(0.031)	(0.029)	(0.029)	(0.055)	(0.093)
× Exper.(10+)	-0.007	-0.068	0.083^{+}	0.042^{+}	0.014	-0.015	0.008	0.012	0.017
	(0.030)	(0.052)	(0.049)	(0.024)	(0.030)	(0.029)	(0.029)	(0.056)	(0.096)
N	3145	3135	3145	2916	3330	3330	3995	3991	3218

Table 5: Effects of labor market entry conditions (OLS): Men, graduates from a 4–5 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	0.047	-0.089*	0.019	0.006	0.020	-0.056*	0.040	-0.031	-0.010
	(0.030)	(0.044)	(0.036)	(0.025)	(0.030)	(0.027)	(0.034)	(0.041)	(0.062)
× Exper.(2–3)	0.039	-0.079^{+}	0.002	0.004	0.016	-0.012	0.019	-0.028	-0.021
	(0.029)	(0.043)	(0.034)	(0.023)	(0.029)	(0.025)	(0.033)	(0.040)	(0.061)
× Exper.(4–5)	0.036	-0.063	-0.008	0.011	0.017	0.031	0.009	-0.012	-0.032
	(0.028)	(0.043)	(0.034)	(0.022)	(0.028)	(0.025)	(0.032)	(0.040)	(0.058)
× Exper.(6–7)	0.032	-0.047	-0.004	0.010	0.017	0.021	0.009	-0.004	-0.039
	(0.029)	(0.044)	(0.035)	(0.022)	(0.027)	(0.025)	(0.032)	(0.041)	(0.059)
× Exper.(8–9)	0.023	-0.042	0.006	0.020	0.018	-0.018	0.019	-0.012	-0.040
	(0.032)	(0.047)	(0.038)	(0.024)	(0.027)	(0.026)	(0.032)	(0.044)	(0.062)
× Exper.(10+)	0.021	-0.062	0.019	0.024	0.030	-0.024	0.023	-0.026	-0.072
	(0.034)	(0.050)	(0.043)	(0.027)	(0.028)	(0.029)	(0.033)	(0.048)	(0.069)
N	5220	5200	5220	4975	5565	5565	6819	6809	5669

Standard errors in parentheses are clustered at the school region-by-cohort level.
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

All specifications control for parents' education, birth order, number of siblings, a cubic in potential experience, graduating year and region fixed effects, linear trends by school regions, and current year fixed effects. The additional controls for college graduates include categorical dummies (1–5) of the three CSAT scores (Korean, Math, and English) and dummies of university rankings (1–20, 21–40, and 41+). The dependent variables comprise the log real monthly earnings, a dummy for firm size larger than or equal to 500 workers, a dummy for overeducation (being more qualified than what is required by the current job), a dummy for temporary contract that is conditional on wage worker, a dummy for self-employment, a dummy for job change (current job tenure being less than a year), a dummy for working full-time (more than 30 hours per week), a dummy for having ever been in a married relationship, and the number of children on the date of survey interview.

Table 6: Effects of labor market entry conditions (OLS): Women, graduates from a 2–3 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.003	0.037	-0.018	-0.014	0.032	-0.055*	-0.027	0.053	0.082
	(0.029)	(0.041)	(0.035)	(0.026)	(0.022)	(0.027)	(0.033)	(0.037)	(0.074)
$\times$ Exper.(2–3)	0.008	0.038	-0.029	-0.015	0.028	-0.015	-0.016	0.031	0.058
	(0.028)	(0.039)	(0.034)	(0.024)	(0.022)	(0.026)	(0.031)	(0.036)	(0.073)
$\times$ Exper.(4–5)	0.013	0.038	-0.036	-0.031	0.022	0.029	-0.009	0.013	0.011
	(0.026)	(0.037)	(0.033)	(0.023)	(0.022)	(0.024)	(0.030)	(0.034)	(0.071)
$\times$ Exper.(6–7)	0.025	0.041	-0.044	-0.038^{+}	0.018	0.026	0.000	0.003	-0.034
	(0.024)	(0.034)	(0.031)	(0.022)	(0.022)	(0.024)	(0.028)	(0.033)	(0.067)
$\times$ Exper.(8–9)	0.045^{+}	0.052	-0.048	-0.042*	0.019	-0.032	0.008	-0.002	-0.074
	(0.023)	(0.033)	(0.032)	(0.021)	(0.024)	(0.023)	(0.026)	(0.031)	(0.064)
$\times$ Exper.(10+)	0.056*	0.056^{+}	-0.054^{+}	-0.057**	0.014	-0.054*	0.021	-0.017	-0.091
	(0.023)	(0.031)	(0.033)	(0.022)	(0.026)	(0.024)	(0.027)	(0.031)	(0.061)
N	4258	4248	4258	4071	4439	4439	6907	6894	5582

Table 7: Effects of labor market entry conditions (OLS): Women, graduates from a 4–5 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	0.020	-0.054	-0.015	-0.041	-0.002	-0.050*	0.016	0.017	0.043
	(0.024)	(0.042)	(0.039)	(0.027)	(0.020)	(0.022)	(0.031)	(0.028)	(0.048)
$\times$ Exper.(2–3)	0.017	-0.055	-0.013	-0.034	-0.002	-0.011	0.025	0.006	0.041
	(0.023)	(0.043)	(0.038)	(0.026)	(0.020)	(0.020)	(0.031)	(0.028)	(0.047)
$\times$ Exper.(4–5)	0.011	-0.052	-0.013	-0.031	-0.007	0.024	0.033	-0.001	0.012
	(0.023)	(0.043)	(0.037)	(0.026)	(0.020)	(0.020)	(0.030)	(0.027)	(0.045)
$\times$ Exper.(6–7)	0.009	-0.056	-0.016	-0.038	-0.010	0.003	0.031	-0.006	-0.009
	(0.023)	(0.042)	(0.037)	(0.026)	(0.021)	(0.020)	(0.030)	(0.026)	(0.045)
$\times$ Exper.(8–9)	0.021	-0.053	-0.010	-0.045	-0.009	-0.029	0.031	-0.013	-0.020
	(0.024)	(0.042)	(0.039)	(0.027)	(0.021)	(0.022)	(0.032)	(0.027)	(0.047)
$\times$ Exper.(10+)	0.022	-0.050	-0.005	-0.047^{+}	-0.012	-0.039^{+}	0.028	-0.013	-0.035
	(0.026)	(0.043)	(0.043)	(0.027)	(0.023)	(0.023)	(0.033)	(0.029)	(0.053)
N	5427	5415	5427	5215	5678	5678	8823	8812	7298

Standard errors in parentheses are clustered at the school region-by-cohort level.
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

All specifications control for parents' education, birth order, number of siblings, a cubic in potential experience, graduating year and region fixed effects, linear trends by school regions, and current year fixed effects. The additional controls for college graduates include categorical dummies (1–5) of the three CSAT scores (Korean, Math, and English) and dummies of university rankings (1–20, 21–40, and 41+). The dependent variables comprise the log real monthly earnings, a dummy for firm size larger than or equal to 500 workers, a dummy for overeducation (being more qualified than what is required by the current job), a dummy for temporary contract that is conditional on wage worker, a dummy for self-employment, a dummy for job change (current job tenure being less than a year), a dummy for working full-time (more than 30 hours per week), a dummy for having ever been in a married relationship, and the number of children on the date of survey interview.

4.3 Main results: IV estimation from YPS07

The IV estimation results of Eq. 1, using the local unemployment rate at 'predicted' graduation as an instrument for the local unemployment rate at actual graduation, are presented in Table 8–13. As expected, the IV results are largely similar to the OLS results for high school graduates for both men and women (Table 8 and 9). The IV estimates are still slightly larger in magnitude, which is mostly due to the (very small) incidents of delayed high school graduation and possible measurement errors in the actual graduation year. The negative effect of graduating during a recession on individual earnings among high school graduates, which is confirmed by the IV estimates, largely remains after conditioning on wage workers. This reflects the impacts of local economic shocks on small or medium enterprises.

Cautious interpretation of the above results is necessary in the case of men, owing to the existence of the mandatory military service for the category. First, the effects of labor market entry conditions for men may not be very clear during their early career. Among men, the number of high school graduates who begin full-time work immediately after graduation is fairly small. Owing to the mandatory military service, ranging from 21–36 months, it takes almost 3 years for men to begin a full-time job.

Second, the timing of military service is a matter of choice for each individual, but this choice is not likely to introduce large biases into the estimates. Most men choose to begin their military service as soon as possible, typically several months after high school graduation, to prevent career discontinuity. This is well understood from the perspective of dynamic optimization and career-specific human capital accumulation. It is also difficult to adjust the timing of military service in practice because a long queue exists—while the armed forces have a fixed number of positions, the number of applicants fluctuates considerably every year.

Concerning college graduates, the IV results also confirm the OLS results in that the effects of graduating during a recession on individual earnings or employment are not sta-

Table 8: Effects of labor market entry conditions (2SLS): Men, high school graduates

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.077*	-0.061	0.079^{+}	0.077	-0.063^{+}	0.038	-0.093*	0.033	0.159^{+}
	(0.038)	(0.069)	(0.044)	(0.058)	(0.034)	(0.061)	(0.040)	(0.040)	(0.084)
$\times$ Exper.(2–3)	-0.044	-0.041	-0.001	0.016	-0.068*	0.028	-0.072*	0.016	0.127
	(0.029)	(0.048)	(0.030)	(0.039)	(0.032)	(0.046)	(0.032)	(0.039)	(0.081)
$\times$ Exper.(4–5)	-0.055*	-0.031	-0.012	0.025	-0.060^{+}	0.075*	-0.041	-0.004	0.094
	(0.024)	(0.041)	(0.023)	(0.033)	(0.032)	(0.036)	(0.027)	(0.039)	(0.078)
$\times$ Exper.(6–7)	-0.052*	-0.022	-0.014	0.012	-0.066*	0.062^{+}	-0.042^{+}	-0.032	0.044
	(0.022)	(0.036)	(0.019)	(0.031)	(0.032)	(0.033)	(0.024)	(0.038)	(0.076)
$\times$ Exper.(8–9)	-0.057**	-0.014	-0.013	0.004	-0.064^{+}	0.059*	-0.034	-0.052	-0.009
	(0.021)	(0.035)	(0.015)	(0.029)	(0.033)	(0.029)	(0.023)	(0.038)	(0.073)
$\times$ Exper.(10+)	-0.053**	-0.016	-0.009	-0.001	-0.065^{+}	0.071**	-0.019	-0.058	-0.028
	(0.020)	(0.034)	(0.014)	(0.031)	(0.034)	(0.027)	(0.023)	(0.039)	(0.076)
N	2077	2072	2077	1826	2200	2200	2960	2959	2343

Table 9: Effects of labor market entry conditions (2SLS): Women, high school graduates

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.061^{+}	-0.090^{+}	0.031	0.052	0.028	-0.014	-0.060^{+}	0.063*	0.123^{+}
	(0.032)	(0.048)	(0.031)	(0.039)	(0.023)	(0.033)	(0.036)	(0.029)	(0.067)
$\times$ Exper.(2–3)	-0.056*	-0.087*	0.051*	0.099**	0.020	0.005	0.002	0.043	0.111^{+}
	(0.028)	(0.038)	(0.023)	(0.032)	(0.022)	(0.029)	(0.032)	(0.027)	(0.058)
$\times$ Exper.(4–5)	-0.048^{+}	-0.076*	0.066**	0.114**	0.012	0.016	0.023	0.013	0.068
	(0.025)	(0.033)	(0.020)	(0.029)	(0.021)	(0.029)	(0.027)	(0.025)	(0.053)
$\times$ Exper.(6–7)	-0.025	-0.061^{+}	0.061**	0.082**	0.006	0.039	0.028	-0.000	0.022
	(0.024)	(0.031)	(0.017)	(0.028)	(0.021)	(0.027)	(0.026)	(0.023)	(0.052)
$\times$ Exper.(8–9)	-0.018	-0.076**	0.058**	0.071**	0.002	0.035	0.032	0.002	-0.006
	(0.023)	(0.029)	(0.014)	(0.027)	(0.022)	(0.024)	(0.024)	(0.021)	(0.051)
$\times$ Exper.(10+)	-0.016	-0.071*	0.048**	0.058*	-0.000	0.021	0.029	0.003	-0.016
	(0.023)	(0.030)	(0.013)	(0.028)	(0.023)	(0.020)	(0.023)	(0.020)	(0.051)
N	1993	1986	1993	1843	2117	2117	4344	4342	3357

Standard errors in parentheses are clustered at the predicted cohort-by-region level.
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

All specifications control for parents' education, birth order, number of siblings, a cubic in potential experience, graduating year and region fixed effects, linear trends by school regions, and current year fixed effects. The dependent variables comprise log real monthly earnings, a dummy for firm size larger than or equal to 500 workers, a dummy for overeducation (being more qualified than what is required by the current job), a dummy for temporary contract that is conditional on wage worker, a dummy for self-employment, a dummy for job change (current job tenure being less than a year), a dummy for working full-time (more than 30 hours per week), a dummy for having ever been in a married relationship, and the number of children on the date of survey interview.

tistically different from zero. Nonetheless, some notable differences are observed in the IV estimates.

First, the 2SLS estimates reveal that male graduates during a recession are more likely to begin their career at a small firm. Additionally, the initial effect on firm size is likely to persist for at least 7 years after graduation and even beyond that period, especially for graduates who are part of a 4–5 year college graduation program. This suggests that the career/job ladder (e.g., Topel and Ward, 1992; Neal, 1999) does not work effectively in Korea. Although the initial wages of graduates who are part of a 4–5 year college graduation program are more insulated from the effects of recessions,[15] it is difficult for such graduates to procure employment in large firms once they miss the opportunity at the beginning of their career. This rigidity is mainly attributed to the hiring strategy of large firms, which are mostly part of business groups (*chaebol*). These firms heavily rely on large-scale open recruiting for new graduates and on the internal labor market for their human resource management, a practice also followed by the Japanese firms (*keiretsu*).

Second, self-employment among low-skilled men can be persistently hampered by the local economic shock at graduation. The ratio of self-employment among male high school graduates drops if they graduate during a recession, and this negative effect is strikingly persistent. In fact, the negative effect in self-employment explains most of the decrease in the probability of working full-time among all male high school graduates.[16] Given the large ratio of self-employed workers in the economy (25.5% of all workers in 2016), Korean high school graduates consider self-employment as an important career option. Those whose comparative advantage is in self-employment may lose their opportunity if they graduate during a local recession, as the expected profits (unconditional on survival) from self-employment decrease.

[15] This protection is double-folded—large firms are protected from adverse domestic shocks because they are part of a business group that provides insurance and workers in large firms are protected because they are more likely to be unionized.

[16] Additional analyses suggest that the probability of working full-time as a self-employed worker (among all male high school graduates) persistently declines if the local unemployment rate at graduation increases. The probability of working full-time as a wage worker (among all male high school graduates) is initially almost unaffected and increases over time—as those who would choose self-employment join this group.

The strong persistence suggests two possibilities: first, those who start a business during the recession are more likely to fail, and the costs of failure are large; second, self-employment requires a certain kind of human capital investment and/or risk-taking, and it becomes harder and harder to start a business later. Additional analyses suggest that the latter is more probable in this context—the probability of self-employment also drops from the beginning.[17]

Third, concerning high school or 2–3 year college educated women, the timings of family formation and childbearing are temporary but significantly affected by labor market conditions at graduation, conditional on graduation.[18] In line with theoretical predictions, these young women who are impacted by the adverse demand shock on labor market entry are more likely to opt for more affordable leisure—by forming a family and giving birth to a child relatively *earlier* (e.g., Hofmann and Hohmeyer, 2016; Schaller, 2016).[19] It must be noted that this factor is related only to the timing of marriage and fertility. The relative increases in marriage and fertility rates among this cohort disappear within 10 years after graduation—in particular, the total fertility rate of women aged 35 years does not change.

Interestingly, female graduates who are part of a 4–5 year college graduation program are more likely to have never been in a married relationship during the first 10 years since graduation if they graduate into a bad economy. They also significantly contribute toward the labor market. While the latter—higher participation rate due to a recession at graduation—sounds somewhat puzzling, it is possible to explain this finding in an extended framework that combines the labor market and the marriage market. Let's suppose there are some highly-educated women who prefer caring for home and family to working in the labor

[17] At the same time, the initial earnings of self-employed workers initially drop and catch up in 4–5 years if they graduate during a recession. It is also possible that self-employed workers just rest for a while because of low demand, but this is clearly different from slow recovery after an immediate failure.

[18] It must be noted that those who do not graduate, possibly due to marriage or pregnancy, are dropped out of the final sample. The above results, thus, should be carefully interpreted—although the number of women who do not graduate due to marriage or pregnancy is small. This research focuses on the possible interconnection between labor market outcomes and family outcomes.

[19] In the case of women, the total effect of a recession on fertility may show a sign that is different from that showing the effect of graduating during a recession on individual fertility. Even if the former is negative (i.e., fertility is pro-cyclical), the latter can be (temporarily) positive for women (e.g., Schaller, 2016).

market. Also, suppose that men and women who graduate together are more likely to be matched. Then, those women, who would have not worked in a normal economy, may work if they graduate into a bad economy because they fail to find a suitable mate.

As expected, the effect of labor market entry conditions on the marital status of men, regardless of their education level, is not statistically significant at a 10 percent level. Since men are more likely to be the primary earners of their respective (would-be) households, the negative income effect offsets the positive substitution effect.

While the childbearing decision making among men also seems positively associated with local unemployment rate at graduation, this relationship may be spurious. It is possible that the observed relationship among men reflects the initial increase in childbearing among women; this possibility arises from the sampling scheme of the YPS07—once a household is selected for the interview, all household members are surveyed together.[20]

[20] Another possibility is the imprecise definition of the number of children in YPS07, as explained in the data section; however, it is unlikely that measurement errors in dependent variable can lead to statistically significant results.

Table 10: Effects of labor market entry conditions (2SLS): Men, graduates from a 2–3 year graduation study programme

	Log Earn.	Firm ≥100	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.007	-0.170	0.058	0.091	0.133^{+}	0.093	-0.084	0.088	0.315*
	(0.079)	(0.126)	(0.110)	(0.068)	(0.080)	(0.080)	(0.071)	(0.100)	(0.155)
$\times$ Exper.(2–3)	0.057	-0.170	0.038	-0.004	0.097	-0.048	-0.081	0.042	0.248
	(0.076)	(0.126)	(0.110)	(0.068)	(0.079)	(0.079)	(0.064)	(0.101)	(0.156)
$\times$ Exper.(4–5)	0.037	-0.161	0.022	0.055	0.074	0.030	0.011	0.021	0.145
	(0.072)	(0.119)	(0.106)	(0.062)	(0.078)	(0.079)	(0.060)	(0.099)	(0.153)
$\times$ Exper.(6–7)	0.033	-0.161	0.004	-0.009	0.060	-0.029	-0.038	0.016	0.111
	(0.065)	(0.111)	(0.101)	(0.063)	(0.074)	(0.067)	(0.053)	(0.097)	(0.144)
$\times$ Exper.(8–9)	0.003	-0.153	0.011	0.078	0.051	0.052	0.026	-0.003	0.049
	(0.066)	(0.111)	(0.102)	(0.061)	(0.078)	(0.071)	(0.053)	(0.100)	(0.148)
$\times$ Exper.(10+)	0.015	-0.149	0.031	0.013	0.049	-0.028	-0.017	-0.001	0.065
	(0.056)	(0.104)	(0.096)	(0.052)	(0.072)	(0.054)	(0.046)	(0.099)	(0.136)
N	3140	3130	3140	2911	3324	3324	3984	3980	3207

Table 11: Effects of labor market entry conditions (2SLS): Men, graduates from a 4–5 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	0.119	-0.533**	-0.138	-0.109	-0.110	0.068	0.186	-0.010	0.355^{+}
	(0.133)	(0.203)	(0.174)	(0.102)	(0.136)	(0.135)	(0.159)	(0.155)	(0.210)
$\times$ Exper.(2–3)	0.109	-0.537**	-0.124	-0.135	-0.104	-0.009	0.186	-0.002	0.302
	(0.125)	(0.186)	(0.172)	(0.089)	(0.124)	(0.131)	(0.151)	(0.141)	(0.204)
$\times$ Exper.(4–5)	0.062	-0.413*	-0.168	-0.100	-0.062	0.060	0.159	0.094	0.246
	(0.139)	(0.210)	(0.171)	(0.132)	(0.127)	(0.143)	(0.102)	(0.136)	(0.188)
$\times$ Exper.(6–7)	0.150	-0.492**	-0.139	-0.127	-0.129	-0.004	0.185	0.000	0.237
	(0.120)	(0.190)	(0.183)	(0.099)	(0.112)	(0.172)	(0.186)	(0.130)	(0.186)
$\times$ Exper.(8–9)	0.016	-0.325	-0.215	-0.061	-0.021	0.056	0.126	0.114	0.213
	(0.172)	(0.261)	(0.209)	(0.189)	(0.129)	(0.223)	(0.128)	(0.151)	(0.195)
$\times$ Exper.(10+)	0.333	-0.587	-0.029	-0.187	-0.238	-0.163	0.227	-0.342	0.153
	(0.299)	(0.447)	(0.431)	(0.363)	(0.194)	(0.606)	(0.493)	(0.267)	(0.290)
N	5195	5175	5195	4950	5540	5540	6791	6781	5641

Standard errors in parentheses are clustered at the predicted cohort-by-region level.
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

All specifications control for parents' education, birth order, number of siblings, a cubic in predicted potential experience, predicted graduation year and region fixed effects, linear trends by school regions, and current year fixed effects. The additional controls for college graduates include categorical dummies (1–5) of the three CSAT scores (Korean, Math, and English) and dummies of university rankings (1–20, 21–40, and 41+). The dependent variables comprise log real monthly earnings, a dummy for firm size larger than or equal to 500 workers, a dummy for overeducation, a dummy for temporary contract that is conditional on wage worker, a dummy for self-employment, a dummy for job change, a dummy for working full-time, a dummy for having ever been in a married relationship, and the number of children on the date of survey interview.

Table 12: Effects of labor market entry conditions (2SLS): Women, graduates from a 2–3 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	-0.036	0.020	0.035	-0.011	0.052^{+}	0.133^{*}	-0.070	0.119^{**}	0.317^{**}
	(0.041)	(0.066)	(0.058)	(0.036)	(0.030)	(0.057)	(0.048)	(0.036)	(0.083)
× Exper.(2–3)	-0.015	0.043	0.023	-0.023	0.053^{+}	0.111^{*}	-0.052	0.090^{*}	0.267^{**}
	(0.037)	(0.059)	(0.054)	(0.032)	(0.030)	(0.051)	(0.043)	(0.035)	(0.080)
× Exper.(4–5)	-0.002	0.038	0.026	-0.040	0.042	0.116^{*}	-0.028	0.058^{+}	0.188^{*}
	(0.034)	(0.052)	(0.048)	(0.029)	(0.029)	(0.046)	(0.039)	(0.035)	(0.076)
× Exper.(6–7)	0.015	0.035	0.016	-0.048^{+}	0.039	0.098^{*}	-0.010	0.042	0.108
	(0.030)	(0.043)	(0.042)	(0.025)	(0.028)	(0.040)	(0.035)	(0.034)	(0.072)
× Exper.(8–9)	0.041	0.056	0.009	-0.036^{+}	0.031	0.019	0.001	0.031	0.036
	(0.028)	(0.038)	(0.038)	(0.021)	(0.029)	(0.034)	(0.031)	(0.031)	(0.068)
× Exper.(10+)	0.040	0.051	-0.020	-0.046^{*}	0.027	0.011	0.012	0.012	-0.008
	(0.029)	(0.033)	(0.034)	(0.019)	(0.031)	(0.029)	(0.031)	(0.031)	(0.069)
N	4249	4239	4249	4062	4430	4430	6897	6884	5572

Table 13: Effects of labor market entry conditions (2SLS): Women, graduates from a 4–5 year graduation study programme

	Log Earn.	Firm ≥500	Over-Edu.	Temp. Cont.	Self-Empl.	Job Chg.	Work >30h	Ever Md.	No.of Chn.
$U_{gr}\times$ Exper.(0–1)	0.067	0.031	0.028	0.033	0.002	0.073	0.062	0.006	0.113^{*}
	(0.043)	(0.059)	(0.062)	(0.048)	(0.024)	(0.052)	(0.053)	(0.031)	(0.053)
× Exper.(2–3)	0.067^{+}	0.008	0.075	-0.009	0.006	0.029	0.111^{*}	-0.029	0.085
	(0.040)	(0.059)	(0.059)	(0.044)	(0.025)	(0.048)	(0.052)	(0.031)	(0.052)
× Exper.(4–5)	0.055	0.019	0.066	0.002	-0.005	0.038	0.123^{*}	-0.042	0.031
	(0.039)	(0.055)	(0.057)	(0.043)	(0.025)	(0.044)	(0.048)	(0.030)	(0.049)
× Exper.(6–7)	0.058	0.006	0.058	-0.015	-0.020	0.027	0.103^{*}	-0.045	0.011
	(0.038)	(0.052)	(0.056)	(0.040)	(0.025)	(0.042)	(0.047)	(0.030)	(0.049)
× Exper.(8–9)	0.060	0.022	0.032	-0.000	-0.026	0.018	0.086^{+}	-0.049	0.002
	(0.039)	(0.052)	(0.059)	(0.042)	(0.027)	(0.044)	(0.046)	(0.032)	(0.051)
× Exper.(10+)	0.057	0.016	0.040	-0.002	-0.040	0.021	0.062	-0.055^{+}	0.000
	(0.037)	(0.052)	(0.063)	(0.040)	(0.028)	(0.044)	(0.045)	(0.032)	(0.057)
N	5420	5408	5420	5208	5671	5671	8813	8802	7288

Standard errors in parentheses are clustered at the predicted cohort-by-region level.
$^{+}$ $p < .1$, * $p < .05$, ** $p < .01$

All specifications control for parents' education, birth order, number of siblings, a cubic in predicted potential experience, predicted graduation year and region fixed effects, linear trends by school regions, and current year fixed effects. The additional controls for college graduates include categorical dummies (1–5) of the three CSAT scores (Korean, Math, and English) and dummies of university rankings (1–20, 21–40, and 41+). The dependent variables comprise log real monthly earnings, a dummy for firm size larger than or equal to 500 workers, a dummy for overeducation, a dummy for temporary contract that is conditional on wage worker, a dummy for self-employment, a dummy for job change, a dummy for working full-time, a dummy for having ever been in a married relationship, and the number of children on the date of survey interview.

4.4 Discussion: endogenous schooling

High school graduates may decide to go to college after a series of unsuccessful job searches. Colleges can serve as "shelters" in adverse economic conditions. The same story can be applied to graduate study for college graduates.

This possibility of continued education due to adverse economic conditions raises a difficult issue of endogenous schooling—unobserved characteristics may systematically differ across graduation cohorts among whose final education is high school (or college) graduation. To test this possibility, I perform a regression analysis of final education status on the local unemployment rate at graduation from high school (or college) and various control variables.

Table 14 shows the regression results. For men, college education is not statistically significantly correlated with the local unemployment rate at high school graduation. The decision to go to graduate school is *negatively* affected by the local unemployment rate at college graduation.[21] Nonetheless, the selection into graduate school is unlikely to alter the main results since the observed characteristics (parents' education, birth order, and number of siblings) of 4–5 year college graduates are similar regardless of whether or not they end up with an advanced degree.

For women, the dummy variable for being college educated is highly significantly correlated with the local unemployment rate at high school graduation, even after controlling for demographic backgrounds and the year and region of graduation fixed effects. This selection into college education can bias the estimation results for women, so those results should be carefully interpreted—the results for both high school graduates and (2–3 year) college graduates are likely biased to the direction of showing negative effects.[22] Nonetheless, the results for female college graduates remain largely the same even if the local unemployment rate at high school graduation are additionally controlled for.

[21] This suggests that negative income effects dominate positive substitution effects (less opportunity costs).

[22] Those who select into college education for an "endogenous" reason are likely to have intermediate abilities—higher than other high school graduates but lower than other college graduates.

The dummy for being college educated at 4–5 year study program is not statistically significantly associated with the economic conditions at high school graduation. The dummy for advanced degree is not likely affected by the local unemployment rate at college graduation, either.

Table 14: Local unemployment rate at graduation and final education

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
	Col(2+)	Col(4+)	Grad. Sch.	Col(2+)	Col(4+)	Grad. Sch.
U_{gr} (HSG)	0.000	0.010		0.048**	0.023	
	(0.017)	(0.018)		(0.014)	(0.016)	
U_{gr} (CLG)			-0.055*			0.020
			(0.027)			(0.022)
Father's Schooling	0.053**	0.083**	0.006	0.056**	0.091**	-0.005
	(0.008)	(0.009)	(0.007)	(0.007)	(0.008)	(0.006)
Mother's Schooling	0.003	0.025*	-0.005	0.024**	0.039**	0.022
	(0.009)	(0.012)	(0.010)	(0.0090)	(0.011)	(0.011)
Birth Order	-0.025	-0.026*	-0.002	-0.026**	-0.026*	0.001
	(0.013)	(0.013)	(0.011)	(0.009)	(0.011)	(0.011)
Number of Siblings	0.032*	0.012	0.004	-0.018*	-0.028**	0.003
	(0.014)	(0.015)	(0.014)	(0.009)	(0.010)	(0.010)
N	3,149	3,149	1,376	4,111	4,111	1,911

Standard errors in parentheses are clustered at the graduation region-by-cohort level.
* $p < 0.05$, ** $p < 0.01$

All specifications control for the year and region of high school (or college) graduation fixed effects.

5 Conclusion

By using a panel data set combined with administrative information, I investigate the long-term effects of local unemployment rate at graduation on various labor market outcomes as well as on family outcomes. Due to the possibility of delayed graduation, I use the local unemployment rate at the predicted time of graduation as an instrument for the local unemployment rate at actual graduation. The possibility of endogenous schooling is also examined.

The main findings can be summarized as follows. First, the labor market entry conditions have strong persistent effects, particularly among high school graduates. A typical recession in Korea reduces initial earnings of high school graduates by 3–4 percent, and this negative effect does not disappear for at least 7–10 years after graduation.

Second, college graduates have persistently low probability of working at large firms if they are impacted by the adverse demand shocks at labor market entry. A typical recession reduces the probability of working at large firms by 27 percentage points[23] for college graduates who are part of a 4–5 year college graduation program, and the negative effect persists for at least 7 years.

Third, self-employment is an important channel for explaining the strong effect of labor market entry conditions among high school graduates. In Korea, both earnings and employment of high school graduates are negatively affected by a local recession at graduation. The negative effect at the intensive margin mostly reflects lower earnings of wage workers, and the negative effect at the extensive margin mostly reflects a lower probability of self-employment.

Fourth, conditional on graduation, family formation and childbearing are negatively but temporarily affected by labor market entry conditions in the case of less educated women. Statistically significant long-term effects are not observed, except for female graduates who are part of a 4–5 year college graduation program and who have a slightly lower probability of having ever been in a married relationship until the date of survey interview.

These results are consistent with the findings of previous literature. For example, low-skill workers are more likely to be affected by a recession on labor market entry in a highly-segmented labor market (e.g., Genda et al., 2010; Fernández-Kranz and Rodríguez-Planas, 2017). Also, the recession at graduation can *advance* the timing of family formation and childbearing, especially among less educated women (e.g., Hofmann and Hohmeyer, 2016; Schaller, 2016).

This study also presents a new set of findings. First, labor market segmentation between protected jobs and unprotected jobs is expected to make the effects of labor market entry conditions persistent, especially among high school graduates. This highlights the impor-

[23] $= 0.5 \times 0.533 \times 100$

tance of labor market institutions, such as employment protection and business group, in understanding the cross-country differences in the effects of labor market entry conditions.

Second, self-employment among low-skill workers can be persistently hampered by labor market entry conditions. In an economy with a large share of self-employment, this channel may play a key role in determining where the long-term effect of graduating during a recession appears—especially between the intensive and extensive margins.

Third, family-related decisions can work as channels of buffering the negative shocks at graduation. Put differently, a recession at graduation may negatively impact graduates in other dimensions; for example, firm size may be associated with non-pecuniary benefits and social recognition that may play a role in matchmaking in the marriage market, and the chances of finding a suitable partner for marriage can decrease as a result of the disruption in the labor market.

Given the daunting task of writing a general model that explains the interactions among labor market institutions, aggregate economic shocks, and life-cycle earnings dynamics, this study does not explicitly model how the long-term effects of labor market entry conditions arise. Also, recessions may have non-linear and heterogeneous effects; for example, Altonji et al. (2016) report the Great Recession in the U. S. was in many ways different from earlier recessions. Likewise, the Asian Financial Crisis may have impacted Korea in different ways, leaving long-term effects that distinguishes the recession from other ones. These are left for future research.

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The Rise of Low-Skilled Service Employment: the Role of Dual-Income Households*

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Abstract

This paper unveils an important but unexplored channel for the growth of low-skilled service employment between 1960 and 2000; the spillover effect from dual-income households. In particular, we analyze the cross-city association between variation in dual-income households and employment growth in home production substitutes. In order to address concerns about endogeneity and reverse causality, we use the fact that dual-income women had been extremely concentrated on administrative support occupations while their birth places were heterogeneously distributed. Our finding supports the spillover hypothesis: One more dual-income couple creates 0.3 low-skilled service jobs in local economies and the spillover effect is mainly driven by the home production service sector.

JEL: E24, J12, J21, R12

Keywords: Dual-income couple; Spillover effcct; Low-skilled service worker; Home production substitute; Job Polarization

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1 Introduction

Why has low-skilled service employment grown over the last several decades? It may be attributed to technology progress (Autor and Dorn (2013); Buera, Kaboski, and Zhao (2017)), spillover from high-skill consumption (Mazzolari and Ragusa (2013); Leonardi (2015)); or immigration (Cortés and Tessada (2011)). In this paper, we suggest another potentially important channel for the growth of low-skilled service employment: the rise of dual-income households. The dramatic rise in married women's labor supply that occurred over the past decades in the U.S. has led to a greater share of dual-income households.[1] Figure 1.1 visually shows this change: Between 1960 and 2000, the number of dual-income couples rose fourfold while the share of dual-income couples relative to total married couples tripled.[2] Motivated by the fact that both low-skilled service employment and numbers of dual-income couples have grown over the past decades, this paper examines whether and the extent to which the growth of low-skilled employment depends on physical proximity of dual-income households (both husband and wife are employed in non-low-skill service sectors).

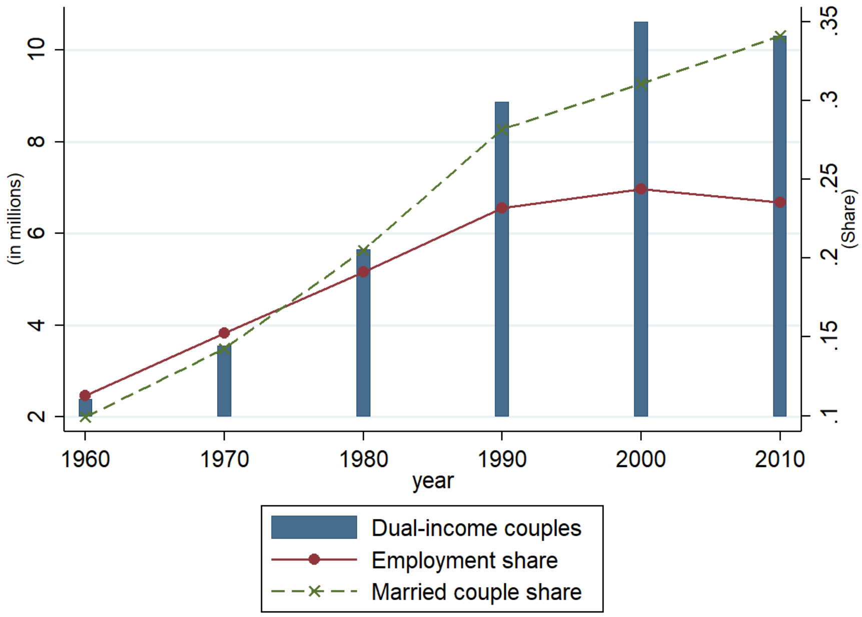
The idea behind our hypothesis is simple. Suppose that there is a female-biased labor market change. Then more female workers will participate into the labor market, and hence the number of dual-income households increases. Since time endowment is fixed, less time can be devoted to home production, which raises demand for low-skilled and time-intensive services such as food preparation, cleaning, maintenance and repairs, and child care, which can be defined as market substitutes for home production. As a result, employment in low-skill service job increases, and we refer it as spillover effect of dual-income households. Time series evidence in the U.S. supports our hypothesis: Over the period of 1960 and 2000, the proportion of workers at the bottom of wage distribution has steadily increased. In particular, service occupations that provide market substitutes for home production have grown more than 190 percent during this period.[3] The positive correlation between dual-earner couples and low-skilled employment suggests evidence of

[1]According to Blau (1998), most of the rise in female labor force participation between 1970 and 1995 comes from married couples (Table 2).

[2]In addition, there has been a trend of assortative mating, which implies resemblance in some characteristics such as education and employment between spouses (Behrman and Rosenzweig, 2002; Lefgren and McIntyre, 2006; McCrary and Royer, 2011). In particular, there is considerable within-occupation marital matching (Mansour and McKinnish, 2018).

[3]Buera and Kaboski (2012) show that the share of the service sector in value-added has grown steadily from 60 percent in 1950 to 80 percent in 2000 and provide a theoretical framework for analyzing the role of high-skilled labor in the growth of the service sector.

Figure 1.1: Trend in Dual-Income Households 1960-2010



Note: Author's calculations from IPUMS (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010)) version of the Decennial Censuses. Employment share is the total number of dual-income workers relative to total employment. Married couple share is the total number of dual-income couples relative to total married couples.

consumption spillovers.

We test our hypothesis that the presence of dual-income households creates demand for low-skilled service by utilizing the cross-city association between the decadal change in the share of dual-income households and employment growth in home production substitutes. In doing so, we use the decennial Census data between the period of 1960 and 2000 as women's labor force participation peaked in 2000 and has gradually declined since then. In particular, we estimate the regression model linking the employment growth in home production service sectors to the change in dual-income earners in the same city over the same period. This local labor market analysis is closely related to Leonardi (2015), Manning (2004), and Mazzolari and Ragusa (2013), who document the cross-city relationship between high-skilled and low-skilled workers, assuming that service providers have to be located near consumers.

Although some studies have found evidence of the positive cross-city relationship between different types of workers, empirical challenges have made it difficult to identify causality: First of all, unobserved city-specific factors affecting dual-income households might have an independent impact on supply of low-skilled workers. Reverse causality is another concern: Low-skilled service workers who substitute for household production might induce more married women into the labor market. We address these reverse causality and endogeneity concerns by employing an instrumental variables approach. In particular, we use the fact that women in dual-income households are extremely concentrated on certain occupations (e.g. administrative support) in 1960, while there is significant heterogeneity in occupations across birth places. Specifically, we use the interaction between the initial (i.e., 1960) concentration and distribution of dual earners for predicting the actual number of dual-income households across cities as an instrument.

Our empirical analysis indicates that spillover effect of dual-income households on low-skill service jobs indeed exists: Between 1960 and 2000, one more dual-income couple created 0.3 to 0.4 low-skilled service jobs and the one percentage point increase in dual-income households was associated with 0.8 to 1.1 percent increases in wages of low-skilled service workers. More importantly, the positive effect is mainly driven by the home production service sector such as cleaning, food preparation, maintenance, and child care. Our finding is robust to adding control variables such as low skilled immigrants, college educated workers, and the initial routine share that have been argued as important sources for rising service sector.

Main contributions of this paper are twofold. First, we provide evidence of an unexplored channel through which dual-income households have an impact on the low-skilled service jobs. In particular, we find that low-skilled service workers are benefitted from dual-income households because dual earners are more likely to purchase service for household production. This spillover effect of dual-income households is still relevant even when we control for other factors that have been suggested to be important for the growth of service employment in the previous literature. Furthermore, our results suggest that wages of low-skilled service workers also have increased with the rise of dual-income earners, which implies that the finding is driven by the demand side not by the supply side of service workers. Second, this paper enhances our understandings of "job polarization" in the U.S. labor market. Since the mid-1980s, employment in high- and low-skilled occupations has increased while job opportunities in middle-skilled occupations have disappeared (see Acemoglu and Autor (2011) for instance). Our finding indicates that the rapid growth of employment in low-skilled occupations, or service occupations, can be understood as a result of spillovers from the change in household structure, rather than routine-replacing technological progress, which has a relatively minor impact on non-routine service sectors (Autor, Levy, and Murnane, 2003; Goos and Manning, 2007). This study, therefore, provides a new perspective on the literature on job polarization, particularly emphasizing consumption spillovers in explaining the growth of low-skilled service jobs in recent decades.

The remainder of the paper is organized as follows. Section 2 presents a framework that provides theoretical predictions on relationship between the change in dual-income couples and employment growth in service sector. Section 3 introduces data and describes trend of dual-income households in the U.S. cities. We discuss our identification strategy in Section 4 and present empirical results in Section 5 together with several robustness checks. Section 6 concludes the paper.

2 Theoretical Framework

In this section, we formalize the main idea of our paper with a simple labor market model and then draw some testable implications. Since we are interested in long-run changes, we consider a static model.[4] As we investigate the extent to which an increase in the numbers of dual-income couples affects jobs in the service sector that can potentially substitute labor by household members, we need an exogenous change that raises labor market participation of female workers.[5] To that end, we assume that the wage rate for a female worker, denoted as w_f, exogenously increases. In addition, we consider an intensive margin of the female worker for the sake of simplicity; an increase in the numbers of dual-income couple is introduced as an increase in labor supply of the female worker to the labor market (h_f^M) rather than explicitly modelling the binary decision of the female worker.

2.1 Couple's Decision Consider the following utility maximization problem of a couple, which is a version of the model introduced in Bar and Leukhina (2011) and Jones, Manuelli, and McGrattan (2014):

$$\max\ \lambda_f u\left(c_f^M, c_f^H, 1-h_f^M-h_f^H\right)+\lambda_m u\left(c_m^M, c_m^H, 1-h_m^M-h_m^H\right) \tag{2.1}$$

subject to

[4] One might consider a dynamic model with two different steady-states, which is basically equivalent to our analysis.
[5] Hence, we focus on a dual-income couple whose members are male and female workers.

$$c_f^M + c_m^M + ps = w_m h_m^M + w_f h_f^M, \tag{2.2}$$

$$c_f^H + c_m^H = zG(h_m^H + h_f^H, s), \tag{2.3}$$

where subscript f (resp. m) refers to female (resp. male), superscript M (resp. H) refers to market good (resp. home good), $\lambda_f > 0$ and $\lambda_m > 0$ are constant, $u(\cdot)$ is a continuous, (at least twice) differentiable, (strictly) increasing, and (strictly) concave function that satisfies Inada conditions. c denotes consumption for each good. $p > 0$ is the price of services (relative to market good whose price is normalized to one) that can be used to produce home produced goods and $s \geq 0$ denotes the amount of services purchased by the household. $w_m > 0$ (resp. $w_f > 0$) is the hourly wage rate of a male (resp. female) worker. Hence, the first constraint, equation (2.2), is the budget constraint of the household and the second constraint, equation (2.3), is the (resource) constraint for a home good. $z > 0$ denotes productivity of the home production. Home production uses two inputs, labor and service purchased at the market. We assume that $G(\cdot)$ is strictly increasing and concave in both inputs (Inada condition is also assumed to hold). Following the literature, we assume that female and male's labor supply to home production are perfectly substitutable. In order to pin down a unique equilibrium, we assume that only female workers work at home (hence $h_m^H = 0$).

2.2 Service sector Note that a couple' decision determines demand for s, a service good. Here, the 'service good' is the good that can substitute for labor input of the household members in home production. In other words, other types of services that do not directly substitute household labor in the home production are excluded in this model.

We assume that this sector is perfectly competitive both in goods market and labor market.

Firm. There is a representative firm that tries to maximize its profit:

$$\max_h pAf(h) - wh, \tag{2.4}$$

where $A > 0$ is the productivity in the service sector and $w \geq 0$ is the wage rate for low-skilled workers who are employed in the service sector. $f(\cdot)$ is assumed to be continuous, strictly increasing, and strictly concave, and to satisfy Inada conditions.

Hence, labor demand is determined by the usual downward-sloping labor demand equation: $\frac{w}{p} = Af'(h)$.

Worker. Low-skilled workers supply their labor according to the following upward-sloping labor supply equation: $w = Bh^{\psi}$ with $\psi > 0$.[6]

2.3 Main Predictions

In this subsection, we derive predictions of the model that will be tested in Section 4. Details of derivations can be found in Appendix B.

By combining the first-order conditions for the labor supply decision of a female worker and that for a service good, we can obtain

$$w_f = p\frac{G_h}{G_s}, \tag{2.5}$$

where $G_h \equiv \partial G / \partial h_f^H$ and $G_s \equiv \partial G / \partial s$.

This equation implies that when the wage rate of a female worker increases, there should be an adjustment in labor supply to a home good (a female worker's labor supply to home production) and/or demand for service that can substitute for the female worker's time devoted to home production.

In order to draw a clear prediction, we assume CES production function for the home production and Cobb-Douglass production function for the service goods-producing firm. Formally,

$$G(h_f^H, s) = \left[\alpha s^{1-\frac{1}{\sigma}} + (1-\alpha)(h_f^H)^{1-\frac{1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{2.6}$$

where $\alpha \in (0,1)$ and $\sigma > 0$ denotes elasticity of substitution between a labor input and a service good, and

$$f(h) = h^{\delta}, \tag{2.7}$$

where $\delta \in (0,1)$.

Using various equilibrium conditions, we obtain the following equilibrium relationship for hours worked and the wage rate in the service sector:

[6] w is the wage rate in terms of the market good. One may consider GHH preference to derive this labor supply equation to eliminate the income effect for simplicity of the discussion.

$$\log h \propto \phi + \frac{\sigma}{\psi+1} \log h_f^M + \frac{1}{\psi+1} \log h_f^H + \frac{1-\sigma}{\psi+1} \log p \tag{2.8}$$

and

$$\log w \propto \log B + \psi \left(\phi + \frac{\sigma}{\psi+1} \log h_f^M + \frac{1}{\psi+1} \log h_f^H + \frac{1-\sigma}{\psi+1} \log p \right). \tag{2.9}$$

We now draw some testable implications of the model as follows.

Prediction (Spillover effect of Dual-income household)**.** *Suppose that the substitution effect dominates the income effect in a female worker's labor supply decision and leisure is flexibly adjusted. If there is an exogenous increase in the wage rate of a (married) female worker so that she supplies more labor into the labor market, the followings hold.*

1. *Employment (or labor input) of the low-skilled workers in the service sector increases.*
2. *The wage rate of the low-skilled workers in the service sector increases.*
3. *The above effects become greater as σ, elasticity of substitution between a labor input and a service good, becomes higher.*

The first two parts of the above prediction are straightforward to understand: Both employment (or labor input) and the wage rate of the low-skilled workers employed in the service sector increase since dual-income couple increases demand for a service good that can substitute out their labor input. As demand curve for the service good shifts out, the service firm's labor demand curve also shifts out hence both of the key variables would become greater. The last part of the prediction is also noteworthy. As the degree of substitutability (σ) becomes greater, the demand for a service good increases more as it easily substitutes hours worked supplied by household members. As a result, the impact on the labor market becomes greater as σ becomes high. Put it differently, a service good that cannot substitute a labor input, say $\sigma = 0$, does not affect the labor market of such a good.[7]

[7] It can indirectly affect the labor market for the service good through changes in $\log h_f^H$ but the magnitude of the effect should be much smaller.

3 Data: Dual-Income Households in U.S. Cities

In this section, we describe the data used for our empirical analysis and provide some key aspects of the data.

3.1 Data For the empirical analysis, we use the Integrated Public Use Microdata Series (IPUMS) version of the U.S. Censuses from 1960, 1970, 1980, 1990, and 2000 to quantify the effects of an increase in dual-income workers on low-skill service sectors. This data provides various individual level information including occupations, wages, and geographic locations of residence. Using this information, we construct city level measures such as the growth of dual-income workers.

Throughout our analysis, we restrict our sample to workers aged between 25 and 54, and exclude workers in group quarters or in schools. We define dual-income households as households in which both husband and wife work at least 50 weeks per year, in non-low-skill service sectors. Although Census records the detailed titles of workers' occupations, the classification system has been redefined in every decennial Census. To consistently follow the low-skill service sectors for the period between 1960 and 2000, we use the occupational classifications of Autor and Dorn (2013) and define low-skill service occupations as service occupations in their classifications. For example, these service occupations include housekeepers, janitors, or child care workers.

The geographical unit of analysis is the metropolitan statistical area (MSA) of residence.[8] The MSA is a region consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core, and the MSA has been widely used to analyze local effects. We identify 105 MSAs which are consistently identified across different Census samples.

3.2 Summary statistics We begin with providing some descriptive statistics on dual-income households. As is evident from Figure 1.1, numbers of dual-income households have remarkably grown: Since 1960, the number of dual-income couples increases by about 8 millions, resulting in approximately 10 millions and 24% of total employment in 2000. This increase has been significant at least until 2000. To analyze the economic impacts from this dramatic increase, we focus on the period between 1960 and 2000.

[8] Throughout the article, we interchangeably refer to MSAs as cities.

While the increase has been national, dual-income households are unevenly distributed across cities in the U.S. Table 3.1 shows the lists of top 10 and bottom 10 MSAs according to the share of dual-income workers out of total employment. There is significant variation across local areas. For instance, in York, PA, almost 25 percent of the employment is dual-income earners, whereas, in El Paso, TX, less than 10 percent are dual-income families. It also shows that the within-state variation is quite large. For example, comparing Albany and New York in New York state, the difference between the two areas is 8.8 percentage points. We exploit this significant variation to estimate the local impact on low-skill service sectors, which will be discussed further in the next section.

Table 3.1: Geographic Distribution of Dual-income households in 2000

Top 10		Bottom 10	
Metro Area	Share dual-income	Metro Area	Share dual-income
York, PA	24.9%	San Francisco, CA	14.0%
Madison, WI	24.7%	New York, NY	13.0%
Des Moines, IA	24.7%	San Diego, CA	12.9%
Minneapolis, MN	23.8%	Stockton, CA	12.7%
Lancaster, PA	23.0%	Riverside, CA	12.1%
Reading, PA	22.9%	Fresno, CA	10.9%
Fort Wayne, IN	22.6%	Los Angeles, CA	10.4%
Harrisburg, PA	22.4%	Miami, FL	10.3%
Omaha, NE/IA	22.2%	Flint, MI	9.9%
Albany, NY	21.8%	El Paso, TX	9.7%

Note: Author's calculation from the Census 2000 5% sample. Dual-income couples means that both husband and wife are employed in non-low-skill service sectors.

Table 3.2 describes another interesting aspect of dual-income earners by comparing occupational distributions of men and women. Among dual-income earners, women's jobs were extremely concentrated on administrative support occupations in 1960, while the distribution of men across occupations was relatively even. Furthermore, the fraction of women in administrative support jobs is surprisingly stable over the period between 1960 and 2000 (Figure 3.1). This means that local economies with lots of women who worked in administrative jobs in 1960 have experienced significant growth in dual-income households due to the increasing labor force participation of women. Based on this historical pattern, we construct predicted changes in dual-income households within cities, which we describe in detail in Section 4.

Table 3.2: Distribution of Dual-Income Workers across Occupations in 1960

Rank	**Men**		**Women**	
1	Machine Operators, Assemblers	14.3%	Administrative Support	34.4%
2	Executive, Administrative	12.7%	Machine Operators, Assemblers	17.0%
3	Transportation and Material Moving	11.1%	Sales	13.8%
4	Sales	8.6%	Teachers	7.2%
5	Precision Production	8.3%	Professional Specialty	6.9%
6	Administrative Support	8.0%	Precision Production	5.0%
7	Mechanics and Repairers	7.4%	Executive, Administrative	4.1%
8	Professional Specialty	6.4%	Other Agricultural and Related	1.9%
9	Construction Trades	5.3%	Technicians and Related Support	1.5%
10	Farm Operators and Managers	4.2%	Transportation and Material Moving	1.0%

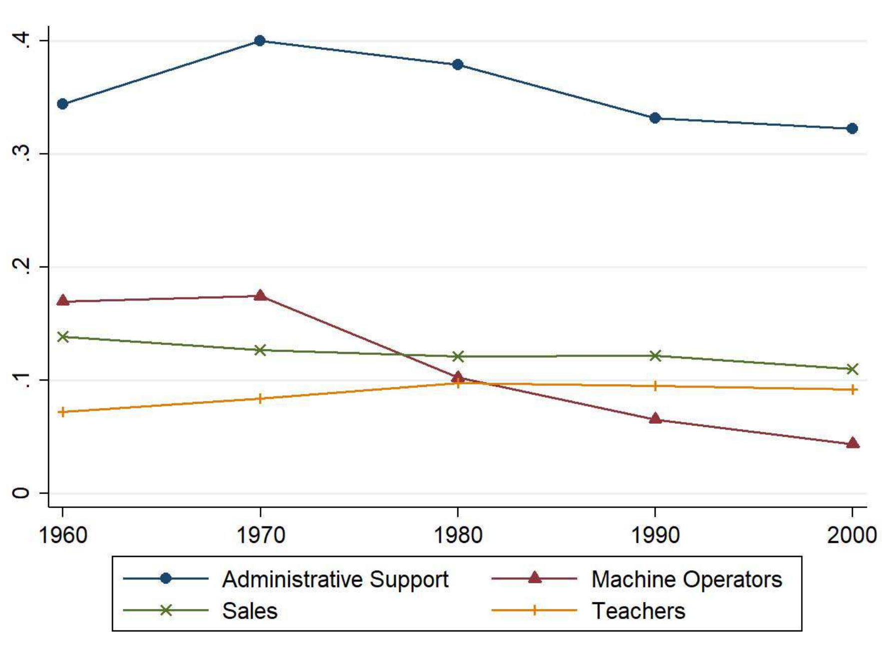
Note: Author's calculations from IPUMS (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010)) version of Census 1960 5% sample. Occupational classification follows Autor and Dorn (2013). Dual-income couples means that both husband and wife are employed in non-low-skill service sectors.

4 Empirical Strategy

In order to empirically validate the predictions introduced in Section 2, this section introduces our empirical strategy to identify the causal effect of the presence of dual-income households on the rise of low-skill service jobs. In other words, we examine whether dual-income couples crowd-in low-skill service workers to local economies.

We first consider an ideal case in which workers are randomly assigned into each city. Under

Figure 3.1: Share of Wives Job among Dual-Income Earners



Note: Author's calculations from IPUMS (Ruggles, Alexander, Genadek, Goeken, Schroeder, and Sobek (2010)) version of the Decennial Censuses. Occupational classification follows Autor and Dorn (2013).

such a random assignment, the causal estimates can be obtained with the following specification.

$$S_{ct} = \alpha + \beta D_{ct} + \varepsilon_{ct}, \tag{4.1}$$

where S_{ct} and D_{ct} represent a MSA (c)'s number of low-skill service workers and dual-income couples, respectively, in a particular year (t). In this case, β indicates numbers of jobs created due to the one more dual-income households in a locality.

Unfortunately, however, the above empirical specification is not appropriate to obtain consistent estimates since workers select into the local labor markets and other unobservable factors that affect the distribution of low-skill workers confound the estimates. We hence utilize a more demanding specification that partially accounts for factors that vary within MSAs as follows.

$$\frac{\Delta S_{ct}}{L_{ct-1}} = \alpha + \beta \frac{\Delta D_{ct}}{L_{ct-1}} + \Theta X_c + \gamma_t + \epsilon_{ct}. \tag{4.2}$$

The dependent variable captures variation in low-skill service jobs, taking first-difference ($\Delta S_{ct} = S_{ct} - S_{ct-1}$) and dividing by the total population in the initial year (L_{ct-1}). Dual-income households are transformed in the same manner. First-differencing effectively removes the influence of fixed local characteristics. Standardizing by the total population in the initial year prevents inherent specification bias from scale effects (Peri and Sparber, 2011). As the outcome and key explanatory variable are simple transformations of the number of workers, the key coefficient β can be interpreted in numbers of workers. If $\beta > 0$, each dual-income couple increases low-skill service workers. If $\beta < 0$, then dual-income couple crowd-out low-skill service jobs. Lastly, $\beta = 0$ means that there is no linear relationship between the two variables of interest. We also include time-period dummies (γ_t) to account for changes in national conditions. The term X_c is a vector of other MSA-specific controls, and ϵ_{ct} is a zero-mean idiosyncratic error term. The analysis estimates the spillover effects for four periods: 1960-1970, 1970-1980, 1980-1990, and 1990-2000. Using time differences over these four decades allows us to add additional location fixed effects occasionally, removing region-specific pre-trends.

While our specification controls for a wide array of potential confounding factors, time-varying city-specific shocks remain a concern. In order to correct these issues, we develop an instrumental variable to predict actual changes in dual-income households, which is discussed in the next subsection.

4.1 Instruments and Controls In order to develop an instrumental variable that is independent of time-varying unobservable confounders, we exploit uneven concentration of dual-income women in administrative support occupations in 1960 and growth of dual-income households, which is documented in Section 3.2. Furthermore, since couple formation may depend on the couple's network, we further consider origins (birth places) of couples to increase the power of the instrument.[9] Specifically, we first predict the number of dual-income households in MSA c for each year t as follows.

$$\widehat{D_{ct}} = \sum_b D_t^b \cdot \frac{A_{c,1960}^b}{A_{1960}^b} \tag{4.3}$$

where the first term D_t^b is the total number of dual-income households from wife's birth place b for the year t. We distribute this D_t^b using the second term, the share of administrative support women for each birth place ($A_{c,1960}^b / A_{1960}^b$), as weight. Specifically, the weight part for each birth place b is

[9] The birth place indicates the U.S. state or the foreign country where the person was born.

obtained by calculating the number of administrative support (married) women in MSA c in year 1960.[10] We multiply these two terms and sum across the birth place b to yield predicted number of dual-income households of MSA c for each year t. This formation indicates that we essentially use variation which comes from the predetermined distribution of administrative support women (by birth place) in 1960.

Recall that equation (4.2) specifies dual-income households in first difference standardized by the total local population. Hence the instruments are formed similarly by taking first-difference in predicted numbers and then it is divided by the predicted total local population in the initial period.[11]

$$\frac{\widehat{\Delta D_{ct}}}{\widehat{L_{ct-1}}} = \frac{\widehat{D_{ct}} - \widehat{D_{ct-1}}}{\widehat{L_{ct-1}}} \tag{4.4}$$

With this instrument, our first-stage regression takes the following form.

$$\frac{\Delta D_{ct}}{L_{ct-1}} = \mu + \phi \frac{\widehat{\Delta D_{ct}}}{\widehat{L_{ct-1}}} + \Gamma X_c + \delta_t + u_{ct} \tag{4.5}$$

The coefficient, ϕ, represents the actual increase in dual-income households due to the predicted increase in dual-earners and the power of this coefficient is the key for our causal interpretation. In large part, the validity of our identification is based on the assumption that the predetermined distribution of administrative support women (for each birth place of women) across cities in 1960–after controlling for other city characteristics–affects the local supply of dual-income workers but is independent of other confounding shocks that influence the employment growth of low-skilled service workers. Our empirical choices aim to reduce this risk of correlation between the instrument and unobserved city-specific factors.

Table 4.1 shows the estimated first-stage results based on equation (4.5). The first column shows the basic specification that controls for log of lagged population (L_{ct-1}), period effects (δ_t), and the well-known Bartik index (Bartik, 1991). This Bartik index captures the industry-driven employment growth, and is constructed in the following way.

[10] In order to overcome the curse of dimensionality, foreign-borns are collapsed into one category.

[11] To avoid endogenous changes in local population at the MSA level, we also predict the local population by augmenting population by birth place and age group in 1960 by the corresponding growth rate in the total national popualtion of each group. Specifically, $\widehat{L^x_{ct-1}} = L^x_{c,1960} \times (L^x_t / L^x_{1960})$, where x is birth place by age group (age 25-40 and age 41-54), and thus $\widehat{L_{ct-1}} = \sum_x \widehat{L^x_{ct-1}}$.

Table 4.1: First-Stage Regressions

	(1) Basic	(2) Control: Demographic controls	(3) Control: Share routine & college-edu.	(4) Control: MSA fixed effects
Predicted value	0.632***	0.636***	0.657***	1.108***
	(0.124)	(0.111)	(0.123)	(0.197)
Bartik	0.087**	0.098**	0.100**	-0.027
	(0.036)	(0.040)	(0.043)	(0.046)
Share routine in 1960			0.042	
			(0.033)	
Share college in 1960			-0.040	
			(0.074)	
1st stage F	26.03	32.74	28.59	31.51
Period FE	Yes	Yes	Yes	Yes
MSA FE				Yes
Observations	420	420	420	420
R-squared	0.317	0.351	0.352	0.609

Note: The dependent variable is the decade change in dual-income couples. The explanatory variable is the predicted change in dual-income couples. Dual-income couples means that both husband and wife are employed in non-low-skill service sectors. The units of observations are MSAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by MSAs. All the regressions are weighted by population aged 25 to 54 in 1960.
***p< 0.01, **p< 0.05, *p< 0.1

$$BIV_{ct} = \sum_s \eta_{sc,1960} \Delta E_{st}, \tag{4.6}$$

where $\eta_{sc,1960}$ denotes the share of total city employment in each industry in 1960, and ΔE_{st} is the log change over the decade for each industry. We include theses variables in all subsequent specifications. In column 2, we add local characteristics including the shares of hispanic, young (aged 25-40), and female population in 1960 as control variables. In column 3, we control for two important factors known to affect the growth in service sectors. The share of routine workers is included to control for possible differences in technology adoption across cities, following Autor and

Dorn (2013).[12] Also, we include the share of college graduates to control for the local multiplier effects of highly educated workers due to the demand for local services generated by the increase in total earnings (Moretti and Thulin, 2013; Mazzolari and Ragusa, 2013).[13] Lastly, in column 4, we also include additional location fixed effects (γ_c) to control for unobserved characteristics that grow linearly within MSAs. Hence, the identification of the key parameter relies on changes in dual-income households within the local economies. Controlling for this additional location fixed effects relieve some concerns regarding using our instrument. Specifically, the location fixed effects absorb any potential confounders in initial year such as the shares of routine and college-educated workers. It also addresses concerns that this type of instrument may conflate short-run and long-run impacts of shocks (Jaeger, Ruist, and Stuhler, 2018).

The estimated coefficients across four columns indicate that the predicted change in dual-income earners correctly predicts the actual change in dual-income households. Specifically, in column 3, the 1 percentage point increase in the predicted value leads to approximately 0.66 percentage point increase in dual-income couples. The power of the instrument, represented by the F-statistic that is about 30, is strong enough to avoid the weak instrument bias. Notably, even with additional MSA fixed effects, in column 4, this specifiaction still leaves the instrument with significant explanatory power, and thus adds the validity of our instrument (Goldsmith-Pinkham, Sorkin, and Swift, 2018).

5 Estimated Effects on Low-skilled Service Workers

In this section, we present our empirical estimates based on equation (4.2). For two-stage least-squares (2SLS) specifications, we use the predicted increase in dual-income couples in equation (4.4) as an instrument.

5.1 Basic Results We estimate equation (4.2) in order to identify the impact of dual-income households on low-skilled service sectors in the same city. Our main outcome variable is the growth of employment of low-skill service as well as the growth of average weekly wages. For 2SLS regressions, we use the imputed change in dual-income couples in equation (4.4) as an instrument for the actual change. The basic specification controls for the log of lagged population (L_{ct-1}), period

[12]The routine occupations are defined as upper 25 pecentile occupations in the distribution based on the routine task intensity.

[13]The specific definitions of these two are available in the Appendix.

effects (δ_t), and the Bartik index. We add other control variables progressively in subsequent specifications. Standard errors are clustered at the MSA level. Results are reported in Table 5.1.

Panel A of Table 5.1 summarizes the benchmark results by reporting the estimated coefficients of interest (β) in equation (4.2). The OLS results reported in the first three columns indicate that one additional increase in dual-income households, which is equivalent to a two-worker increase, is associated with about a 0.7-person increase in the low-skilled service sector. In columns 4–6, the estimates from the 2SLS specifications are reported. Column 4 is the basic specification. Column 5 controls for local characteristics including the shares of routine workers, college-educated, hispanic, female, and aged 25 to 40. Lastly, Column 6 controls for additional MSA fixed effects instead of fixed local characteristics in 1960. The 2SLS estimates are in general smaller than the OLS estimates, and range between 0.29 and 0.39. Therefore, it is reasonable to argue that unobservable period specific shocks have affected the changes in dual-income households and low-skilled service workers in the same way, resulting in upward bias in the simple OLS specifications.

To examine how large these estimates are, we use the back of the envelope calculations to figure out how much of the increase in low-skill service job can be attributed to the rise in dual-income couples. The 2SLS estimates indicate that ten more dual-income couples (twenty workers) create approximately 3 low-skill service jobs in local economies. Since the numbers of dual-income couples have increased by approximately 1.3 millions during the period 1960–2000, the increase in low-skill service jobs due to the dual-income earners is about 39,000, which comprises 34 percent of the total 114,000 increase in low-skill service workers.

In Panel B of Table 5.1, we examine the impact on the growth of average wages to further verify if the increase in dual-income households creates demand for local services. The positive and statistically significant estimates confirm this hypothesis. Each column uses the same specification in Panel A of Table 5.1. For the OLS results, the one percentage point increase in dual-income households is associated with about 0.2 percent increase in wages of low-skilled service workers. Contrary to the results in employment growth, the estimates for the wage growth in the 2SLS specifications range between 0.8 and 1.2 and are larger than the estimates from the OLS. This is not surprising because the estimates from the OLS capture unobservable factors that increase supply of low-skilled workers, making the OLS estimates for wage growth underestimated. Overall, the results reported in Table 5.1 suggest that an increase in dual-income couples expands the local

Table 5.1: Effects on Low-Skilled Service Workers: Employment and Wages

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			**2SLS**	
	Basic	Control: Share routine & college-edu.	Control: MSA fixed effects	Basic	Control: Share routine & college-edu.	Control: MSA fixed effects
Panel A: Employment						
Dual-income	0.651***	0.699***	0.679***	0.331**	0.288**	0.387***
	(0.045)	(0.041)	(0.054)	(0.139)	(0.140)	(0.103)
Bartik	0.112***	0.099***	0.088***	0.151***	0.138***	0.063**
	(0.029)	(0.023)	(0.033)	(0.035)	(0.035)	(0.030)
Share routine in 1960		0.036			0.047*	
		(0.022)			(0.026)	
Share college in 1960		-0.101***			-0.067	
		(0.035)			(0.049)	
Panel B: Wages						
Dual-income	0.229***	0.167**	0.182*	0.849***	1.153***	1.033***
	(0.073)	(0.067)	(0.095)	(0.248)	(0.271)	(0.255)
Bartik	-0.023	-0.017	-0.083	-0.099	-0.112	-0.008
	(0.042)	(0.051)	(0.088)	(0.063)	(0.069)	(0.078)
Share routine in 1960		0.064*			0.037	
		(0.036)			(0.058)	
Share college in 1960		-0.067			-0.149	
		(0.061)			(0.093)	
1st stage F				26.03	28.59	31.51
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE			Yes			Yes
Observations	420	420	420	420	420	420

Note: The explanatory variable is the change in dual-income couples. Dual-income couples means that both husband and wife are employed in non-low-skill service sectors. The units of observations are MSAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by MSAs. All the regressions are weighted by population aged 25 to 54 in 1960.
***p< 0.01, **p< 0.05, *p< 0.1

low-skilled service sectors due to the increased demand for local services.

We finally comment regarding the two important control variables, the initial share of routine workers and that of the college graduates. First, as is argued by Autor and Dorn (2013), the city that was historically specialized in routine task-intensive industries could have experienced more pronounced job polarization hence low-skill service jobs have expanded more than the city that was not. The coefficient on the share of routine workers is positive and significant, and thus confirms the previous findings of Autor and Dorn (2013). Second, another important channel that has been emphasized was the spillover effect from the high-skilled workers on the low-skill service markets (Mazzolari and Ragusa, 2013). While we need to control for the change in collge-graduates, the initial share of college graduates would be sufficient to capture this education spillover channel. Even after controlling for these channels, reassuringly, the estimated coefficients on dual-income families are robust. We will further examine other hypotheses that might drive our results in subsection 5.4.

5.2 Results by Sub-occupations One interesting prediction of our model is that substitutability of labor and service good is positively related to the spillover effect. Hence, another interesting exercise would be to examine which occupations within low-skilled service sectors are greatly affected by an increase in dual-income households. Namely, if dual-income workers are likely to demand services that substitute home production, home production-related services such as cleaning or child care should benefit the most. Table 5.2 tests this hypothesis by separately estimating the effects of dual-income earners on sub-occupations of the low-skills service sectors.

In columns 1 and 2, we first broadly divide the low-skill service sectors into home production services and the other services. Interestingly, while the presence of dual-income earners significantly increases the employment of home production service workers, it lowers the employment of other service workers although the magnitude is smaller. This may suggest that some of low-skill workers switch their jobs to home production service sectors from the other service sectors.

In columns 3 through 6 of Table 5.2, we further estimate the effects on sub-occupations of home production services including cleaning, food preparation, maintenance and janitors, and child care. The effects of these occupations are highly significant. For example, for cleaning services, one dual-income couple increase leads to approximately 0.17-workers increase. Therefore, our results are

Table 5.2: Effects on Low-Skilled Service Workers: by Sub–Occupations

Dependent Variable:	(1) Home Production Service	(2) Other Service Jobs	(3) Cleaning Service	(4) Food Preparation	(5) Maintenance & Janitors	(6) Child Care
Dual-income	0.518***	-0.202*	0.175***	0.195***	0.083***	0.064***
	(0.088)	(0.119)	(0.040)	(0.042)	(0.029)	(0.018)
Bartik	0.041**	0.116***	-0.030***	0.023**	0.043***	0.005
	(0.020)	(0.033)	(0.011)	(0.010)	(0.008)	(0.003)
Share routine in 1960	0.025	0.033*	0.007	0.019**	0.001	-0.001
	(0.016)	(0.020)	(0.007)	(0.007)	(0.006)	(0.002)
Share college in 1960	-0.060**	-0.023	0.009	-0.040***	-0.032***	0.004
	(0.027)	(0.038)	(0.010)	(0.013)	(0.012)	(0.004)
1st stage F	28.59	28.59	28.59	28.59	28.59	29.34
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420	420	420	420	420	401
R-squared	0.660		0.511	0.620	0.611	0.534

Note: The explanatory variable is the change in dual-income couples. Dual-income couples means that both husband and wife are employed in non-low-skill service sectors. The units of observations are MSAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by MSAs. All the regressions are weighted by population aged 25 to 54 in 1960.
***p< 0.01, **p< 0.05, *p< 0.1

consistent with the predictions from our model. It is also important to note that other factors, the share of routine workers or that of college graduates in 1960, do not seem to have more significant impacts on employment of home production service, suggesting that the dual-income channel is more relevant for the growth of low-skilled employment.

5.3 Falsification Tests

The identifying assumption for using our instrument is that the predetermined differences in administrative support women in 1960 across cities, conditioning on fixed effects and other shocks, are independent of unobservable local factors that affect low-skill service sectors. As it is not possible to directly test this identifying assumption, we instead present suggestive evidence by examining the correlations between the pre-trends of our outcome variables and our instrument. If our instrument is credible, we expect to see weak correlations between the instrument and the pre-trends. To be specific, similar to equation (4.5), we can regress change in low-skill service workers between 1950 and 1960 on the instrument, and observe if the instrument predicts the pre-trends. By doing so, we test whether dual-income couples select into local areas with large supply of low-skill services.

Table 5.3 describes the results from the falsification tests that regress the pre-trends of four outcome variables of main interest on our instrument. Columns 1 and 2 examine the pre-trends of employment and wages of low-skill service sectors and columns 3 and 4 runs for the employment of sub-occupations. Reassuringly, although the correlations are not exactly zeroes, they are at least not statistically significant, and hence our estimates should not be significantly biased by the pre-trends. Furthermore, in next section, when we estimate equation (4.2) using our instrument, we include the additional location fixed effects (γ_c) to absorb the pre-trends of the outcomes to relieve the concerns regarding the pre-trends.

Table 5.3: Falsification Tests

	(1)	(2)	(3)	(4)
Dependent Variable:	Low-skilled Service Employment 1950–60	Low-skilled Service Wages 1950–60	Home Production Employment 1950–60	Other Service Employment 1950–60
Predicted value	0.520	0.360	0.411	0.175
	(0.460)	(0.444)	(0.287)	(0.215)
Bartik	0.081	0.231	0.039	0.056
	(0.120)	(0.163)	(0.086)	(0.048)
Share routine in 1960	0.083	0.077	0.048	0.036
	(0.108)	(0.105)	(0.069)	(0.052)
Share college in 1960	-0.149	-0.141	-0.085	-0.091
	(0.142)	(0.173)	(0.079)	(0.072)
Observations	105	105	105	105
R-squared	0.370	0.034	0.374	0.261

Note: The explanatory variable is the predicted change in dual-income couples between 1960 and 1970. The dependent variable is change in low-skilled workers between 1950 and 1960. The units of observations are MSAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by states. All the regressions are weighted by population aged 25 to 54 in 1960.
***p< 0.01, **p< 0.05, *p< 0.1

5.4 Robustness Checks While we use plausibly exogenous variation in dual-income households driven by the predetermined distribution of administrative support women in 1960, and control for a rich set of local characteristics and fixed effects, there may still be other shocks to local economies that might drive our results. In this subsection, we introduce potential threats to our identification and present the robustness of our estimates. Since our main conclusion is that dual-income earners expand local services that substitute home production, we display the estimates on the employment growth of home production services for the sake of simplicity.

There are three potential time-varying local shocks that might bias our estimates. The first concern is that our instrument could be highly correlated with the inflow of low-skilled immigrants. Between 1960 and 2000, significant numbers of foreign-born workers had arrived to the U.S. and many of them worked in low-skilled service sectors. For example, while immigrants in 1960 were less than 10 millions, they were more than 30 millions in 2000, occupying 11 percent of the total population (Census of Population, 1960 to 2000). If some number of administrative support women is foreign-born, our instrument will capture the impacts of immigrants and bias our estimates. The second concern is regarding the spillover effect from the high-skilled workers (Mazzolari and Ragusa, 2013), although we control for the initial share of college graduates in Table 5.1. The third concern is that growth of non-dual income female workers could be correlated with the growth in dual-income earners. As we have shown in our theoretical model, the exogenous shock comes from the increased labor market participation of women which also includes non-dual income female workers. Furthermore, single workers could spend less time in home production thanks to the technology change that could save time for home production. Therefore, our estimates may mix the effects from the increase in non-dual income women.

Since directly controlling for these shocks would introduce endogeneity problem, we impute each shock (the growth of immigrants, the wage bill of top wage earners, and single workers), and include them as control variables in columns 1 through 3 of Table 5.4. For simplicity of analysis, we only report results from IV regression. To be specific, we control for well-known immigrants enclave instrument (Altonji and Card, 1991; Card, 2001), the occupation-driven growth in the wage bill of top wage earners (Mazzolari and Ragusa, 2013), and the predicted growth of female workers based on administrative women across areas in 1960 (similar to the way that we construct our instrument for dual-income earners). The detailed procedure for these imputed shocks are included in Appendix A.

Table 5.4: Robustness Checks

	(1) Control: Δlow-skilled immigrants	(2) Control: Δtop wage bill share	(3) Control: Δfemale employment	(4) Control: Δimputed service	(5) Control: full controls	(6) Non-power couples only
Dual-income	0.514***	0.516***	0.468***	0.437***	0.461***	0.606***
	(0.089)	(0.085)	(0.079)	(0.069)	(0.068)	(0.110)
Bartik	0.038*	0.042**	0.046**	0.055***	0.052***	0.048**
	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.021)
Share routine	0.023	0.023	0.026*	0.030*	0.026	0.030**
in 1960	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.015)
Share college	-0.059**	-0.064**	-0.066**	-0.071**	-0.071**	0.005
in 1960	(0.027)	(0.027)	(0.029)	(0.031)	(0.029)	(0.026)
1st stage F	27.33	28.92	33.96	62.45	50.96	23.84
Observations	420	420	420	420	420	420
R-squared	0.663	0.660	0.661	0.659	0.666	0.650

Note: The dependent variable is change in employment of home production services. The explanatory variable is the change in dual-income couples. Dual-income couples means that both husband and wife are employed in non-low-skill service sectors. The units of observations are MSAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by states. All the regressions are weighted by population aged 25 to 54 in 1960.
***p< 0.01, **p< 0.05, *p< 0.1

In columns 1 through 3, the growth in dual-income earners strongly increases the employment of home production sectors, and the magnitude of the coefficients are comparable to that of Column 1 in Table 5.2. The first stage powers are also reasonably strong.

Our identifying assumption is that the predicted change in dual-income couples affects the change in low-skilled workers only through the actual change in dual-income couples. In other words, if there is any direct effects from the instrument on low-skilled service sectors, our estimates would be biased. In column 4 of Table 5.4, we present a robustness check that controls for this direct effect of administrative support women in 1960 on the employment growth of low-skilled services. Specifically, using the distribution of administrative support women in 1960 as weight, we impute increase in low-skilled service workers. The effects of dual-income couples on service employment remains significant.

In column 5, we run a regression with full set of controls that include all the imputed shocks and the direct effects from our instrument. Even with this rich set of controls and other shocks, increase in dual-income couples significantly increases the home production service workers: One dual-income couple increases 0.46 home production workers approximately.

Finally, in column 6, we test the robustness of our results by further considering heterogeneity within dual-income households. Column 6 considers the skills of dual-income earners by excluding power couples (both husband and wife are college-educated) in our explanatoy variable because Costa and Kahn (2000) and Compton and Pollak (2007) document that college educated couples are increasingly located in large metropolitan areas. Notably, the estimate is strongly significant, showing robustness of our results.

5.5 Heterogeneious Effects of Dual-income Couples Dual-income couples with different characteristics may have heterogeneous effects on local low-skilled services. For example, if some couples spend more time for market work, they would have even lesser time to devote for home production. On the contrary, if families have a child, the amount of home good that households need could be greater, requiring either more services from market or home production participation. In this subsection, we investigate heterogeneity within dual-income couples by focusing on full-time dual-income couples (both husband and wife work more than 40 hours per week) and dual-income couples with at least one child. If the spillover mechanism works, increase in these families should have greater effects on low-skill services, compared to increase in other dual-income couples.

Table 5.5 shows these heterogeneous effects of dual-income couples. Column 1 examines the effects of full-time dual-income couples. Column 2 is for dual-income households with at least a child. The estimates are 0.6 and 0.66 respectively and slightly greater than the estimates in Table 5.2.[14] Therefore, these results confirm that time constraints in households play a crucial role in home production.

In columns 3 through 6 of Table 5.5, we further estimate the heterogeneous effects on sub-occupations of home production services, similar to Table 5.2, to check whether greater effects are

[14]The estimate of column 1 in Table 5.5 is very similar to that of column 6 in Table 5.4. This is because full-time dual-income workers and non-power couples are highly correlated.

found for each sub-occupation. As is expected, compared to the estimates in 5.2, the estimated effects are slightly greater. Overall, the results are consistent with our hypothesis.

Table 5.5: Heterogeneity across Dual-income Couples

	(1) Full-time couples only	(2) Couples with kids only	(3) Outcome: cleaning service	(4) Outcome: food preparation	(5) Outcome: maintenance & janitors	(6) Outcome: child care
Dual-income (full-time)	0.605*** (0.099)		0.205*** (0.043)	0.228*** (0.049)	0.097*** (0.034)	0.075*** (0.021)
Dual-income (with kids)		0.652*** (0.140)	0.221*** (0.059)	0.246*** (0.059)	0.105*** (0.040)	0.080*** (0.024)
Observations	420	420	420	420	420	401

Note: The dependent variable is change in employment of home production services. The explanatory variable is the change in dual-income couples. Dual-income couples means that both husband and wife are employed in non-low-skill service sectors. The units of observations are MSAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by states. All the regressions are weighted by population aged 25 to 54 in 1960.
***p< 0.01, **p< 0.05, *p< 0.1

6 Conclusion

The structure of employment in the U.S. has changed dramatically over the past decades. One of the most prevalent aspects of the change is rising female labor supply and hence the emergence of dual-income households. This study investigates whether the presence of dual-income households creates demand for low-skill service between 1960 and 2000. Dual-income households are more likely to buy low-skilled, time-intensive, services that free them from home production tasks. In particular, we study the cross-city association between variation in dual-income households and employment growth in home production substitutes. Endogeneity concerns are addressed by exploiting concentration of women in dual-income households on administrative support occupations in 1960 and uneven distribution of dual earners across birth places. The results show that employment in the low-skilled service sectors that substitute for home production has increased between 1960 and 2000 with the increase in a city's dual-income households, suggesting further evidence of consumption spillover. That is, the changes in household structure, which are driven by rising female labor supply and dual earners' opportunity costs of home production, could increase demand for low-skilled services. This paper particularly contributes to the existing literature on job polarization by helping to understand the rapid growth of employment in service sectors. Rather than focusing on technological progress, which has been cited as the main reason for job polarization, we explore a new channel, consumption spillover from dual-income households, in explaining the growth of low-skilled service jobs in recent decades.

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A Data Appendix

A.1 The growth in immigrants To construct the predicted growth in immigrants, we first calculate the imputed number of immigrants for MSA c in year t for the following way.

$$\widehat{I_{ct}} = \sum_o I_t^o \cdot \frac{I_{c,1960}^o}{I_{1960}^o}, \tag{A.1}$$

where the first term I_t^o is the total number of immigrants from country of origin o for year t and $(I_{c,1960}^o / I_{1960}^o)$ is the share of foreign-born in MSA c in year 1960 for each country of origin o. The country of origins are collapsed into 12 categories. Then we take first-difference in these numbers and divide them by the total local population in the initial period (L_{ct-1}).

A.2 The change in the wage bill of top wage earners Our measure of the change in the wage bill of top wage earners follows Mazzolari and Ragusa (2013). Specifically,

$$\overline{\Delta WB_{ct}^{90}} = \sum_j \lambda_{c,1960}^j \cdot \Delta w_{jt}, \tag{A.2}$$

where $\lambda_{c,1960}^j$ is the share of wage earners in the top decile of the MSA wage distribution in 1960 employed in occupation j and Δw_{jt} is change over decade t in the log wages of workers in that same occupation j. Occupations are defined on the basis of 18 occupation cells.

A.3 The growth in nondual-income female workers To construct the predicted growth in the other female workers, we first impute the number of the other female workers for MSA c in year t for the following way.

$$\widehat{F_{ct}} = \sum_b F_t^b \cdot \frac{A_{c,1960}^b}{A_{1960}^b}, \tag{A.3}$$

where the first term F_t^b is the total number of non-dual-income female workers from birth place b for year t and $(A_{c,1960}^b / A_{1960}^b)$ is the share of administrative support women (not married) in MSA c in year 1960 for each birth place b. Then we take first-differences in these numbers and divide them by the total local population in the initial period (L_{ct-1}).

A.4 Direct effects from administrative support women in 1960 To control for the direct effects from our instrument on low-skill service workers, we first predict the growth in low-skill service workers, using the same share of administrative support women (married) in MSA c in year 1960 for each birth place b.

$$\widehat{S_{ct}} = \sum_{b} S_t^b \cdot \frac{A_{c,1960}^b}{A_{1960}^b}, \tag{A.4}$$

where the first term S_t^b is the total number of low-skilled service workers from birth place b for year t and $(A_{c,1960}^b/A_{1960}^b)$ is the share of administrative support women (married) in MSA c for each birth place b. Then we take first-differences in these numbers and divide them by the total local population in the initial period (L_{ct-1}).

B Derivation of Predictions

Let q^M (resp. q^H) denote the Lagrangian multiplier attached to the budget constraint (resp. constraint for home good). Using the first order conditions for labor supply decision of the female worker (FOCs with respect to h_f^M and h_f^H), we can obtain

$$zG_h = \frac{q^M}{q^H} w_f, \tag{B.1}$$

where $G_h \equiv \partial G / \partial h_f^H$.

The first order condition with respect to s is given by

$$pq^M = zG_s q^H, \tag{B.2}$$

where $G_s \equiv \partial G / \partial s$.

Using the CES function, we can rewrite the equation (2.5) as follows:

$$w_f = \frac{1-\alpha}{\alpha} p \left(\frac{s}{h_f^H} \right)^{\frac{1}{\sigma}}. \tag{B.3}$$

Taking logs to the both sides and rearrange the terms, we obtain

$$\log s = -\sigma \ln \frac{1-\alpha}{\alpha} - \sigma \log p + \sigma \log w_f + \log h_f^H. \tag{B.4}$$

Hence, the above equation is the demand function for the service good.

We further assume that the production function of the firm that produces the service good takes the usual Cobb-Douglass form:

$$f(h) = h^\delta, \tag{B.5}$$

where $\delta \in (0, 1)$.

Since the labor market equilibrium condition is $pAf'(h) \equiv pA\delta h^{\delta-1} = Bh^\psi$ and $s = Af(h)$ as the service good market clearing condition, we can obtain the following equilibrium condition in log:

$$\log s = (\psi + 1) \log h - \log p - \log \frac{\delta}{B}. \tag{B.6}$$

Combining the demand and supply equations (equation (B.4) and (B.6)), we obtain the following equation:

$$\log h = \phi + \frac{\sigma}{\psi+1} \log w_f + \frac{1}{\psi+1} \log h_f^H + \frac{1-\sigma}{\psi+1} \log p, \tag{B.7}$$

where $\phi \equiv \frac{-\sigma \log \frac{1-\alpha}{\alpha} + \log \frac{\delta}{B}}{\phi+1}$.

Hence, the above equation provides a prediction that labor input in the service good sector (h) is increasing in the wage of female worker (w_f).

Let's further consider the first order conditions of the couple with respect to c_f^M and h_f^H:

$$w_f = \frac{u_{c_f^M}}{u_{l_f}}. \equiv MRS_{c_f^M, l_f} \tag{B.8}$$

Under the assumption that income effect is dominated by the substitution effect, $w_f \propto h_f^M$. Hence, we can rewrite the equation (B.7) as

$$\log h \propto \phi + \frac{\sigma}{\psi+1} \log h_f^M + \frac{1}{\psi+1} \log h_f^H + \frac{1-\sigma}{\psi+1} \log p. \tag{B.9}$$

Notice that $h_f^H = 1 - h_f^M - l_f$ hence it also responds to changes in w_f. One can show that $\partial l_f / \partial h_f^M < \sigma \frac{h_f^H}{h_f^M} - 1$ is the sufficient condition for $\log h$ to increase with respect $\log h_f^M$. Since $\partial l_f / \partial h_f^M$ is negative in the usual case, this implies that the prediction requires that leisure to decline sufficiently.

Labor supply equation of the service sector ($w = Bh^{\psi}$) implies

$$\log w \propto \log B + \psi \left(\phi + \frac{\sigma}{\psi + 1} \log h_f^M + \frac{1}{\psi + 1} \log h_f^H + \frac{1 - \sigma}{\psi + 1} \log p \right). \tag{B.10}$$

[Christian Dustmann said it was OK to submit just an abstract for now. Thanks.]

The Value of Commuting Time and Efficient Job Assignment in the Gig Economy

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The online “Gig Economy” highlights the importance of efficiently matching workers and firms given the short-term nature of job assignments and the frequent re-matching process. We estimate the potential value of optimally matching workers and firms on one specific dimension - - commuting time. We analyze short term (one day or less) assignments between workers and firms made on a Gig Economy platform that specializes in shift work. Workers can apply for shifts on a first come/first served basis. We estimate a hedonic model of worker preferences for shift attributes to understand the trade-offs workers make. We estimate the dollar value of commuting time for users of mass transit and drivers and compare that to the value of work time. We also estimate the value to firms of workers they have used before and, given the "stickiness" of firm/worker matches on the site, we calculate the economic value of creating high value (that is, low commute time) matches early in a firm/worker relationship. The analysis provides insights into how much economic value can be created by matching workers and firms more successfully based on commute time, as well as the value of commuting infrastructure investments.

JOB SECURITY PERCEPTIONS AND ITS EFFECT ON WAGE GROWTH[1]

James Foster and Rochelle Guttmann[2]

Reserve Bank of Australia

Version – 30 November 2018

Abstract

A concern that low job security is constraining wage growth has been expressed in many countries. In this paper, we use Australian household panel data to: (1) analyse the trends and drivers of self-assessed job security; and (2) examine its relationship with wage growth. We construct measures of industry-level trade exposure and occupation-based automation risk to assess the oft-cited conjecture that technological change and globalisation are leading to fears of job loss. We find some evidence that those in jobs with a higher trade exposure, automation risk or those working on a casual or fixed-term contract feel more insecure in their job. However, regardless of one's characteristics, there has been a broad-based fall in job security in recent years that cannot be explained by the model variables. Exploiting the panel dimension of the survey, we find that heightened job insecurity has been a small, but statistically significant, drag on wage growth in Australia and that this result is robust to various model specifications.

1. Introduction

Workers' perceptions of their own job security may influence how hard they bargain over their wages. Several factors may contribute to these subjective assessments of job security, including labour market conditions, the type of employment contract, union membership status, as well as the potential for their work to be automated or sent offshore. Shifts in these factors could make workers feel less secure in their job and so more likely to accept smaller wage rises. The concern that low job security is constraining wage growth has been expressed across a number of advanced economies recently (Haldane 2017; Lowe 2017), as well as in the United States two decades ago (Greenspan 1997). Yet there has been little research that empirically tests this relationship.

We study perceived (or self-assessed) job security, which is a worker's subjective expectation that they will retain their job. These beliefs – whether justified or not – can influence wage bargaining behaviour. For instance, if an employee believes that their job could be moved offshore, they may accept lower wage rises to encourage their employer to keep the job onshore. It does not matter whether or not the job is eventually moved, because it is this fear of job loss, or perceived contestability of the job, that would keep wage growth contained. This is in contrast to actual (or objective) job security, which is the likelihood that a worker does hold on to their job. Actual job insecurity is typically equated with jobs that have relatively high turnover or are temporary in nature.[3] In recent years, there has been little change in actual job security in Australia (Borland 2017). Determinants of objective job security, such as casualisation and labour market conditions, can contribute to perceptions of job security, though personal circumstances, popular narratives, expectations of the future, and domestic or international events may also play a role.

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1 The views in this paper are those of the authors and do not reflect views of the Reserve Bank of Australia. We thank Natasha Cassidy for her valuable suggestions. The unit record data from the HILDA Survey were obtained from the Australian Data Archive, which is hosted by The Australian National University. The HILDA Survey was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views based on the data, however, are those of the author and should not be attributed to the Australian Government, DSS, the Melbourne Institute, the Australian Data Archive or The Australian National University and none of those entities bear any responsibility for the analysis or interpretation of the unit record data from the HILDA Survey provided by the author.

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3 See de Ruyter and Burgess (2000) for an overview of the various dimensions of the job security definition.

This paper documents the decline in perceptions of job security in Australia, the cyclical and structural factors that have driven it, and shows that it explains a small part of the recent weak wage growth. We use the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is a household panel survey that asks respondents about their feelings of job security and perceived likelihood of job loss. Along with questions on income, job and personal characteristics, this allows us to track whether workers who felt more secure in their job received a higher pay rise than their counterparts who were more anxious about their job security. We explore the existing literature on this topic in the next section. In Section 3 we describe the data and construction of the trade exposure and automation variables used. Next we explore the determinants of job security and its relationship to wage growth. We then perform a series of robustness checks, including accounting for selection and endogeneity effects. Section 6 concludes.

2. Previous Literature

2.1 Determinants of Job Security

The literature on the determinants of perceived job security in Australia is small. Some of the HILDA Statistical Reports have included a broad overview of the determinants of perceived job security, using the measure of the expected probability of losing one's job (Heady and Warren, 2008; Wilkins, 2015). Taken together they find age, tenure, education, hourly wage, occupation and industry influences job security perceptions, whereas gender and union membership do not. In addition, Borland (2002) found that perceived job-security moves pro-cyclically with the business cycle. Previous work using HILDA has found that job insecurity can be explained by regional unemployment, casual work, fixed term jobs (Milner *et al*. 2014) and job tenure (Green and Leeves 2013).

The international literature supports this, with job insecurity in the UK, for example, being partially explained by temporary contracts and short tenures (Green 2003). Other characteristics that are found to reduce perceived job security overseas include previous unemployment experience, regional unemployment, having a job that is manual, in the private sector, being male and being older (Böckerman 2004; de Bustillo and de Pedraza 2010; Campbell et al. 2007; Demoussis and Giannakopoulous 2007; Green, 2003; Hubler and Hubler 2006; Lurweg 2010; Näswall and de Witte 2003). All these studies examine this question with household cross-section or panel datasets. Despite globalisation and automation often being cited as drivers of job insecurity, there is little quantitative research to show this. Lurweg (2010) explores the relationship between globalisation and job security fears, finding that those in trade-exposed service industries in Germany had greater perceived and realised job insecurity. Conde Vietez *et al*. (2010) studied workers at a particular factory and showed that types of technology used in their job influenced their perception of job security.

2.2 Job Security and Wages

The relationship between job security and wages can arise through either a bargaining framework model or a compensating wage differentials model. Under the bargaining model, job security influences the relative bargaining strength of employees (or unions) and employers. Greater perceived job security by employees raises their relative bargaining power, so they can demand higher wages; as such, wages and job security are complements and have a positive relationship. Bargaining models tend to be specified in terms of wage levels, but wage growth easily fits within this framework. The alternative framework sees monetary compensation (wages) and non-monetary features (such as job security) as substitutes within a total compensation package. For example, government employment may accept lower wages as a trade-off for greater job security, whereas a professional services firm may provide higher monetary compensation due to employment prospects fluctuating with the business cycle. However, this mechanism is more relevant for wage levels rather than wage growth.

Hübler and Hübler (2006) test both these theories and find support for the bargaining hypothesis. Using household-level panel data, they find that the level of job insecurity negatively affects wage levels, and the change in job security negatively affects wage growth, in Germany and the United Kingdom, although the growth effect was not robust. Also using household level data, Campbell et al. (2007) found that job insecurity lowers the rate of wage growth for men, but not women, in the United Kingdom. For the United States, Aaronson and Sullivan (1998) use regional data to augment a wage Phillips Curve with average regional perceived job security and find there is a negative, but not statistically significant, relationship between wage growth and fears of job loss. The relationship between perceived job security and wage growth has not been examined in detail for Australia.[4]

Before examining the role of self-assessed job security on wage growth, it is helpful to assess whether job security is useful in predicting unemployment itself. The literature shows that perceived job security can modestly predict job loss (Dickerson and Green 2012; McGuinness *et al*. 2014). However, workers tend to overestimate their probability of job loss. This overestimation lends credence to the idea that expectations of potential job loss can put downward pressure on wages, independent of actual labour market conditions.

3. Data

This paper uses the HILDA Survey from 2001 to 2016. It is a household panel dataset that includes several measures of self-assessed job security, as well as labour income and a vast array of personal and job characteristics. As such, we can use it to track workers and measure whether their levels of job security influenced their growth in wages over the following year. We also incorporate data from the Australian Bureau of Statistics (ABS) and Frey and Osbourne (2017) to measure risks of offshoring and automation, as well as data on price growth.

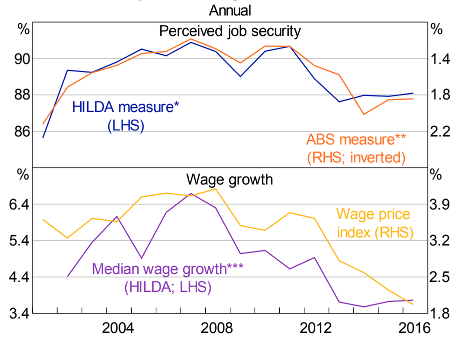
3.1 Measures of Subjective Job Security

The HILDA survey includes a range of indicators that can be used to gauge a worker's perception of their own job security. The key measure we focus on is a probability measure, which asks respondents the percentage chance of losing their job over the next 12 months. We invert this measure to frame it as the self-assessed probability of retaining one's job over the next year. That is, the probability of job retention is 100 less the stated probability of job loss. This measures perceptions of short-term job security, which should be more correlated with near-term wage outcomes, as opposed to concerns of future job loss through long-term changes in the structure of the economy.

An alternative variable is one that measures subjective job security satisfaction. It is an ordinal measure, which asks how satisfied one is with their job security on a scale of 0–10. A potential issue with this measure is whether different responders interpret the scale differently. As such, we prefer the probability measure, which should provide a more objective common benchmark for responders. In addition, the variable closely matches a similar measure of the probability of job retention from the Australian Bureau of Statistics (Graph 1). This provides some external validity that this measure is a sensible one to use. Nonetheless, the ordinal job security satisfaction measure moves closely with the probability measure and we examine its determinants in Section 5 for robustness.

4 Examining the relationship between job security and wage *levels*, in a compensating differentials analysis, Kelly, Evans and Dawkins (1998) found that job security matters most to those on low incomes.

Graph 1
Job Security and Wage Growth Measures
Annual

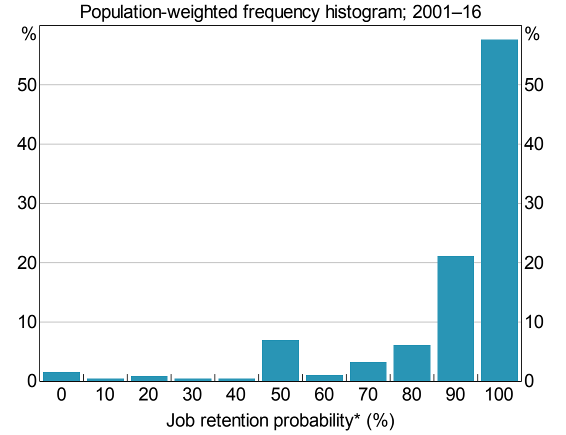


* Average job retention probability (100 less probability of job loss over next 12 months)
** Expect to leave employer over next 12 months due to downsizing/ closing or is a temporary worker; annual average employment share
*** Median of log difference in wage per hour worked in main job
Sources: ABS; HILDA Release 16.0; RBA

While job security perceptions do not vary much, they appear to move in line with changes in overall labour market conditions. Job security is relatively low when there is ample spare capacity in the labour market or underutilisation in the economy. There was a brief spike in the unemployment rate and slowdown in growth in 2001. Low subjective job security at the time appears to reflect this. Aggregate wage growth also tends to be lower when workers felt less secure on average the year earlier. This suggests that perceived job security moves with the business cycle. As such, it is unclear whether job security can help explain movements in wage growth over and above general labour market conditions. These issues are explored in this paper.

Workers tend to have a high rate of self-assessed job security; the probability of expected job retention averages 89 per cent across the whole sample period. The variable is also highly skewed (Graph 2). Almost 60 per cent of workers said they had a 100 per cent chance of retaining their job in the next 12 months. For those who have some uncertainty around job loss, the probability they assign to job retention is still high, with less than 4 per cent of workers expecting more than a 50 per cent chance of job loss. This highlights that only a small share of the workforce has concerns about holding on to their job over the following year.

Graph 2
Probability of Job Retention over the Next Year
Population-weighted frequency histogram; 2001–16



* Buckets are for 0–9, 10–19, ... per cent probability up to 100
Sources: HILDA Release 16.0; RBA

When we model the determinants of job security, we transform this probability measure into a dummy variable. We refer to it as 'job retention certainty' and it is equal to 1 if a worker is 100 per cent sure of retaining their job over the next year, and 0 otherwise. We do this for a number of reasons. First, the job security dependent variable is non-normally distributed, being bounded by 0 and 1 and highly skewed. As such, making inferences would be problematic without transforming the variable. Second, respondents may interpret the in-between probabilities differently (say, 90 per cent probability of job retention may feel high for one person, but low for another). The bunching at round numbers suggests there is difficulty in interpreting the probabilities. Finally, much of the variation in this measure over the past decade has been in the proportion of workers that are completely certain that they will keep their job. At its peak in 2007, 63 per cent of workers had absolute certainty that they would keep their job over the next year. This proportion troughed at 53 per cent in 2016. When we turn to the wage growth model, we use the raw probability variable, which goes from 0 to 1. This allows us to retain the full information from the variable. The non-normality of the distribution is no longer a concern as it is an independent variable, in this case.

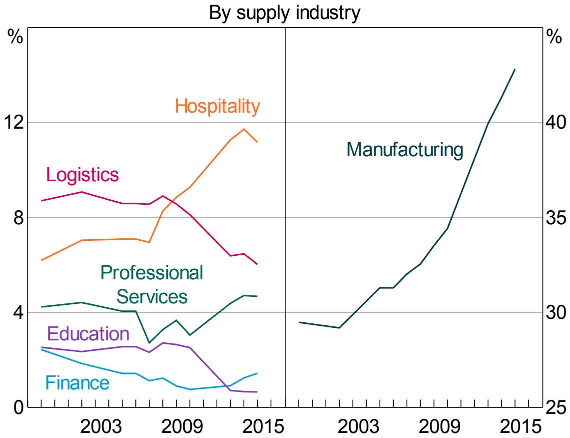
3.2 Measuring Wage Growth

We use the HILDA data to calculate annual growth in average hourly earnings for each worker. We take weekly gross wages and salary divided by hours usually worked per week in one's main job. We omit observations where the respondent has changed employers over the year, or report zero wages or hours in a year. These are log-differenced and the highest and lowest 5 per cent of the hourly wage growth distribution for each year are winsorised, to mitigate the influence of outliers. The 25th percentile, median, mean and 75th percentile of wage growth over the whole period is -6.9, 4.6, 5.7 and 18.2 per cent, respectively. Our measure tracks aggregate wage growth measured by the ABS fairly well, although it has been more stable of late (Graph 1).

3.3 Measuring Trade Exposure and Automation Risk

Two factors that are commonly suggested to influence both actual job loss and perceptions of job security are globalisation and technological change. An industry's exposure to global trade can be measured using its import penetration ratio. These ratios are calculated as the import share of the total output supplied by an industry, and represent the foreign share of the competition that firms in that industry face in the domestic market. Data are available from the ABS input-output tables for each industry subdivision across a range of financial years, with data for any missing years interpolated linearly. The import penetration ratio of the manufacturing industry is relatively high and has been increasing over the past decade as domestic demand for manufactured goods is increasingly met by imports (Graph 3). The hospitality and professional services industries have also faced rising import penetration, whereas trade exposure in the education industry is lower and has declined somewhat in recent years.

Graph 3
Import Penetration Ratio*
By supply industry



* Selected industries; financial year; missing data are interpolated linearly
Sources: ABS; RBA

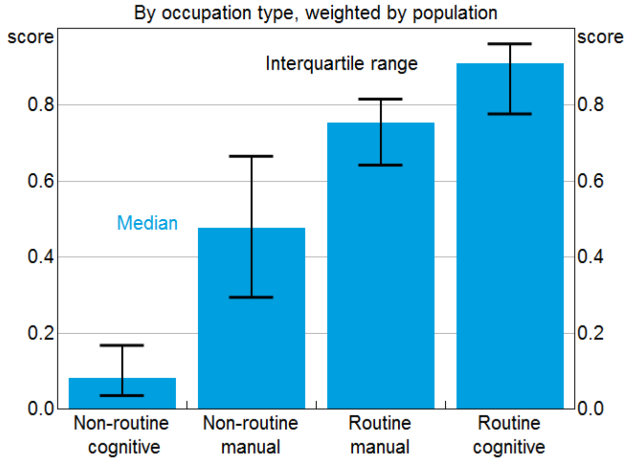
Overall, the import penetration ratios of most industry subdivisions have been increasing in recent years. However, the effect of this on the aggregate labour market has been offset by stronger employment growth in industries that are less exposed to international trade. As a result of this compositional shift, the trade exposure faced by the representative worker has been little changed over the past decade, having declined over several years prior to that.

Another source of job insecurity is the risk that technology could be used to automate tasks that were previously completed by skilled workers. We capture this risk using the computerisation scores devised by Frey and Osborne (2017). These scores measure the likelihood that an occupation's tasks could be automated using current computing technology.[5] We map these scores to the Australian unit group occupations to capture the potential for each of these jobs to be automated. The scores are not available over time and so we cannot evaluate how job security is being affected by the pace of technological change. As would be expected, routine occupations are the most at risk of automation, and non-routine cognitive jobs are the least automatable (Graph 4).[6] As is the case with industries highly exposed to global trade, occupations that have a greater potential to be automated have been decreasing as a share of total employment in recent years (Edmonds and Bradley 2015).

Graph 4

Automation Score

By occupation type, weighted by population



Sources: ABS; Frey and Osborne (2017); HILDA Release 16.0; RBA

In the models, the trade exposure and automation variables are entered into the models linearly (quadratic terms were statistically insignificant). However, for exposition purposes, when examining trends in the next section, an industry is classified as having high trade exposure if the import penetration ratio is above 5 per cent, while an occupation has a high automation probability if the automation score is above 50 per cent.

4. Job Security Trends, Determinants and its Relationship to Wage Growth

4.1 Trends in Job Security

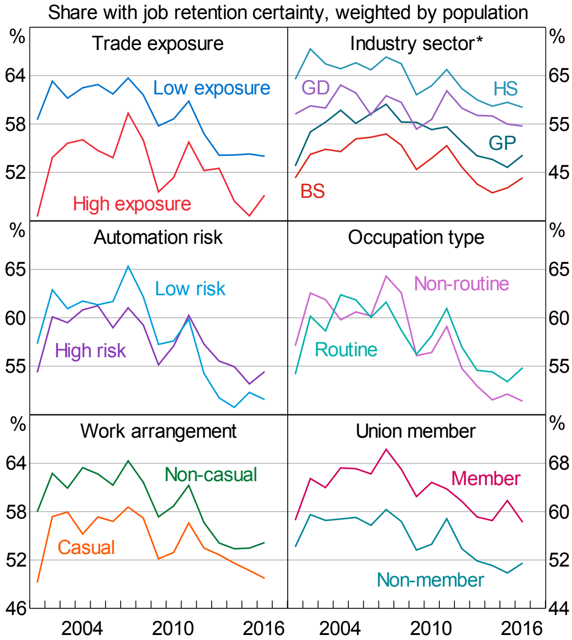
This section explores how economic conditions, structural factors and individual characteristics affect perceptions of job security in Australia. Perceived job security can be influenced by factors such as industry sector, occupation and work arrangements, as well as more general concerns about globalisation and automation. We find that perceived job security is lower in industries that are more exposed to international competition (Graph 5). This finding can help explain the lower job security in the goods production sector, the industries of which have quite high import penetration ratios. The decline in perceptions of job security in recent years is a touch larger in more trade-

5 A shortcoming of the Frey and Osborne (2017) approach is that the automation scores depend on the initial subjective decisions about which tasks have the potential to be automated using current technology (Borland and Coelli 2017). The method also does not allow for technology to complement labour and change the nature of an occupation. Therefore, these scores may not accurately measure the likelihood for each occupation to be automated. Nonetheless, the scores are well suited to measuring general perceptions of technological job loss, which is relevant to the topic of this article.

6 The routine–non-routine and cognitive–manual occupation classification definitions are described in Heath (2016).

exposed industries, but generally appears to be broad based across all industry sectors. The fall in job security perceptions in business services has occurred despite strong employment growth in that sector, which suggests that labour market conditions are not the only driver of job security concerns.

Graph 5
Job Security by Job Characteristics
Share with job retention certainty, weighted by population



* Industry sectors are household services, business services, goods production and goods distribution

Sources: ABS; Frey and Osborne (2017); HILDA Release 16.0; RBA

Workers in occupations with a high risk of automation reported greater job security fears prior to 2011. However this relationship has reversed in recent years as the fall in job security has been more pronounced for those in low-risk occupations. As expected, the perceived job security of those in routine occupations matches the trend seen in occupations with a high automation risk. The decline in job retention certainty has been broad based across different types of occupations, although a little steeper for those in non-routine roles. As expected, workers in casual roles report lower job security than those in non-casual roles. There is only a small difference in the job security of part-time and full-time workers. Union members feel more secure in their job, relative to non-union members. Those that are satisfied with their hours have higher job security than those wanting fewer or more hours, but concerns about job security have declined for both types of workers. Finally, those in regions with higher unemployment on average tend to have lower job security.

Despite some differences in the *level* of job security perceptions, the *decline* has occurred across a range of job characteristics, regardless of industry, occupation, contract type or union membership. The decline has also been broad based across a range of personal characteristics, such as age, sex and educational attainment, as well as across most states. Overall, these patterns suggest that job and personal characteristics influence the level of perceived job security, but that the decline has been experienced across the board.

4.2 Determinants of Job Security

The descriptive analysis above suggests a range of factors influence job security perceptions. To examine their relative importance, we estimate a random effects probit model for the job certainty dummy variable.[7] The model is estimated on an unbalanced panel of workers from 2001–2016. We

7 A fixed-effects probit model would provide inconsistent estimates (Greene 2003, pp. 697). Nonetheless, random effects models have strong assumptions around orthogonality of the independent variable and heterogeneity, which

include a range of job, firm and personal characteristics. The summary statistics for these independent variable and coefficient estimates are shown in Table 1. We have not included interaction terms. We include time dummies for each survey year, allowing them to capture any non-observed determinants that vary over time and are common across individuals. This can include macroeconomic, technological, legislative and international factors. However, we attempt to isolate labour market slack by exploiting regional variation in the unemployment rate, where unemployment is included for the 13 ABS major statistical regions.

Table 1: Regression Coefficient Estimates - Random Effects Models

2002–16

	Variable Summary[(a)]		**Job Security**[(b)] Probit model		**Wage Growth**[(c)] Linear model	
	Mean	S.D	Coefficient estimate	S.E	Coefficient estimate	S.E
Job security (t-1)[(d)]	0.92	0.17	--		1.67***	0.52
Economic Factors						
Unemployment (by region)	5.21	1.02	-0.03***	0.01	0.19	0.13
Trade exposure	0.05	0.11	-0.25***	0.07	-1.54**	0.71
Automation	0.48	0.35	-0.08***	0.03	-1.05***	0.35
State consumer price growth	2.50	0.85	--		0.60**	0.30
Industry (base: Goods production)						
Business services	0.16		-0.09***	0.03	-0.37	0.30
Household services	0.38		0.16***	0.03	-1.03***	0.29
Goods distribution	0.18		0.08***	0.03	-1.11***	0.29
Other	0.11		0.08**	0.03	-0.39	0.34
Occupation (base: Non-routine cognitive)						
Routine manual	0.23		0.17***	0.03	0.17	0.31
Non-routine manual	0.15		0.09***	0.03	-0.44	0.28
Routine cognitive	0.25		0.10***	0.03	-0.41	0.31
Job Characteristics						
Lost a job in the past year	0.00		-0.28***	0.03	1.05	1.62
Changed jobs in the past year	--		-0.09***	0.01	--	
Promoted in the past year	0.11		0.13***	0.02	3.60***	0.29
Full time	0.70		0.08***	0.02	-4.09***	0.23
Casual	0.17		-0.13***	0.02	-0.10	0.30
Temporary contract	0.08		-0.27***	0.02	0.54*	0.32
Work from home	0.19		0.06***	0.02	-0.86***	0.23
Number of years in a job	8.22	8.07	0.01***	0.00	-0.02*	0.01
Trade union member	0.32		0.01	0.02	0.09	0.18
Firm-type (base: private sector)						
NGO	0.09		0.10***	0.03	0.14	0.32
Public	0.30		0.19***	0.02	0.50**	0.23
Firm-size (base: small firms)						
Medium	0.32		-0.08***	0.02	0.08	0.20
Large	0.37		-0.12***	0.02	0.14	0.20
Hours preference (base: same)[(e)]						
Fewer	0.27		-0.09***	0.01	2.89***	0.20

we have not addressed. Estimating a random effects model of the continuous probability variable leads to similar results.

More	0.12	-0.08***	0.02	-2.23***	0.30
Personal Characteristics					
Female	0.50	0.35***	0.02	-1.34***	0.17
Primary language is not English	0.08	-0.02	0.04	1.30***	0.31
Born outside of Australia	0.19	0.05	0.03	-0.58***	0.21
Outside a capital city	0.38	0.15***	0.02	-0.28	0.18
Age (base: over 55s)					
Under 25	0.14	-0.32***	0.03	6.40***	0.33
25 to 39	0.32	-0.23***	0.03	1.23***	0.23
40 to 54	0.38	-0.15***	0.02	-0.34*	0.20
Education (base: high school)					
Diploma or Certificate	0.33	-0.03	0.02	-0.04	0.17
University	0.30	-0.25***	0.03	-0.30	0.22
State (base: NSW)					
Victoria	0.25	-0.02	0.02	-0.59***	0.19
Queensland	0.21	0.02	0.03	0.17	0.20
South Australia	0.09	0.15***	0.03	-0.31	0.27
Western Australia	0.09	0.35***	0.04	0.45	0.27
Tasmania	0.03	0.03	0.05	-0.60	0.38
Northern Territory	0.01	0.03	0.09	0.43	0.83
ACT	0.02	0.07	0.06	0.97**	0.49
Year (base: 2002)					
2003	0.06	-0.06**	0.03	0.69	0.63
2004	0.06	-0.04	0.03	1.14*	0.60
2005	0.06	-0.07**	0.03	1.07*	0.58
2006	0.06	-0.10***	0.03	1.68***	0.59
2007	0.06	-0.03	0.03	2.25***	0.64
2008	0.06	-0.13***	0.03	0.17	0.68
2009	0.06	-0.27***	0.03	1.55**	0.65
2010	0.06	-0.20***	0.03	0.52	0.54
2011	0.06	-0.20***	0.03	-0.14	0.53
2012	0.08	-0.36***	0.03	0.91	0.66
2013	0.08	-0.40***	0.03	-0.39	0.54
2014	0.08	-0.43***	0.03	-0.69	0.52
2015	0.08	-0.41***	0.03	-0.02	0.67
2016	0.09	-0.45***	0.03	-0.13	0.73
Constant	--	0.60***	0.03	4.24***	1.54
Pseudo log-likelihood	--	-56415.32		--	
R-squared	--	--		0.02	
Rho	--	0.48		0.02	
Individuals	13 706	18 621		13 706	
Observations	65 837	100 255		65 837	

***, ** and * show statistical significance at the 1, 5 and 10 per cent level, respectively. Standard errors are clustered by individual.

(a) Summary statistics shown for the wage regression sample. Standard deviations are shown for continuous variables only; remaining variables are dichotomous.

(b) Dependent variable equals 1 if 100 per cent certain to retain job over next year; 0 otherwise.

(c) Those that changed jobs over the year are omitted. The dependent variable, wage growth, is calculated as the log difference of weekly gross wages and salary divided by usual weekly hours worked in one's main job. It is winsorised at the top and bottom 5 per cent of the distribution for each year.

(d) Self-assessed probability of retaining job over the next year.

(e) Lagged one year in the wage growth model.

Sources: ABS; Frey and Osborne (2017); HILDA Release 16.0; RBA

The results confirm that labour market conditions are an important influence on job security. Higher unemployment modestly contributes to lower job security, where a 1 percentage point rise in the unemployment rate is associated with a 1 percentage point fall in the probability of feeling certain about job retention. Those who would prefer more hours have a lower expectation of job retention. This suggests underemployment may weigh on feelings of job security, although those wanting to work fewer hours also had low job security.

Trade exposure and automation have the expected significant negative relationship with perceived job security. In terms of marginal effects, an industry with no exposure to international competition has job retention certainty about 3 percentage points higher than one in which imports make up around one-third of an industry's total supply (such as some of the manufacturing industries). After controlling for trade exposure and other factors, those in the goods production and business services sectors still have relatively low perceptions of job security, with those in household services having relatively high security. The average likelihood of feeling certain about job retention falls 3 percentage points when moving from an occupation with no automation risk to one that has the highest likelihood of being automated. Once automation risk is controlled for, being in a routine or manual occupation contributes to higher job security, in contrast to what is suggested by the summary statistics.

Regarding other job and personal characteristics, those that are associated with higher job security include: working full time, having a permanent position, having longer tenure, being female, being older, having less formal education and living outside a capital city.[8] The effect of union membership on job security is not statistically significant. Thus, the difference in average job security perceptions between union and non-union members can be accounted for by their job and personal characteristics.

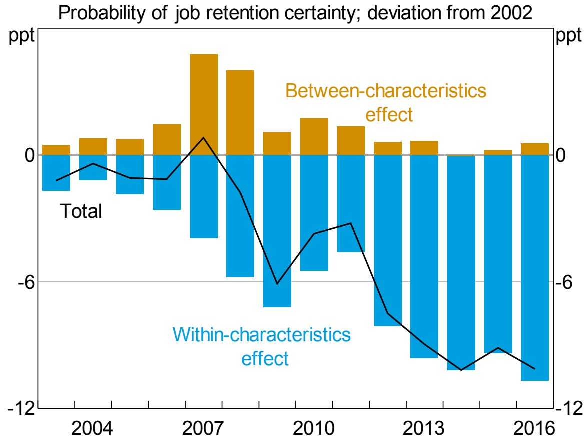
The time dummy variables are estimated to be increasingly negative in recent years. This suggests that there are aggregate factors weighing on job security that are not being captured by the other variables in the model.

Overall, the model estimates reveal the average propensity to feel secure for each personal, firm or job characteristic over time. However, these feelings of job security can and do change over time. Additionally, the changing composition of the workforce will affect aggregate job security. For instance, an increase in the share of part-time employment would be associated with more people feeling insecure, and so lower overall job security, all else being equal. A shift in the labour market to jobs that are less likely to be automated will increase the share of people feeling secure. As such, we decompose the change in job security over time into these within-characteristic and between-characteristic, or compositional, effects. By estimating the model for each year we can disentangle the roles of the within and between effects on aggregate job security. We conduct a pooled two-fold Oaxaca-Blinder decomposition for the probit model (Jann 2008). We run separate models for each year and compare the change in job security to the 2002 group.

The decline in job security has been broad based across the characteristics we examine in the model (Graph 6). This is highlighted by the persistently negative within-characteristics effect, and confirms the broad-based decline in job security shown by the trends. Compositional change had been working in the opposite direction, with employment moving towards characteristics that generally make workers feel more secure, providing a boost to aggregate job security. The drag from perceived job security within characteristics has been growing since around 2004, with the offset from compositional shifts diminishing over the post-crisis period.

8 Some of these characteristics may be affected by selection bias. For instance, those groups with lower rates of labour market attachment – such as females and older workers – may leave the workforce if they cannot find secure employment, which would bias the results. Selection bias is examined in Section 5.

Graph 6
Contributions to Change in Job Security
Probability of job retention certainty; deviation from 2002

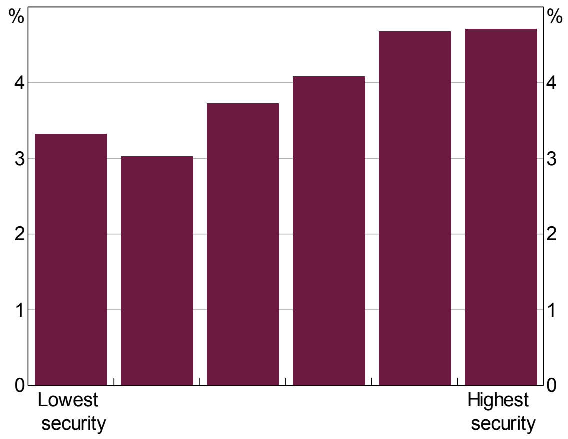


Sources: ABS; Frey and Osborne (2017); HILDA Release 16.0; RBA

4.3 Job Security and Wage Growth

Perceived job security is associated with higher wage growth the following year (Graph 7). Splitting job security into groups from low (0 per cent) to high (100 per cent secure), there is a rough positive relationship. A nonparametric K-sample test on the equality of medians shows the differences are statistically significant ($\chi^2(5) = 23.6$; p-value=0.00). However, the fall in wage growth in recent years has been experienced by both secure and less secure workers.

Graph 7
Median Wage Growth by Lagged Job Security*
2002–16



* Job retention probability is split into 6 categories from lowest to highest. Those who changed jobs over the year are omitted
Sources: HILDA Release 16.0; RBA

We examine this relationship by regressing annual hourly wage growth on the lagged self-assessed probability of job retention. As discussed above, we use the full continuous probability measure of job security. The control variables included are the same as those used in the job security model above. The only difference is the inclusion of inflation – measured as growth in each capital city's consumer price index – as it should influence nominal wage growth. Therefore this model captures the effect of job security perceptions on wage growth over and above the many factors that can influence job security itself. We use random effects estimation. The Breusch-Pagan LM test recommends this over pooled OLS (χ^2= 1098.04, p-value = 0.00); fixed-effects modelling is less compelling as it would suggest that certain people should have permanently lower or higher wage growth.

The results show that a higher perceived likelihood of job retention has a statistically significant positive relationship with wage growth over the following year (Table 1). A one standard deviation fall in job security (a change of 20 percentage points) is associated with a 0.3 percentage point decline in annual wage growth. However, this finding explains little of the fall in average wage growth observed in recent years. From 2010 to 2014 (the most recent peak and trough), average self-assessed job retention probability declined by only around 3 percentage points. This explains around 0.05 percentage points of the 1 percentage point fall in average wage growth over the corresponding period.

Automation risk and trade exposure are both found to significantly contribute to lower wage growth. Despite the negative relationships, these measures have not been substantially weighing on aggregate wage growth. This is because, in recent years, employment growth has been shifting away both from industries with a higher trade exposure and occupations that are more easily automated.

Several variables that capture economic and labour market conditions were statistically significant. The coefficient on inflation is significant, and subdued inflation explains a noticeable amount of the fall in average wage growth in recent years. Those who would prefer more hours have lower wage growth in the subsequent year, which suggests an additional role of underemployment in suppressing wage outcomes. Surprisingly, unemployment has a weakly positive relationship with wage growth, though it does have the expected negative effect when the time dummy variables are excluded. In fact, these time dummies provide most of the explanatory power in the model, suggesting that changes in the local labour market are less relevant for wage growth than economic conditions at the national level.

5. Robustness Checks

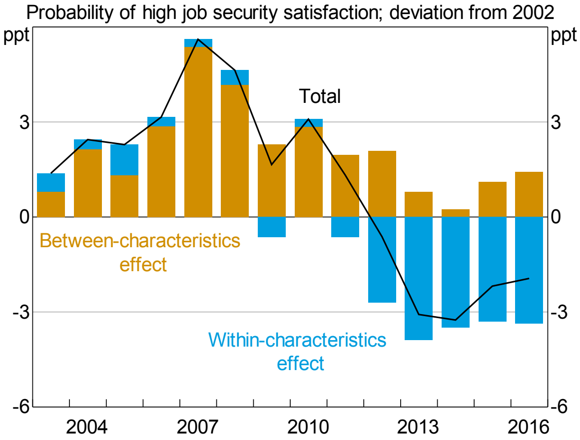
5.1 An Alternative Measure of Job Security

We introduced an alternative self-assessed job security measure in Section 3. It is an ordinal measure of how satisfied a worker is of their job security on a scale of 0–10. It is similarly skewed as the continuous job security measure used in the main analysis, with the vast majority of workers feeling secure. Almost a quarter of workers have the highest job security, 44 per cent chose the next two levels (i.e. 8 or 9 out of 10), close to a quarter chose the middle of the spectrum and only 8 per cent chose the bottom 5 categories. To model this variable, we divide it into three categories: high (8–10), medium (5–7) and low (0–4) job security satisfaction categories. The variable moves closely with the main job retention certainty measure and wage growth over time.

We estimated the determinants of job security satisfaction using a random effects ordered probit. The key results are similar to the main results above.[9] Unemployment, trade exposure and automation have a negative relationship with job security, although the latter is statistically insignificant. Those in routine manual roles had significantly lower perceived job security satisfaction, which is as expected but a different result to that of the job security certainty measure. Like the main model, the year dummies have substantial explanatory power. To explore the role of these unexplained aggregate economic factors further we decomposed the job security satisfaction into within- and between-characteristics factors. For ease of computation, we modelled a simple probit just for the high job security category. Compositional change appears to have had a much larger positive effect prior to 2010, with the model covariates explaining much of the rise in job security in that period (Graph 8). While compositional change continued to positively contribute to aggregate job security, the within-characteristics effect dominates in the latter part of the sample, putting substantial downward pressure on job security (similar to the job retention measure). This underlines the broad-based nature of the fall in job security in recent years.

9 Model results are available on request.

Graph 8
Contributions to Change in Job Security
Probability of high job security satisfaction; deviation from 2002



Sources: ABS; Frey and Osborne (2017); HILDA Release 16.0; RBA

5.2 Alternative Models of Wage Growth

Alternative models were estimated to test the robustness of the relationship between wage growth and job security. We examined a range of specifications and samples within the panel framework. We also address the issues of sample selection and endogeneity. Table 1 presents the coefficient estimates of the lagged job security probability measure on wage growth for various models.

Table 2: Model Coefficients of Lagged Job Security on Wage Growth[a]

	Coefficient	St. Error	R-squared (overall / pseudo)	Observations[b]
Main model				
Random effects	**1.67*** **	**(0.52)**	**0.02**	**65 837**
Alternate panel structure				
Pooled OLS	1.65***	(0.51)	0.02	65 837
Fixed effects	1.91***	(0.71)	0.00	65 837
Alternate model structure				
Heckman selection	1.60***	(0.51)	--	64 703
Instrumental variables	1.10	(5.70)	0.02	65 825
Median (quantile) regression	1.78***	(0.32)	0.01	65 837
Alternate specification or sample (random effects)				
Not promoted	1.75***	(0.55)	0.02	58 899
Post 2009 data	2.46***	(0.66)	0.02	35 207
No time dummies	1.82***	(0.52)	0.02	65 837
No controls	1.69***	(0.52)	0.00	68 765
Job security dummy variables				
Job retention certainty	0.33*	(0.17)	0.02	65 837
High job security satisfaction	0.63	(0.42)	0.02	66 555
Medium job security satisfaction	0.50	(0.46)	0.02	66 555

(a) Standard errors are clustered by individual. *, **, *** denotes significance at the 10, 5 and 1 per cent levels, respectively.

(b) The number of individuals is 13 706 for most of the models. The number of observations is 93 152 in the selection equation.

Sources: ABS; Frey and Osborne (2013); HILDA 16.0; RBA

In the random effects wage growth model, the coefficient on job security was largely unchanged when we did not control for any other factors. This was also the case when we excluded those who were promoted over the year or when we excluded the year dummy variables. The relationship between job security and wage growth was stronger when we model only the post-crisis period. The relationship between job security and wage growth also appears robust to outliers, as the effect was similar under a median regression. However, we find a mostly insignificant effect of job security on wage growth when we include either the dummy variable of job retention certainty (i.e. the variable used in the job security determinants regression) or the job security satisfaction dummy variables. This is in line with the results of Dickerson and Green (2012), who find that continuous probability measures of subjective job loss explain labour market outcomes better than ordinal measures.

Wages and job security are only observed for those in employment. Given a person with low perceived job security is more likely to be unemployed in the following period, their omission from the sample may lead to selection bias. In other words, the characteristics of the unemployed and those with low job security may be correlated. We estimate a Heckman selection model of wage growth to correct for the bias. To estimate the selection equation we need to include variables that will influence the probability of being employed, but be unrelated to annual wage growth. We used one's unemployment history (the number of years they have ever been unemployed), their health status (whether they have self-assessed poor or fair health and whether they have a chronic illness) and an interaction term for being female with a dependent child under five. We also included year dummies, age, education, regional unemployment rate, state, gender, having an English-speaking background, being an immigrant and living in a regional area. Despite the presence of selection effects (ρ=-0.07; χ^2=31.07; p-value =0.00), the estimate and statistical significance of job security was almost identical to the random effects model. This implies that selection bias is not a material concern in our analysis.[10]

The wage growth model may suffer from reverse causality (endogeneity), where the expectation of a large wage rise may make one feel more secure in their job. Alternatively, a common factor, such as the business cycle, may drive both variables (Hubler and Hubler 2006). Although job security enters the model as a lag, this does not necessarily adequately control for endogeneity (Bellemare et al. 2017). As such, we re-estimate a pooled model using instrumental variables. Our instrument is lagged subjective life satisfaction, based on a question that asks "how satisfied are you with your life (on a scale of 0–10)?". This captures how optimistic one feels about life and is expected to be correlated with one's perceptions of their job security, but unlikely to be related to wage growth in the following period.[11]

In the IV regression, we instrument lagged job security with two lagged dummy variables denoting high and medium life satisfaction (which equals 1 for those with life satisfaction of 9 or 10 or between 6 and 8, respectively). The first-stage regression F-statistic is large, so we reject the null of weak instruments (F=128.51; p-value = 0.00). We further test for instrument validity by performing the Wooldridge score test of overidentifying restrictions. We fail to reject the hypothesis of valid instruments (χ^2=0.52; p-value =0.47).

Given the instrument appears valid, we can test for endogeneity of job security with respect to wage growth. Using the Wu–Hausman test we fail to reject the null of exogeneity (F=0.01; p-value =0.92). As such, IV regression will lead to consistent but inefficient estimates, and our main random effects model is more appropriate. This is confirmed with the results of the model. While the point estimate of job security on wage growth in the IV regression is similar to the main model result, it has an enormous standard error. As such, our main model estimates are not biased by endogeneity.

10 We also estimated the job security probit model in the same selection framework. Most coefficient estimates of interest had similar sign and magnitude, although the effect of regional unemployment was a bit smaller. This is despite the likelihood ratio test suggests selection effects are present (ρ=-0.16; χ^2=23.05; p-value =0.00).

11 Ambrey and Fleming (2012) show personality, demographic factors and current circumstances affect life satisfaction.

6. Conclusion

This paper used household panel data to examine factors – including automation and globalisation risks – that influence workers' perceptions of their own job security. We then examine whether these job security perceptions have contributed to low wage growth in recent years. We find that perceptions of one's job security are lower for those in casual work, areas of high unemployment, jobs with a high risk of automation and industries more exposed to global trade. However, aggregate conditions not captured in our model appear to be the key driver of job security concerns. The recent decline in perceived job security has been broad based across industries, occupations, job structure and personal characteristics. As such, we cannot pinpoint any one factor that has led to the decline in perceptions of job security.

We find that greater perceived job security is associated with higher wage growth, over and above the other factors in the model. A worker who is only 50 per cent sure that they will keep their job over the next year will have annual wage growth that is around 0.8 percentage points lower than a worker who is certain they will keep their job. As such, weaker job security perceptions have provided a small drag on wage growth in recent years. Nonetheless, the relatively small magnitude of the fall in average job security means that the decline in aggregate wage growth is mostly explained by other factors. Subdued inflation contributed to more of the decline in wage growth, with most of the fall explained by aggregate factors that are not directly captured in our model.

Our strategy for identifying the effect of job security on wage growth was to use panel data to track whether those with low job security received lower wage rises the next year, controlling for a range of other factors. In theory this arises from lower job security leading to more constrained bargaining by the employee. A limitation of our work is that wages are determined by the interaction between the firm and employees bargaining strengths, and yet we only observe the final outcome. Future work could look at surveying employees directly about their own bargaining behaviour to get at the issue directly. An extension of our work would be to examine the role of self-assessed job security on hours worked. Part-time employment and underemployment have been increasing, allowing both workers and firms to adjust and bargain over hours. If workers are concerned about their job security they may not only accept lower wage rises, but also less hours, as a trade-off for stable employment.

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