Asymmetric Information, Durables, the Business Cycle, and the Labour Market

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Declaration

I, Ran Gu, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in this thesis.

Signature:

Date:

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Abstract

This thesis studies how workers are partially insured against business cycle shocks in an imperfect labour market. Business cycle shocks have large effects on the stability of worker's wage and employment. This study shows these shocks are partially insured by firms, using durable goods, and by social insurance policies. Chapter "Adaptation Costs, Asymmetric Information, and the Business Cycle Effects on the Postgraduate Wage Premium" studies how cyclical wage shocks are insured by long-term contracts provided by firms. I document a new fact that postgraduates have smaller wage shocks than bachelor graduates over the business cycle. I argue the reason for this phenomenon is the adaptation costs, which reduce the value of worker's outside options and lead workers and firms to agree on a contract with smoother wages. I provide empirical evidence that postgraduates have higher adaptation costs. So postgraduates are better insured by firms and have smaller cyclical wage shocks. Chapter "Asymmetric Information, Durables, and Earnings Shocks" addresses the question of how workers insure themselves against earnings shocks using durable goods. Asymmetric information about the quality of used cars works like a transaction cost, and it implies that used cars are a poor savings vehicle. Chapter "The Impact of Unemployment Insurance on the Cyclicality of Labour Force Participation" studies how business cycle affects worker's decision on labour force participation, and it shows the level of unemployment insurance benefit plays an important role in shaping fluctuations in the participation rate.

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Introduction

This thesis studies how workers are partially insured against business cycle shocks in an imperfect labour market. Business cycle shocks have large effects on the stability of worker's wage and employment. This study shows these shocks are partially insured by firms, using durable goods, and by social insurance policies.

The first chapter studies the business cycle effects on the postgraduate wage premium. Using US data, I show this wage premium is counter-cyclical — postgraduates have smaller wage shocks than bachelor graduates over the business cycle. I argue the reason for this phenomenon is the adaptation costs due to the relatively low productivity of new hires who need time to adapt to their jobs. These adaptation costs reduce the value of workers' outside options and thus the degree to which firms will offer contracts with smoother wages. I provide empirical evidence that postgraduates have higher adaptation costs than bachelor graduates. To understand how adaptation costs affect wage cyclicality, I develop an equilibrium search model with aggregate shocks. In the model, imperfect monitoring of workers' effort creates a moral hazard problem that requires firms to pay an efficiency wage and restricts risk-sharing between firms and workers. Workers with higher adaptation costs have more to lose when they leave the current jobs, so they exert more effort regardless of what the firm offers, which alleviates moral hazard and improves risk-sharing. The estimation shows that adaptation costs alone can explain the differences both in the labour market turnover rates and in the wage cyclicality between postgraduates and bachelor graduates. The model also shows that postgraduates will accept relatively lower starting wages, but have

faster wage growth. Finally, I find that unemployment insurance (UI) crowds out firm insurance, but the effect is smaller for lower educated workers. Lower educated workers have higher welfare gain than postgraduates, which supports the argument for a lower UI replacement rate for postgraduates.

In my second chapter, co-authored with Richard Blundell, Soren Leth-Petersen, Hamish Low and Costas Meghir, we address the question of how workers insure themselves against earnings shocks using durable goods. Asymmetric information about the quality of used cars generates an endogenous transaction cost — lemons penalty, and it implies that used cars are a poor savings vehicle. In this paper we model sales and purchases of new and second-hand cars and quantify the lemons penalty. We do this by formulating a stochastic life-cycle general equilibrium model of car ownership in which dealers buy old cars from consumers without knowing their exact quality. Dealers are offered cars that on average are of lower quality than similar cars in the population. Dealers, therefore, will not pay the expected value of cars being owned to an offered car. They will ask for a price discount, which is the lemons penalty. We structurally estimate the model using a population-wide Danish administrative data set with complete information about car ownership for the period 1992-2009. The data is linked to longitudinal income-tax records of the owners with information about income and wealth. Our results show that 1-year-old car has the largest lemons penalty, which declines over time. Lemons penalty delays car replacement and substantially lowers transaction volumes. Then we use the estimated model to study the impact of lemons penalty for cars to act as a self-insurance device in the event of unemployment.

In my final chapter, I study how the level of unemployment insurance benefit (UI) changes labour force participation over the business cycle. Standard theory predicts that labour force participation should fall in recessions, as the returns of job search decline. In fact, it is acyclical (moves independently of the business cycle). I argue that the level of UI, being negatively correlated with the business cycle, is the reason. I document a new fact that the Maximum UI Weekly Benefit Amount increases more in recessions than in booms. My theory is that as UI is more generous in reces-

sions, unemployment becomes more attractive than out-of-labour-force. I embed the counter-cyclical UI schedule into a search model with aggregate productivity shocks and endogenous labour force participation. I show that although the cyclical variation in the level of UI is small, it plays a vital role in shaping fluctuations in the participation rate. The model is also able to capture other cyclical movements in labour market stocks and gross worker flows. The model also shows that counter-cyclical UI can stabilise the economy by reducing the variation in employment and GDP.

Chapter 1

Adaptation Costs, Asymmetric Information, and the Business Cycle Effects on the Postgraduate Wage Premium

Figure 1.1: Detrended Real GDP and Postgraduate Wage Premium
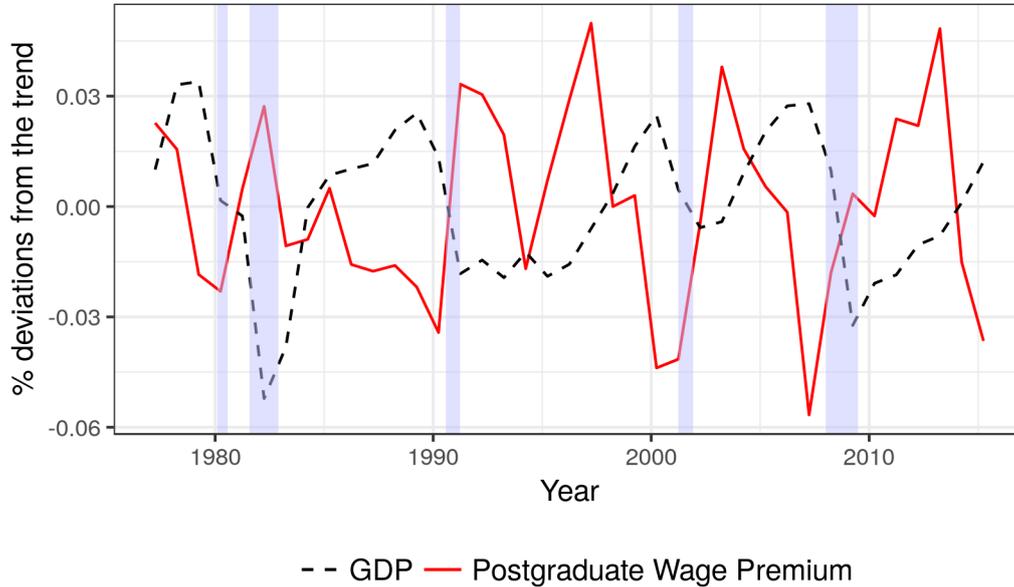
Note: March CPS 1976–2016. Males 26–64 in the private sector.
NBER recessions are shaded. Series are logged and HP-filtered with parameter 100.
Corr(GDP, postgrad wage premium) = -0.45

1.1 Introduction

College graduates receive a wage premium over non-college workers[1]. However, both types of workers experience similar wage shocks over the business cycle (Keane and Prasad, 1993). In this paper, I document a new fact: in the US, the growing share of workers with postgraduate degrees are subject to smaller cyclical wage shocks than those with bachelor degrees[2]. Thus the postgraduate wage premium, i.e. wage differentials between postgraduates and bachelor graduates, is counter-cyclical.

Figure 1.1 uses the 1976-2016 March Current Population Survey (CPS) to plot the detrended real GDP and the postgraduate wage premium. I restrict the sample to male workers aged 26-64 in the private sector. To detrend, I use a Hodrick–Prescott (HP)

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[1]Noncollege workers include high school dropouts, high school graduates, and those with some college education.

[2]Postgraduate degrees include Masters, PhD, and professional degrees. Lindley and Machin (2016) show that the share of workers with postgraduate degrees has doubled since 1980, and in 2012 nearly 15% of the adult workforce, or 40% of all college graduates, have a postgraduate degree.

filter with parameter 100. NBER dated recessions are shaded. In all of the recent recessions, the postgraduate wage premium increases substantially, and its correlation with real GDP is -0.45, indicating the postgraduate wage premium is counter-cyclical. Later in Section 1.2, I show that it is because postgraduate wages respond less to business cycle shocks than bachelor wages. After controlling for observables, I document that for every 1 percentage point increase in the unemployment rate, the average real hourly wage for postgraduates declines by 0.26% and that for bachelor graduates declines by 1.17%.

In this paper, I show that the counter-cyclical postgraduate wage premium is not due to changes in the composition of workers. My theory to explain this phenomenon is that postgraduates have higher adaptation costs than bachelor graduates. For example, postgraduates have more specific skills on the current jobs which are non-portable to other jobs, and they need longer time to adapt to new jobs[3]. So postgraduates are more willing to keep their current jobs. Because of this, in booms, firms do not need to keep postgraduates by raising wages. Then when the economy gets worse, firms do not need to cut their wages. As a result, firms offer postgraduates more stable wages over the business cycle.

I provide empirical evidence that postgraduates have higher adaptation costs. I document that postgraduates need 58.5 weeks on average to adapt to their jobs, and they suffer 17.8% losses in wages if they were exogenously removed from their current jobs. These two dimensions of adaptation costs for postgraduates are twice as large as those for bachelor graduates. Besides, as workers with longer tenures are more likely to be fully adapted, I show that workers with longer tenures have larger differences in the wage cyclicality between postgraduates and bachelor graduates. This is consistent with the theory that adaptation costs reduce wage cyclicality.

To quantify the effects of adaptation costs on wage cyclicality, I develop an equilibrium search model with aggregate shocks. In the model, risk-neutral firms provide

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[3]One can think of adaptation costs as a measure of non-portable specific skills (Becker, 1962) in more specialised jobs and more narrowed industries. Blatter, Muehlemann, and Schenker (2012) have found these costs to be large.

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long-term contracts, and risk-averse workers choose their effort level to avoid job separation. I assume workers' effort is unobserved by firms. Without this assumption, because of the difference in risk aversion, firms should take away all the risk from workers and offer constant wages regardless of business cycle shocks (Baily, 1974; Azariadis, 1975). With this assumption, workers might shirk in their effort, and firms have to adjust wages to incentivize workers. So the moral hazard problem requires firms to pay an efficiency wage, which restricts the amount of risk-sharing between firms and workers. Adaptation costs work the opposite way. Workers with higher adaptation costs have more to lose when they leave the current jobs, so they exert more effort regardless of what the firm offers, which alleviates moral hazard and improves risk-sharing.

I parametrize the model by using empirical measures of adaptation costs from the Multi-City Study of Urban Inequalities and CPS Displaced Worker Supplement. Although the model is parsimonious, it can capture the differences both in the labour market turnover rates and in the wage cyclicality between postgraduates and bachelor graduates, showing the differences in adaptation costs are an important driving force. The model also shows that as postgraduates have higher adaptation costs, their starting wage is relatively lower, but their subsequent wage growth is faster. This result extends the specific human capital hypothesis in Chapman and Tan (1980) – that industry starting wage and rate of wage growth are negatively related – to the context of postgraduates versus bachelor graduates.

Also, the literature on partial insurance, e.g. Blundell, Pistaferri, and Preston (2008), suggests noncollege workers have relatively less partial insurance against earnings shocks. My paper implies that lower educated workers, even bachelor graduates, are unlikely to get much insurance from firms, hence, increasing the demand for social insurance among this group. I conduct a counter-factual policy experiment to raise the unemployment insurance (UI) replacement rate by 10%. I find that this policy increases wage cyclicality, indicating UI crowds out the implicit insurance provided by firms. However, the effect is smaller for the lower educated than postgraduates. Lower

educated workers have higher welfare gain than postgraduates from such a policy, which supports the argument for a lower UI replacement rate for postgraduates.

This paper is related to several strands of the literature. First, it contributes to the literature studying cyclical wage shocks across education levels. Keane and Prasad (1993) and Lindquist (2004) found that college graduates and non-college workers are subject to similar cyclical wage shocks[4]. I document that postgraduates have smaller cyclical wage shocks than bachelor graduates, indicating that education can provide shelter against cyclical wage shocks, but only at the postgraduate level. Besides, Guvenen, Ozkan, and Song (2014) studied cyclical earnings shocks across past earnings levels. My paper studies how these shocks vary across another observable: education. My paper also combines two strands of literature on specific skills. The first strand of literature is the equilibrium search models studying the effects of specific skills on labour market turnover rates (Hudomiet, 2015; Cairó and Cajner, 2016). The second strand of literature is the theoretical bargaining models studying the effects of specific skills on wage cyclicality (MacLeod and Malcomson, 1995; Lagakos and Ordonez, 2011). I quantify the effects both on labour market turnover rates and on wage cyclicality in an equilibrium search model with long-term contracts. Finally, my model extends Lamadon (2017) by adding adaptation costs and aggregate shocks. I also derive the theoretical implication that adaptation costs reduce wage cyclicality and provide sufficient conditions for this property.

In Section 1.2, I compare wage cyclicality between postgraduates and bachelor graduates. In Section 1.3, I provide empirical evidence on adaptation costs by education. In Section 1.4, I present the equilibrium search model and prove that adaptation costs reduce wage cyclicality. In Section 1.5, I outline the estimation strategy and discuss the identification of the model. This section also reports the estimation results. In Section 1.6, I analyze the estimated model and report the counter-factual simulations.

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[4]Lindquist (2004) combine investment-specific technology shocks and capital-skill complementary in production function to explain the acyclical behaviour of college-noncollege wage premium. The same explanation can not be used to explain the postgraduate wage premium, since this is not acyclical but counter-cyclical. One advantage of my model is that it can explain the cyclicality of both types of wage premium at the same time.

Section 1.7 evaluates the effect of an increase in the UI replacement rate. In Section 1.8, I explore other possible explanations. Section 1.9 concludes.

1.2 Data on Postgraduate Wage Premium

In this section, I provide evidence that postgraduate wage premium is counter-cyclical.

1.2.1 Aggregate Cyclicality

I start by showing the aggregate cyclicality of wage premium across different education levels. The postgraduate wage premium in this paper is defined as the ratio of the postgraduate wage to the bachelor wage ($\frac{w_{PG}}{w_{BA}}$). The college wage premium is defined as the ratio of the bachelor wage to the non-college wage ($\frac{w_{BA}}{w_{NC}}$).

I use the March CPS from 1976 to 2016. I restrict the sample to prime-age males aged 26-64 in the private sector. Hourly wages are computed as annual earnings divided by annual hours and are deflated to the year 2000 dollars. The price deflator used is the Bureau of Labor Statistics CPI-U series, all items. I log and HP-filter all annual time series with parameter 100. Table 1.1 shows the business cycle statistics for hourly wages and wage premium by education.

The postgraduate wage is about 30% higher than the bachelor wage, and bachelor wage is about 50% higher than the non-college wage. The bachelor wage is more volatile than other education groups. Regarding the cyclicality, the college wage premium $\frac{w_{BA}}{w_{NC}}$ is pro-cyclical in the mean, but not in the median or the top 25%. As a main finding of the paper, the postgraduate wage premium $\frac{w_{PG}}{w_{BA}}$ is significantly counter-cyclical across the mean, median and top 25%. This is because of the bachelor wage w_{BA} is more pro-cyclical than the postgraduate wage w_{PG}. Similar results hold for females. Please see Appendix A.1.1 for details.

Table 1.1: Cyclical Properties of Real Hourly Wages and Wage Premium

	w_{PG}	w_{BA}	w_{NC}	$\frac{w_{PG}}{w_{BA}}$	$\frac{w_{BA}}{w_{NC}}$
Mean	32.1	25.3	16.4	1.27	1.54
Std	.024	.028	.018	.025	.02
Corr. with URATE	-.03	-.48	-.40	.50	-.31
Corr. with GDP	.24	.62	.56	-.45	.36
Regress on log GDP (Elasticity)					
Mean	.29	.87***	.50***	-.58***	.36**
	(.19)	(.18)	(.12)	(.18)	(.15)
Median	.34**	.58***	.57***	-.24*	.01
	(.14)	(.16)	(.12)	(.14)	(.14)
Top 25%	.04	.72***	.53***	-.68***	.20
	(.19)	(.15)	(.11)	(.16)	(.12)

Note: Data is March CPS 1976–2016. Sample is males aged 26–64 in the private sector.
"PG" refers to postgraduates, "BA" refers to bachelor graduates, and "NC" refers to noncollege workers. "URATE" refers to the unemployment rate. The row labelled "mean" refers to the levels. The other rows refer to the log of the variable in each column, which are also HP filtered with parameter 100. Wages are deflated to 2000 dollars. Standard errors are in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$.

1.2.2 Regression of Individual Wage on Degree Interaction

I go on to use individual-level data to compare the wage cyclicality between postgraduates and bachelor graduates controlling for observed characteristics. To estimate the effects of postgraduate degree on the cyclicality of a worker's real wage, I follow Keane and Prasad (1993) and run the regression of log real hourly wage

$$\ln W_{it} = X_{it}\beta + \alpha U_t + \gamma \text{PG}_i \times U_t + \varepsilon_{it} \tag{1.1}$$

X_{it} is a vector of observables including a state dummy, a postgraduate degree dummy PG_i, a race dummy, a marriage dummy, a quadratic in age, and a quadratic time trend. I use the aggregate unemployment rate in the economy, U_t, as an indicator of the business cycle[5]. α indicates the relation between the bachelor wage and the business cycle. For instance, a negative estimate of α would imply that the average real wage of bachelor graduates declines when the aggregate unemployment rate rises, i.e. the bachelor wage is pro-cyclical. PG_i is the postgraduate degree dummy (included in X_{it}) which equals 1 if the worker has a postgraduate degree and 0 if he only has a bachelor degree. The coefficients γ on the interaction term $\text{PG}_i \times U_t$ captures the difference between the cyclicality of the postgraduate wage and the bachelor wage, and $\alpha + \gamma$ indicates the cyclicality of the postgraduate wage. A positive estimate of γ would indicate a counter-cyclical postgraduate wage premium — the premium increases when the unemployment rate rises. I allow for the interdependence of error terms at the state level and avoid a downward bias of the standard errors of aggregated variables (Moulton, 1986, 1990) by using cluster-robust standard errors with states as clusters.

Empirical results

Table 1.2 shows the empirical results. I use the 1976-2016 March CPS and restrict the sample to males aged 26-64 in the private sector with at least a bachelor's degree. Following Robin (2011), the unemployment rate is successively log-transformed, HP

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[5]The results are not affected by choice of the business cycle. See the discussion in the next section.

filtered and exponentiated. I HP-filter the annual series with a conventional smoothing parameter 100. The results are robust to the detrending method[6].

The first column of Table 1.2 shows the regression result on log real hourly wages. The estimated coefficient α on the unemployment rate U_t is -0.0117 (s.e. 0.0013) indicating that a 1 percentage point rise in the aggregate unemployment rate causes a 1.17% decline in the real wage for bachelor graduates. The estimated coefficient γ on the interaction term $\text{PG}_i \times U_t$ is 0.009 (s.e. 0.0028) indicating that when the unemployment rate goes up by 1 percentage point, postgraduates face a 0.9% increase in their real wage relative to that of bachelor graduates. The sum of the coefficients α and γ is -0.0026. The estimates imply that, in a downturn, postgraduates find their wages increasing relative to the wages of bachelor graduates.

I have tried the median regression and found that when the unemployment rate goes up by 1 percentage point, the median wage of bachelor graduates falls 0.9% and that of postgraduates falls 0.4%. I also experiment with other indicators of the business cycle, such as log real GDP. I found that when real GDP increases 1%, bachelor graduates face a 1.16% increase in their real wage, and postgraduates face a 0.52% increase in their real wage. See column (3) and (4) of Table A.2 in Appendix A.1.2 for the estimates.

Appendix A.1.2 explores other robustness checks of regression 1.1. It shows that having a postgraduate degree significantly reduces wage cyclicality for different age groups, particularly for elder workers. It also shows that the results are robust in different time periods.

The second column of Table 1.2 provides estimates of the cyclical variability of annual hours worked. The estimation framework is identical to that used for real hourly wages (equation 1.1). The coefficient on U_t is -0.008 (s.e. 0.00064) and the coefficient on $\text{PG}_i \times U_t$ is 0.0039 (s.e. 0.0013). So for postgraduates, annual hours worked are less procyclical than those for bachelor graduates. The difference in the cyclicality of hours

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[6]I have also tried detrending the unemployment rate using a cubic trend and obtained very similar results. See column (2) of Table A.2 in Appendix A.1.2.

Table 1.2: Regression on Degree Interaction

| Data | | March CPS | | PSID |
| Method | | OLS | | FE |
Dependent	lnWage	lnHour	lnEarnings	lnWage
$U_t\,(\alpha)$	-.0117***	-.0080***	-.0196***	-.0132***
	(.0013)	(.00064)	(.0016)	(.0034)
$\text{PG}_i \times U_t\,(\gamma)$	.0090***	.0039***	.0129***	.0067***
	(.0028)	(.0013)	(.0034)	(.0026)
$\alpha + \gamma$	-.0026	-.0041***	-.0067**	-.0064*
	(.0021)	(.0012)	(.0027)	(.0036)
Clustering		State		Individual
Observations	331,375	331,375	331,375	19,732
Workers	331,375	331,375	331,375	1,571

Note: Hourly wages are computed as annual earnings divided by annual hours, and are deflated to 2000 dollars.

across education groups is smaller than that of wages. The third column of Table 1.2 shows estimates of cyclical variability of annual earnings. When the unemployment rate goes up by 1 percentage point, the real earnings of bachelor graduates fall 1.96%, and that of postgraduates fall 0.67%. The postgraduate earnings are less pro-cyclical than the bachelor earnings. In conjunction, these results suggest that postgraduates have more stable wages, hours, and earnings than bachelor graduates.

Does regression (1.1) yield biased estimates of γ? The typical selection bias prob-

Table 1.3: Labour Market Stocks and Flows by Education

Education	Noncollege	Bachelor	Postgraduate
Unemployment rate	.061	.029	.020
Labour force participation rate	.853	.933	.935
Job separation rate	.016	.0072	.0050
Job finding rate	.272	.263	.245
Job-to-job transition rate	.021	.019	.018

Note: Job-to-job transition rate uses monthly CPS 1994-2014. Other variables use monthly CPS 1979–2014.

lem is: recessions cause low-skill workers leave employment. As a result, the average labour force quality and the average wage increase. The standard way of eliminating such systematic selection is to use the Heckman (1979) selection model. It estimates the wage equation jointly with a probit choice equation that determines whether a worker is employed. I report the results in Appendix A.1.2. I use number and age of own children as additional variables in the employment equation. I find that the coefficient γ on $\mathrm{PG}_i \times U_t$ does not change[7]. In the same appendix, I run the regression only for job stayers as an additional check[8]. You can think this as comparing average postgraduates with good bachelor graduates, so the estimated coefficient should be smaller. Indeed, the coefficient γ changes from 0.009 to 0.007, but still strongly significant.

Table 1.3 shows the labour market states by education. In the sample of males aged 26-64, for both the bachelor graduates and the postgraduates, the unemployment rate is less than 3%, and the labour force participation rate is more than 93%. These statistics imply that prime-age males with either bachelor or postgraduate degree are always working. So the effect of the selection bias problem is very limited. Table 1.3 also shows that the noncollege workers have a much higher unemployment rate and a much lower labour force participation rate. The rest of the table shows that the labour market turnover rates decrease in the level of the education, which are highest for the noncollege workers. The job separation rate for bachelor graduates is 0.007, which is 40% higher than that for postgraduates (0.005). The job finding rates for bachelor graduates is 0.263, which is 7% higher than that for postgraduates (0.245). The job-to-job transition rate for bachelor graduates is 0.019, which is 6% higher than that for postgraduates (0.018).

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[7]The variables included in the employment equation but excluded from wage equation are: number of own children in the household, number of own children under age 5 in the household, and age of youngest own child in the household.

[8]Job stayers are workers who stayed in the same job last year, had no stretch of looking for work, and worked for 52 weeks.

1.2.3 Individual Fixed Effects

The best way to control for the selection bias problem is to use individual fixed-effect regression. I use the data constructed by Heathcote, Storesletten, and Violante (2010) from the Panel Study of Income Dynamics 1968–2002 (PSID), available from the website of the *Review of Economic Dynamics*. I run equation 1.1 with individual fixed effects, controlling for a quadratic in age and a quadratic time trend.

The results are presented in the fourth column of Table 1.2. The estimated coefficient α on the unemployment rate U_t is -0.0132 (s.e. 0.0034) indicating that a 1 percentage point rise in the aggregate unemployment rate causes a 1.32% decline in the real hourly wage for bachelor graduates. The estimated coefficient γ on the interaction term $\text{PG}_i \times U_t$ is 0.0067 (s.e. 0.0026) indicating that when the unemployment rate goes up by 1 percentage point, postgraduates face a 0.67% increase in their real wage relative to that of bachelor graduates.

Using 1968-1992 PSID, Swanson (2007) regress log real hourly wage on unemployment rate without distinguishing education levels. He found that a 1 percentage point rise in the aggregate unemployment rate causes a 1.22% decline in the real wage, which is of the similar magnitude as my estimates.

1.2.4 Regression by Industries and Occupations

Is it because postgraduates and bachelor graduates sort into different industries that are subject to different cyclical variation in productivity? To test whether this argument holds, I run the wage equation at the industry and occupation level. Table 1.4 presents the estimates at the industry level. Postgraduates have smaller cyclical wage shocks in the following industries: Nondurable manufacturing, Durable manufacturing, T.C.U (Transportation, Communications, and Utilities), F.I.R (Finance, Insurance, and Real Estate), and Services, which added up to 82% of the population. Table 1.5 shows the estimates at the occupation level. Postgraduates have smaller cyclical wage shocks in the following occupations: Managerial, Professional Specialty, Technical, and

Sales occupations, which added up to 83.4% of the population. So sorting into industries and occupations can not fully explain the counter-cyclicality of the postgraduate wage premium.

1.3 Adaptation Costs

In the previous section, I show that postgraduates have smaller wage shocks than bachelor graduates over the business cycle. This section documents a fact which will be useful in understanding the relationship between the cycle and the postgraduate wage premium: adaptation costs due to the relatively low productivity of newly hired workers who need time to adapt to their new jobs. These costs have two dimensions: the time needed for new hires to adapt to their jobs and the specific skills they have to learn. Hudomiet (2015) and Blatter, Muehlemann, and Schenker (2012) show that adaptation costs are higher for college graduates than for non-college workers. However, adaptation costs for the postgraduates have not been explored. In what follows, I document that postgraduates have higher adaptation costs than bachelor graduates, which will form the empirical basis for the parameterization of my model.

1.3.1 Adaptation Duration

First, I look at the time dimension. I use a US employer survey, the Multi-City Study of Urban Inequalities (MCSUI), to show that postgraduates have longer adaptation duration than bachelor graduates.

The MCSUI was collected in four large US cities (Los Angeles, Boston, Detroit and Atlanta) in 1992-1994. The survey was conducted in the middle of the time period this paper is concerned. One important part of the survey asked employers about the last hired worker. In particular, employers were asked to think about the last new employee the company hired. Then a series of specific questions were asked about the new employee. One of the questions is particularly useful to analyze the adaptation duration. The question reads "How many weeks does it take the typical employee in

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Table 1.4: Regression of Real Wage at the Industry Level

Dependent: $\ln \text{Wage}_{it}$	U_t	$\text{PG}_i \times U_t$	% pop	% PG	PG ratio
All industries	**-.0117*****	**.0090*****	100%	100%	38.27%
	(.0013)	(.0028)			
Agriculture	-.0086	.020***	.75	.55	27.99
	(.0078)	(.0059)			
Mining	.016*	.016**	.85	.69	31.25
	(.0078)	(.0069)			
Construction	-.00079	.0040	3.52	1.86	20.21
	(.0074)	(.0036)			
Nondurable manufacturing	**-.011*****	**.016*****	6.51	5.06	29.76
	(.0039)	(.0039)			
Durable manufacturing	**-.014*****	**.012*****	12.59	10.61	32.26
	(.0028)	(.0028)			
T.C.U	**-.0064**	**.010*****	7.92	4.81	23.24
	(.0046)	(.0033)			
Wholesale trade	-.0067	.0045	4.67	2.32	18.96
	(.0045)	(.0034)			
Retail trade	-.014***	.0053	8.2	4.21	19.63
	(.0038)	(.0037)			
F.I.R	**-.017*****	**.010*****	10.43	7.85	28.79
	(.0036)	(.0030)			
Services	**-.012*****	**.0083*****	44.56	62.05	53.29
	(.0017)	(.0026)			

Note: "% pop": the proportion in the population. "% PG": the proportion in all postgraduates. "PG ratio": the ratio of postgraduates to college graduates (PG+BA). T.C.U: Transportation, Communications, and Utilities.
F.I.R: Finance, Insurance, and Real Estate.
Controls: postgraduate degree, state, race, marriage dummies, a quadratic age trend, and a quadratic time trend. Standard errors are clustered at the state level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 1.5: Regression of Real Wage at the Occupation Level

Dependent: $\ln \text{Wage}_{it}$	U_t	$\text{PG}_i \times U_t$	% pop	% PG	PG ratio
All occupations	**-.0117***	**.0090***	100%	100%	38.27%
	(.0013)	(.0028)			
Managerial	**-.012***	**.012***	29.09	27.85	36.64
	(.002)	(.003)			
Professional Specialty	**-.012***	**.008***	36.71	54.03	56.32
	(.002)	(.003)			
Technical	**-.005**	**.006***	5.58	4.55	31.25
	(.004)	(.003)			
Sales	**-.01***	**.007****	12.02	5.8	18.45
	(.003)	(.003)			
Administrative support	-.009**	0	5.21	2.76	20.31
	(.004)	(.003)			
Service	-.015**	-.008**	2.78	1.39	19.1
	(.006)	(.004)			
Farming, Forestry, Fishing	-.022	-.006	.54	.22	15.34
	(.014)	(.009)			
Precision production,Craft,Repair	-.01**	.001	4.4	1.81	15.74
	(.004)	(.003)			
Operators, Fabricators, Labourers	-.014	-.009*	1.4	.62	16.87
	(.009)	(.005)			
Transport, Material moving	.005	-.008**	2.27	.97	16.37
	(.009)	(.004)			

Note: "% pop": the proportion in the population. "% PG": the proportion in all postgraduates. "PG ratio": the ratio of postgraduates to college graduates (PG+BA). Controls: postgraduate degree, state, race, marriage dummies, a quadratic age trend, and a quadratic time trend. Standard errors are clustered at the state level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 1.6: Time to become fully competent by Education

Education	Noncollege	Bachelor	Postgrad.
Weeks to become fully competent	22.5	29.2	58.5
	(.88)	(2.32)	(8.98)
Observations	2566	515	159

Note: Data is Multi-City Study of Urban Inequalities 1992-1994 (MCSUI). Time to become fully competent is significantly longer for postgraduates than that for bachelor graduates at the one percent level and is significantly longer for bachelor graduates than that for noncollege at the one percent level. Robust standard errors are in parentheses.

Table 1.7: Percent Losses in Wages for displaced workers by Education

Education	Noncollege	Bachelor	Postgrad.
$\mathbb{E}\left(\log w_t - \log w_{t-1}\right)$	-.086	-.086	-.178
	(.013)	(.030)	(.060)
Observations	2576	543	210

Note: Data is 1994-2008 Displaced Worker Supplement to the CPS, with sample restricted to males who were involuntarily displaced from a full-time job last year and are reemployed in a full-time job now. Percent losses in wages are significantly larger for postgraduates than those for bachelor graduates at the ten percent level. Robust standard errors are in parentheses.

this position to become fully competent in it?" Table 1.6 provides descriptive statistics on this measure of adaptation duration. There is a considerable difference between postgraduates and bachelor graduates: a newly hired postgraduate needs 58.5 weeks on average to become fully adapted, which is twice as long as the time needed for a newly hired bachelor (29.2 weeks). The difference is significant at the one percent level. So postgraduates have a longer duration of job adaptation than bachelor graduates. A newly hired noncollege worker needs 22.5 weeks to become fully adapted, which is about 80% of the time needed for a newly hired bachelor. So the difference in the adaptation duration between postgraduates and bachelor graduates is much larger than that between bachelor graduates and noncollege workers.

1.3.2 Wage Loss after Job Displacement

The second dimension is the amount of specific skills new hires have to learn. Wage loss after job displacement could arise from the productivity gap between new hires and experienced workers, and Cairó and Cajner (2016) show that the initial productivity gap is larger for college graduates than that for the non-college workers. In what follows, I document a complementary fact that postgraduates have higher percent losses in wages after displacement than bachelor graduates.

I use the 1994-2008 Displaced Worker Supplement (DWS) to the Current Population Survey in the US. The DWS identifies displaced workers who have been separated from their employers due to (i) insufficient demand for the worker's services, (ii) the worker's position being abolished, or (iii) the worker's plant closing — reasons which have been taken by the literature to instrument for "exogenous" layoffs. DWS records information on earnings on the displaced and current job. I construct a sample of male workers who were involuntarily displaced from a full-time job last year and are reemployed in a full-time job at the time of their interview.

In Table 1.7, I show the log differential in each worker's weekly wages across the current job and the displacement job. The resulting statistics represent the fraction of a typical worker's wage that would be lost if he was exogenously removed from his current match and left to find a new job. Percent losses in wages are significant from zero for all education levels, showing a sizable productivity gap between new hires and experienced workers. The percent losses in wages are significantly larger for postgraduates than bachelor graduates at the ten percent level, and the difference is large: it is -0.178 for postgraduates, which is twice as large as that for displaced bachelor graduates (-0.086). The difference between bachelor graduates and noncollege workers is not significant.

In the following section, by targeting at the percent losses in wages for displaced workers by education, I estimate the initial productivity gaps of new hires in my model, which is indeed higher for postgraduates than bachelor graduates.

1.3.3 Current Job Tenures

The theory is that, after being fully adapted, postgraduates have a relatively lower outside option than bachelor graduates and are more willing to keep the current jobs. Firms don't have to increase wages to keep postgraduates in booms. As a result, postgraduates are offered contracts with smoother wages over the business cycle.

As workers with longer tenures on the current job are more likely to be fully adapted, we should expect that current job tenure should increase the differences in the wage cyclicality between postgraduates and bachelor graduates. To test this implication, I estimate the wage equation by job tenure. Specifically, I include interactions of U_t and $\text{PG}_i \times U_t$ with tenure dummies in the following regression:

$$\ln W_{it} = X_{it}\beta + \text{ShortTenure}_{it} \times (\alpha_1 U_t + \gamma_1 \text{PG}_i U_t) + \text{LongTenure}_{it} \times (\alpha_2 U_t + \gamma_2 \text{PG}_i U_t) + \mu_i + \varepsilon_{it}$$

$$(1.2)$$

If worker i has a short tenure on the current job at time t, $\text{ShortTenure}_{it} = 1$ and $\text{LongTenure}_{it} = 0$. Otherwise, $\text{ShortTenure}_{it} = 0$ and $\text{LongTenure}_{it} = 1$. For workers with short job tenures, the coefficient α_1 measures the cyclicality of the bachelor wage, and γ_1 measures the difference in wage cyclicality between postgraduates and bachelor graduates. For workers with long job tenures, the coefficients α_2 measures the cyclicality of the bachelor wage, and γ_2 measures the difference in wage cyclicality between postgraduates and bachelor graduates.

I use Health and Retirement Study (HRS) of the US from 1992 to 2014, which is a panel study. The data is for elder workers, so I restrict the sample to males aged 50-64. An advantage of HRS is that it has information on the length of uninterrupted tenure on the current job. I estimate equation 1.2 with individual fixed effects. The results are presented in Table 1.8. I set ShortTenure as at most 6 years of uninterrupted tenure on the current job, which added up to 40% of the population. For workers with short tenures, the estimated coefficient γ_1 on the interaction term $\text{PG}_i \times U_t$ is 0.0115 (s.e.

Table 1.8: Fixed-effect Regressions by Tenure

	lnWage
ShortTenure$_{it}$	
$U_t\,(\alpha_1)$	-.0171*
	(.0093)
$\text{PG}_i \times U_t\,(\gamma_1)$	.0115
	(.011)
LongTenure$_{it}$	
$U_t\,(\alpha_2)$	-.0161**
	(.0079)
$\text{PG}_i \times U_t\,(\gamma_2)$	.0245**
	(.010)
$\gamma_2 - \gamma_1$	.0130*
	(.0068)
Observations	6947
Workers	1818

Note: Health and Retirement Study 1992-2014. Male aged 50-64.
Controls: a quadratic in age and a quadratic time trend.
"Short Tenure":at most 6 years of uninterrupted tenure on the current job.
Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

0.011), which has the positive sign but not significant. For workers with long tenures, the estimated coefficient γ_2 is 0.0245 (s.e. 0.010), indicating that when the unemployment rate goes up by 1 percentage point, postgraduates face a 2.45% increase in their real wage relative to that of bachelor graduates. The difference between γ_2 and γ_1 is 0.0130 (s.e. 0.0068)[9], indicating job tenure increases the difference in the wage cyclicality between postgraduates and bachelor graduates. Thus this tenure heterogeneity is consistent with the theory that adaptation costs reduce cyclical variation in wages. Overall, empirical evidence suggests that postgraduates have higher adaptation costs than bachelor graduates.

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[9]I have also tried different values for the cutoff θ. When $\theta = 2$ — the 20th percentile, the difference between γ_2 and γ_1 is 0.01. When $\theta = 9$ — the median, the difference between γ_2 and γ_1 is 0.007.

1.4 The Contracting Model of Asymmetric Information

I construct a contracting model of asymmetric information, which will be used to quantify the empirical patterns of wage cyclicality by education. The model extends the search model of Lamadon (2017) by adding aggregate productivity shocks and job adaptation costs[10]. In the model, workers initially have zero endowment of any specific skills which they obtain through a period of job adaptation. Supported by the empirical evidence presented in the previous section, my model let postgraduates require a longer duration of job adaptation for exogenous reasons. A firm provides long-term contract specifying wages for each future state. Given the wage profile, workers choose their effort level, which affects the job separation probability. The effort is private information and thus unobserved to the firm. Firms take this into account and provide contracts that incentivize workers with the optimal level of effort after any realization of aggregate productivity. Job search is directed, and the equilibrium is block-recursive, such that individuals' optimal decisions and optimal contracts are independent of the distribution of workers.

1.4.1 Setup

Time is discrete, indexed by t and continues forever. Aggregate productivity z_t evolves as a first-order Markov chain with transition probabilities $\pi(z_{t+1}|z_t)$. Workers are characterized in terms of their education being either noncollege (NC), or bachelor (BA), or postgraduate (PG). Workers in each education group possess a certain amount of general human capital, denoted by $h \in \{h_{NC}, h_{BA}, h_{PG}\}$.

Following the literature on implicit contracts (for example, Azariadis (1975) and Baily (1974)), I assume risk-averse workers and risk-neutral firms[11], which makes it

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[10]Mortensen and Pissarides (1994) type search models have been used extensively to model long-term relationships between workers and firms, which typically assume continual Nash wage bargaining. These models usually produce a counter-factually high elasticity of wages to productivity. Besides, workers are risk-neutral in these models, so they do not care about wage insurance. Allowing risk-aversion will make these models as complicated as mine.

[11]This assumption is based on the arguments that entrepreneurs are less risk-averse than workers, and their risk can be insured through better access to asset markets.

optimal to have long-term contracts. I follow the standard approach in search and matching literature by assuming a firm is a single-worker production unit. Workers are initially unskilled in the match with the adaptation costs depending on their education. I let $s \in \{0, 1\}$ represent the possession of specific skills in the match, where $s = 1$ represents a worker possessing match-specific human capital and $s = 0$ represents a trainee without specific skills. So an active match is characterized by a worker's level of education h and specific skill s. I let τ^h measures the extent of the productivity gap between new hires and skilled workers.

In aggregate state z, a match between a firm and a worker of education h produce according to following technology

$$y^h (s, z) = hz - \tau^h (1 - s)$$

In other words when the worker is skilled $s = 1$, the output from the match is hz, whereas a trainee produces $hz - \tau^h$. In each period untrained workers experience a probability ϕ^h of being upgraded to a skilled worker. Note that $1/\phi^h$ yields the average duration of adaptation.

Workers are risk-averse. They are endowed with one unit of labour each period which they supply in-elastically to the firms for a wage w_t. There are no asset markets or storage technology, and so the worker's consumption each period equals her wage[12]. Given his wage, workers choose the effort level e_t, which equals the probability that the job continues to exist next period. This captures the idea that a negligent worker might lose a client or break the machine and cause the job to disappear. The date-t utility function takes the form

$$u_t = u (w_t) - c (e_t)$$

---

[12]A search model combing saving, long-term contracts is very complicated in a business cycle setting, because job search depends on wealth. In the setting of wage posting, it requires firms to post jobs depending on wealth. But this is an interesting extension, and I will explore it in future research. The paper's point is that postgrad don't need social insurance, if they have access to self-insurance method, it will reinforce the results.

where the utility of consumption $u : \mathbb{R} \to \mathbb{R}$ is differentiable, increasing, and concave. The cost of effort $c : \mathbb{R} \to \mathbb{R}$ is differentiable, increasing, and convex. I assume the cost is 0 when the effort is 0, i.e. $c(0) = 0$. So by choosing $e_t = 0$, employed workers can quit their jobs in every period. An unemployed worker receives a flow income b^h for the period.

1.4.2 Timing

A period is then divided into four stages:

1. Production, the firm collects output y and pays wage w to the worker.

2. The worker consumes w, chooses effort level e.

3. With probability e the employment persists to next period. With probability $1-e$ the worker moves to unemployment.

4. With probability ϕ a trainee is upgraded to a skilled worker.

1.4.3 Recursive Contracts

Firms commit to long-term contracts, which is defined as a recursive contract following Spear and Srivastava (1987). Assume that the worker is currently entitled to a particular promised value V. The recursive contract is defined at each state (s, z, h, V) by

$$\{(w, W_{s'z'}), e\}$$

where w is the wage. $W_{s'z'}$ is the promised value for each realization of aggregate state z' and skill type s' next period, i.e. when the aggregate productivity tomorrow is z', the promised value is

- $W_{1z'}$ if the worker is a skilled worker tomorrow.

- $W_{0z'}$ if the worker is a trainee tomorrow.

e is the effort level suggested by the contract. However, workers cannot commit to it, as the effort is not observed by the firm. Workers respond to the contract by choosing an optimal effort level. If it turns out to equal the effort level suggested by the contract, the recommendation of the contract is incentive compatible.

1.4.4 Employed Workers and Effort Choice

An employed worker optimally chooses the amount of effort e

$$\max_e u\left(w\right) - c\left(e\right) + \beta\left(1 - e\right)\mathbb{E}_{z'}U_{z'}^h + \beta e W_{sz} \tag{1.3}$$

where U_z^h is the value of unemployment. Here W_{sz} is the expected promised value tomorrow. Specifically, in aggregate state z, the expected promised value tomorrow for a skilled worker $(s = 1)$ is

$$W_{1z} = \mathbb{E}_{z'}W_{1z'}$$

A trainee $(s = 0)$ might be upgraded to a skilled worker with probability ϕ^h, and the expected promised value tomorrow is

$$W_{0z} = \mathbb{E}_{z'}\left\{\phi^h W_{1z'} + \left(1 - \phi^h\right)W_{0z'}\right\}$$

The first order condition for the optimal level of effort $\tilde{e}$ is

$$c'\left(\tilde{e}^h\left(s, z, W_{sz}\right)\right) = \beta\left(W_{sz} - \mathbb{E}_{z'}U_{z'}^h\right) \tag{1.4}$$

which gives a unique maximizing solution $\tilde{e}^h\left(s, z, W_{sz}\right)$. Note that $\tilde{e}$ depends on the expected promised value tomorrow W and not on the promised value this period V.

1.4.5 Firm Profit

I can now describe the firm problem in terms of promised values. Let $\Pi^h\left(s, z, V\right)$ be the value function of a firm offering value V to a worker of skill s and education h when

aggregate productivity is z. The firm problem is

$$\Pi^h (s, z, V) = \max_{w W_{sz} W_{s'z'}} y^h (s, z) - w + \beta \tilde{e}^h (s, z, W_{sz}) \cdot \mathbb{E}_{s'z'} \Pi^h \left(s', z', W_{s'z'} \right) \tag{1.5}$$

$$s.t. \quad V = u (w) - c \left(\tilde{e}^h (s, z, W_{sz}) \right) + \beta \left(1 - \tilde{e}^h (s, z, W_{sz}) \right) \mathbb{E}_{z'} U_{z'}^h + \beta \tilde{e}^h (s, z, W_{sz}) W_{sz}$$

$$W_{sz} = \mathbb{E}_{s'z'} W_{s'z'}$$

where $\mathbb{E}_{s'z'} \Pi^h (s', z', W_{s'z'})$ is the expected profit to a firm next period. Specifically, if the firm is matched with a skilled worker ($s = 1$), then the expected profit is

$$\mathbb{E}_{s'z'} \Pi^h \left(s', z', W_{s'z'} \right) = \mathbb{E}_{z'} \Pi^h \left(1, z', W_{1z'} \right)$$

If the firm is matched with a trainee ($s = 0$), who might be upgraded to a skilled worker with probability ϕ^h, then the expected profit is

$$\mathbb{E}_{s'z'} \Pi^h \left(s', z', W_{s'z'} \right) = \mathbb{E}_{z'} \left\{ \phi^h \Pi^h \left(1, z', W_{1z'} \right) + \left(1 - \phi^h \right) \Pi^h \left(0, z', W_{0z'} \right) \right\}$$

The firm chooses the current period wage w and the promised value $W_{s'z'}$ for each state (s', z') tomorrow, subject to the promise-keeping constraint. This constraint makes sure that the choices of the firm honours the promise made in previous periods to deliver the value V to the worker. By increasing future promises the firm can increase the effort level, and thus increase the probability that the match continues. If the match is separated, the firm is left with zero profit.

1.4.6 Search Markets

The meeting process between unemployed workers and vacancies is constrained by search frictions. The labour market is organized in a set of queues indexed by (h, v) where h is the required education level, and v is the value promised to workers in that given queue.

Each firm chooses in which queue they want to open a vacancy, and each unem-

ployed worker chooses where to queue. Each sub-market is characterized by its tightness represented by θ, which is the ratio of the number of vacancies to the number of unemployed workers in this sub-market. The tightness captures the fact that a high ratio of vacancies to workers will make it harder for firms to hire. In a directed search model like the one presented here, the tightness is queue specific. I use a standard matching function that in queue (h, v), a vacancy is filled with probability $q(\theta) = \theta^{\alpha-1}$, and a worker matches with probability $\mu(\theta) = \theta^\alpha$, so

$$\mu(\theta) = q(\theta)^{\frac{\alpha}{\alpha-1}} \tag{1.6}$$

I assume the vacancy posting cost is η^h.

In principle different sub-markets could co-exist at the same time but, as will become clear later, it will not happen in equilibrium. Anticipating such an outcome, the equilibrium definition specifies the labour market as a single promised value and tightness pair (v_z^h, θ_z^h) for each aggregate productivity z and education h.

1.4.7 A Competitive Search Equilibrium

Definition 1. A competitive search equilibrium consists of: for each z and h, a value for unemployment U_z^h, a market tightness θ_z^h and a wage contract $v_z^h = \mathbb{E}_{z'} v_{z'}^h$ such that:

1. Search offers zero profit to a firm, i.e. the free entry condition equalizes the costs of posting a vacancy with the expected discounted profit

$$\beta q\left(\theta_z^h\right) \cdot \mathbb{E}_{z'} \Pi^h\left(0, z', v_{z'}^h\right) - \eta^h = 0 \tag{1.7}$$

where η^h is the per period vacancy posting cost, and $q\left(\theta_z^h\right)$ is the probability of filling a vacancy. As the worker is initially untrained, $\mathbb{E}_{z'} \Pi^h\left(0, z', v_{z'}^h\right)$ is the expected profit to the firm when matched with a trainee (s=0).

2. No Pareto improving market is possible, i.e. there does not exist a sub-market $\left(\hat{v}_z^h, \hat{\theta}_z^h\right)$,

s.t.

$$\mu\left(\hat{\theta}_z^h\right)\left(\hat{v}_z^h - \mathbb{E}_{z'}U_{z'}^h\right) > \mu\left(\theta_z^h\right)\left(v_z^h - \mathbb{E}_{z'}U_{z'}^h\right)$$

and

$$\beta q\left(\hat{\theta}_z^h\right) \cdot \mathbb{E}_{z'}\Pi^h\left(0, z', \hat{v}_{z'}^h\right) - \eta^h > 0$$

3. The value for unemployment U_z^h is consistent:

$$U_z^h = u\left(b^h\right) + \beta\left(1 - \mu\left(\theta_z^h\right)\right)\mathbb{E}_{z'}U_{z'}^h + \beta\mu\left(\theta_z^h\right)v_z^h \tag{1.8}$$

where b^h is the flow income of unemployment, and $\mu\left(\theta_z^h\right)$ is the job finding probability.

1.4.8 Unique Search Market

The definition of equilibrium can be collapsed to the problem:

$$\max_{v_z^h, \theta_z^h} \mu\left(\theta_z^h\right)\left(v_z^h - \mathbb{E}_{z'}U_{z'}^h\right)$$

s.t.

$$\beta q\left(\theta_z^h\right) \cdot \mathbb{E}_{z'}\Pi^h\left(0, z', v_{z'}^h\right) - \eta^h = 0$$

For any contract delivering a high value to the worker, the market tightness must be low for firms to break even in offering such a contract. The low market tightness makes the contract less attractive to workers because their job-finding probability is low. As the contract value to the worker rises, the declining job-finding probability eventually begins to dominate the rising contract value, and there is a unique optimal wage level balancing these effects.

1.4.9 Contract Characterization

Proposition 1. *For any current state (s, z, h, w), the following relationship between wage change and expected firm profit holds*

$$\frac{\partial ln \tilde{e}^h (s, z, W_{sz})}{\partial W} \mathbb{E}_{s'z'} \Pi^h \left(s', z', W_{s'z'} \right) = \frac{1}{u_w (w')} - \frac{1}{u_w (w)} \qquad (1.9)$$

$\mathbb{E}_{s'z'} \Pi^h (s', z', W_{s'z'})$ *is the expected profit for the firm. The right-hand side represents the change in marginal utilities. $\partial ln \tilde{e}^h (s, z, W_{sz}) / \partial W$ is the semi-elasticity of effort with respect to promised value, which represents the severity of the moral-hazard problem and captures the incentive problem the firm is facing when paying the worker.*

Proof. The proof is similar to Proposition 1 of Lamadon (2017). See Appendix A.2.1. □

This proposition provides a clear prediction for how wages move dependent on the aggregate productivity. Whenever the expected profit for the firm is 0, the wage will not change $w' = w$. If the right-hand side of equation 1.9 is positive, i.e. $1/u_w (w') - 1/u_w (w) > 0$, then $w' - w > 0$ by concavity. Since the semi-elasticity $\partial \ln \tilde{e}^h (s, z, W_{sz}) / \partial W > 0$, the wage growth will have the same sign as the expected profit for the firm. Whenever the firm expects positive (negative) profits due to aggregate productivity increases (decreases), it will be optimal to increase (decrease) the wage. This implies that the wage tracks the aggregate productivity shocks.

1.4.10 Higher Adaptation Costs Increase Wage Smoothing

I now show the extent of wage smoothing is affected by the level of adaptation costs, in particular, the parameters of the upgrading probability ϕ and initial productivity gap τ. Proposition 2 needs the sufficient condition that the second derivative of the effort cost function is weakly increasing in the level of effort, as summarized in assumption 1:

Assumption 1. *For any two distinct effort levels $e_1 > e_0 > 0$, the effort cost function is such that $c'' (e_1) \geq c'' (e_0)$.*

Proposition 2. *Given assumption 1, wage smoothing increases in the level of adaptation costs.*

Proof. First, I claim that a lower value of a worker's outside option increases wage smoothing. The optimal level of effort can be derived from the maximization problem of the employed workers (equation 1.4):

$$c'\left(\tilde{e}^h\left(s, z, W_{sz}\right)\right) = \beta\left(W_{sz} - \mathbb{E}_{z'}U_{z'}^h\right)$$

Since the cost of effort $c : \mathbb{R} \to \mathbb{R}$ is increasing and convex, $c'(e)$ is increasing in e. Hence, the optimal level of effort $\tilde{e}^h(s, z, W_{sz})$ is decreasing in the value of the worker's outside option $\mathbb{E}_{z'}U_{z'}^h$. I can solve for the optimal level of effort $\tilde{e}^h(s, z, W_{sz}) = (c')^{-1}\left(\beta\left(W_{sz} - \mathbb{E}_{z'}U_{z'}^h\right)\right)$. The derivative of $\tilde{e}^h(s, z, W_{sz})$ with respect to the value promised to the worker tomorrow is

$$\frac{\partial \tilde{e}^h\left(s, z, W_{sz}\right)}{\partial W} = \frac{\partial\left(c'\right)^{-1}\left(\beta\left(W_{sz} - \mathbb{E}_{z'}U_{z'}^h\right)\right)}{\partial W} = \frac{\beta}{c''\left(\tilde{e}^h\left(s, z, W_{sz}\right)\right)}$$

By Assumption 1, $c''\left(\tilde{e}^h(s, z, W_{sz})\right)$ is weakly increasing in $\tilde{e}^h(s, z, W_{sz})$, thus is weakly decreasing in $\mathbb{E}_{z'}U_{z'}^h$. Hence, $\partial \tilde{e}^h(s, z, W_{sz})/\partial W$ is weakly increasing in outside option $\mathbb{E}_{z'}U_{z'}^h$. Therefore, the severity of the moral-hazard problem $\frac{\partial \ln \tilde{e}^h(s,z,W_{sz})}{\partial W} = \frac{\partial \tilde{e}^h(s,z,W_{sz})/\partial W}{\tilde{e}^h(s,z,W_{sz})}$ is increasing in outside option $\mathbb{E}_{z'}U_{z'}^h$. Apply it to equation (1.9), we know that if the value of the worker's outside option decreases, wage smoothing increases.

Second, I claim that the value of a worker's outside option is decreasing in the level of adaptation costs. Combining the free entry condition of the firm (equation 1.7) and the relationship between the probabilities of finding a job and filling a vacancy (equation 1.6), we have the equilibrium job finding rate as follows:

$$\mu\left(\theta_z^h\right) = \left(\frac{\beta\mathbb{E}_{z'}\Pi^h\left(0, z', v_{z'}^h\right)}{\eta^h}\right)^{\frac{\alpha}{1-\alpha}}$$

which is an increasing function of $\Pi^h\left(0, z', v_{z'}^h\right)$, the expected profit to the firm when

matched with a trainee (s=0). By equation (1.5), for a given aggregate state z and a fixed promised value v, we know

$$\Pi^h\left(0, z, v\right) = hz - \tau^h - w + \beta \tilde{e}^h\left(0, z, W_{0z}\right) \cdot \mathbb{E}_{z'}\left\{\phi^h \Pi^h\left(1, z', W_{1z'}\right) + \left(1 - \phi^h\right) \Pi^h\left(0, z', W_{0z'}\right)\right\}$$

Then an increase in the level of adaptation costs (equivalent to a lower upgrading probability ϕ and a higher initial productivity gap τ) reduces the value of a new job. Consequently, firm's incentives to post vacancies should decrease, leading to a decrease in the job finding rate in every queue in the search market. Hence, by equation 1.8, the worker's outside option decreases.

Therefore, wage smoothing increases in the level of adaptation costs. $\qquad\square$

Note that the intuition behind proposition (2) is that higher adaptation costs reduce the outside options in all aggregate states. As there is more to lose when the worker leaves the current job, the worker will give higher effort to avoid job separation regardless of what the firm offers, which reduces the severity of the moral-hazard problem and improves risk-sharing. Thus the worker gets a contract with smoother wages over the business cycle.

1.5   Estimation

To be able to use the model for quantifying the effect of adaptation costs on wage cyclicality, some of the model parameters will be calibrated or fixed at externally estimated values while others will be directly estimated. I start out describing fixed and externally estimated parameters and then turn to the parameters which are estimated by the simulated method of moments.

Table 1.9: Exogenous Parameter Values

Description	Param.	Value	Source
discount factor	β	.996	
general skills for BA	h_{BA}	1	normalization
matching function elasticity	α	.28	Shimer (2005)
upgrading probability for a new hire			
Postgraduates	ϕ_{PG}	.07	MCSUI
Bachelor graduates	ϕ_{BA}	.15	MCSUI
Noncollege workers	ϕ_{NC}	.19	MCSUI

1.5.1 Fixed and Externally Estimated Parameters

The parameter values that are fixed or externally estimated are listed in Table 1.9. A period in the model is 1 month. The discount factor is consistent with an annual real interest rate of 5%. I normalize general skills for bachelor graduates $h_{BA} = 1$. For the elasticity of the matching function, I draw from the evidence reported in Shimer (2005) and accordingly set $\alpha = 0.28$. The probability of being upgraded from a new hire to a skilled worker ϕ is calculated as the inverse of the empirical adaptation duration in Table 1.6 using MCSUI. Weeks are transformed to months by multiplying 4.33, so that

$$\phi_{PG} = 4.33/58.52 = 0.07, \quad \phi_{BA} = 4.33/29.17 = 0.15, \quad \phi_{NC} = 4.33/22.46 = 0.19$$

1.5.2 Model Specification

Given the parameters above, I estimate the model using the simulated method of moments and a parametrized model. I present the specification I use in this section.

I use the constant relative risk aversion utility function

$$u(w) = \frac{w^{1-\gamma} - 1}{1 - \gamma}$$

The aggregate productivity follows an AR(1) in logs, such that

$$\ln z_t = \rho_z \ln z_{t-1} + v_{zt} \quad \text{where } v_{zt} \sim \mathcal{N}\left(0, \sigma_z^2\right)$$

The worker effort function is

$$c(e) = c_0\left[(1-e)^{-c_1} - 1\right]$$

such that $c(0) = 0$, $\lim_{e \to 1} c(e) = \infty$, $c'(.) > 0$, $c''(.) > 0$, $c'''(.) > 0$.[13] I assume the flow income of unemployment and the vacancy posting cost are proportional to general skills to rule out different profitability (Pissarides, 2000; Chodorow-reich and Karabarbounis, 2016)

$$b^h = b * h \tag{1.10}$$

$$\eta^h = \eta * h \tag{1.11}$$

These specifications leave us with the following 12 parameters to estimate:

$$\{\rho_z, \sigma_z, \eta, b, c_0, c_1, \gamma, \tau_{PG}, \tau_{BA}, \tau_{NC}, h_{PG}, h_{NC}\}$$

1.5.3 Data Moments

Estimation is performed using the simulated method of moments. The objective function is minimized over all parameters. The parameters of the aggregate productivity shock, ρ_z and σ_z are identified by the standard deviation and auto-correlation of log GDP. The amount of general skills $\{h_{PG}, h_{NC}\}$ are pinned down by the postgraduate wage premium (w_{PG}/w_{BA}) and the college wage premium (w_{BA}/w_{NC}).

The vacancy cost η affects the meeting rate through firm's free entry condition (1.7). The probabilities of starting a job also determine the value of being unemployed, since individuals without jobs will choose where to apply based on current present value.

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[13] $c'(e) = c_0 c_1 (1-e)^{-c_1-1}$, $c'(0) = c_0 c_1$, $\lim_{e \to 1} c'(e) = \infty$. To deal with the corner solutions, I set effort to 0 if $c'(0) < c_0 c_1$, and effort can never be 1 as the cost is infinite.

Thus the job finding probabilities by education pin down η and the unemployment insurance replacement rate b. The parameters of the effort cost function c_0 and c_1 affect the average rate at which workers lose their jobs, and are pinned down by job separation rates by education. I construct these turnover rates from monthly Current Population Survey 1979-2014. As GDP is only provided on a quarterly frequency, I take the quarterly average for all monthly series. Then I log and HP filter the data with smoothing parameter 10^5 to produce business cycle statistics[14].

The parameter of risk aversion γ controls how quickly changes in aggregate productivity get transmitted into wage changes. I target it at the elasticity of median wage with respect to GDP for bachelor graduates ($\partial \log w/\partial \log GDP$). Please note that the wage elasticity for postgraduates and noncollege workers are not targeted. I leave them as model outcomes and show that the model is successfully able to match the non-targeted moments.

For the initial productivity gaps between trainees and skilled workers $\{\tau_{PG}, \tau_{BA}, \tau_{NC}\}$, I target at the empirical data on percent losses in wages after job displacement.

1.5.4 Estimation Results

Estimation is performed using the simulated method of moments. Since the model is strongly parametrized, I choose the weighting matrix to reflect how informative each moment should be about the parameters of interest. The default weight is chosen to be the inverse of the level to minimize a distance in relative deviation. The computation of standard errors is based on the pseudo-likelihood estimator presented in Chernozhukov and Hong (2003). Using Markov Chain Monte Carlo (MCMC) rejection sampling, I can perform the estimation without having to compute derivatives and still obtain standard errors on the parameters. Please see Appendix A.2.2 for the solution of the model.

The parameter estimates are displayed in Table 1.10. The monthly aggregate productivity shock has a persistence of 0.985. The standard deviation of the shock to the

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[14]The smoothing parameter is suggested by Shimer (2005).

aggregate productivity is 0.005. The vacancy posting cost is about 7.3. The unemployment income flow parameter is 0.557. The level and the curvature of effort cost are 0.157 and 0.096 respectively. The risk aversion parameter is 1.116. The initial productivity gap for bachelor graduates is about 0.173, which is 35% of that for postgraduates. The initial productivity gap for noncollege workers is 0.137. The amount of general human capital for noncollege workers is 0.682 and for postgraduates is 1.222.

The fitted moments in the data and their model simulations are shown in the columns "Data" and "Baseline" of Table 1.11. The job separation rate for non-college workers is much lower than its counterpart in the US. This is due to job separation only comes from lack of effort in the model. On the one hand, it suggests that the estimation might benefit from making the parameters for the effort cost function heterogeneous across education levels. On the other hand, there are many other reasons cause higher job separation for this group, and thus imposing an exogenous job separation rate would move the fit in the right direction.

The model fits other moments quite well. One success of the model is that it can capture the turnover rates between postgraduates and bachelor graduates: bachelor graduates have higher probabilities both in job finding and job separation comparing to postgraduates, and the relative differences are about right. As the job separation rate equals 1 minus the average level of effort, postgraduates give a higher level of effort on the current job than bachelor graduates.

1.6   Results Analysis

1.6.1   Cyclical Properties of Wages and Wage Premium

Table 1.12 shows the cyclicality of wages and wage premium in the data and their model simulations. Please note only the wage cyclicality for bachelor graduates are targeted in the estimation, and the wage cyclicality for postgraduates and noncollege workers are not targeted.

Overall, the model correctly captures the cyclicality of wages and wage premium:

Table 1.10: Parameter Estimates

Parameters		Value	s.e.
Persistence of aggregate productivity	ρ_z	.985	.0056
Std. of shock to aggregate productivity	σ_z	.0052	.0019
Vacancy posting cost	η	7.324	2.022
Unemployment insurance replacement rate	b	.557	.077
Level of effort cost	c_0	.157	.048
Curvature of effort cost	c_1	.096	.024
Risk aversion	γ	1.116	.028
Initial productivity gap			
Postgraduate	τ_{PG}	.498	.065
Bachelor graduate	τ_{BA}	.173	.051
Noncollege	τ_{NC}	.137	.053
Formal human capital			
Postgraduate	h_{PG}	1.222	.041
Noncollege	h_{NC}	.682	.061

Note: The computation of standard errors is based on the pseudo-likelihood estimator presented in Chernozhukov and Hong (2003).

Table 1.11: Model Fit

Moments	Data	Baseline
Postgraduates		
Job separation rate	.005	.005
Job finding rate	.245	.248
Percent wage losses after displacement	-.178	-.176
Bachelor graduates		
Job separation rate	.007	.009
Job finding rate	.263	.263
Percent wage losses after displacement	-.086	-.089
Elasticity of median wage to GDP	.58	.58
Noncollege workers		
Job separation rate	.016	.009
Job finding rate	.272	.265
Percent wage losses after displacement	-.086	-.086
Common moments		
Median postgraduate wage premium	1.23	1.219
Median college wage premium	1.47	1.466
std $[GDP]$	.024	.024
autocorr $[GDP]$	.954	.955

Table 1.12: Cyclicality of Wages and Wage Premium

Moments	Type	Data	Baseline
Elasticity of median wage to GDP			
Postgraduates	Non-targeted	.34	.322
Bachelor graduates	Targeted	.58	.58
Noncollege workers	Non-targeted	.57	.574
Elasticity of median wage premium to GDP			
Postgraduate wage premium (w_{PG}/w_{BA})	Non-targeted	-.24	-.258
College wage premium (w_{BA}/w_{NC})	Non-targeted	.01	.006

Note: Non-targeted moments are not targeted in the estimation.

The bachelor wage is more pro-cyclical than the postgraduate wage, and is about the same as the noncollege wage. The postgraduate wage premium is counter-cyclical, and the college wage premium is acyclical. The elasticity of median postgraduate wage premium to GDP is -0.258, and the elasticity of college wage premium is 0.006, which are about the same size as the data.

Figure 1.2 plots the GDP and wages simulated from the model. The dotted line is the GDP, the solid line is the postgraduate wage, and the dashed line is the bachelor wage. As each series is logged and demeaned, it shows the percentage deviation from the mean. It shows both the postgraduate wage and the bachelor wage are pro-cyclical, but the postgraduate wage fluctuates less than the bachelor wage. Therefore, the model picks up the fact that the postgraduate wage is smoother than the bachelor wage over the business cycle.

1.6.2 Effect of Adaptation Costs on Wage Cyclicality

To examine the importance of adaptation costs on wage cyclicality, I run the counterfactual simulation where postgraduates have the low level of adaptation costs of the bachelor graduates: upgrade probability ϕ is increased from 0.07 to 0.15, and the initial productivity gap τ is reduced from 0.498 to 0.173. I report the simulation results in the column "Low Cost" of Table 1.13.

The first row of column "Low Cost" shows that when postgraduates have lower

Figure 1.2: Demeaned Log GDP and Log Wages by Education
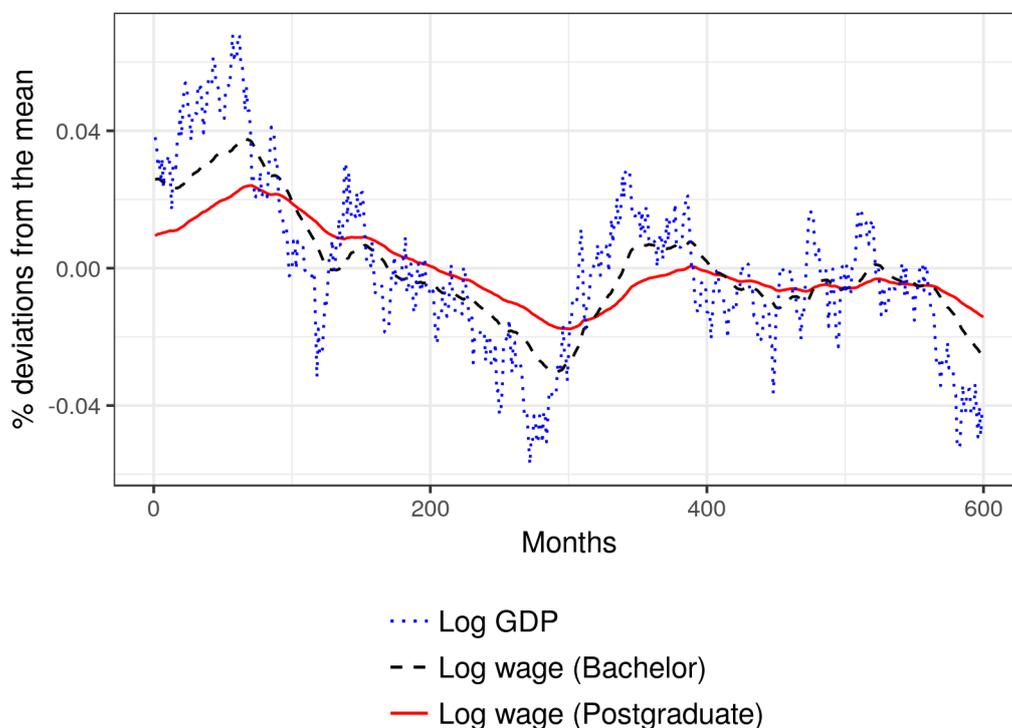
adaptation costs, the job separation rate increases to 0.01 from 0.005 in the baseline. As there are less to lose if they move to a new job, they give a lower effort to keep the current job. A decrease in the average duration of adaptation and the initial productivity gap increase the value of a new job. Consequently, firms have more incentives to post vacancies. In the second row of "Low Cost", the job finding rate of the postgraduates increases to 0.265 from 0.248 in the baseline. Hence, when holding the same level of adaptation costs, postgraduates and bachelor graduates have the same level of labour market turnover rates.

The most important changes are in the wage cyclicality. The 4th row of "Low Cost" shows that when postgraduates have lower costs, the wage elasticity to GDP increases 86% from 0.322 to 0.599, indicating the postgraduate wage becomes more fluctuate over the business cycle and is as cyclical as the bachelor wage. In the last row of "Low Cost", the elasticity of postgraduate wage premium to GDP changes from -0.258

to 0.018, i.e. the postgraduate wage premium changes from counter-cyclical to acyclical. So once holding the level of adaptation costs equal, the model generates same wage cyclicality across education groups. This result shows that adaptation costs alone can explain the difference in the wage cyclicality between postgraduates and bachelor graduates.

Figure 1.3 compares log median wages with different level of adaptation costs. The solid line is the log median wage of postgraduates in the baseline simulation, the dashed line is the log median wage of postgraduates in the "Low Cost" simulation, and the dotted line is the log median wage of bachelor graduates in the baseline. First comparing between educations levels, postgraduate wages are higher than bachelor wages. Comparing within postgraduate wages, the postgraduate wage in the baseline is smoother than that in the "Low Cost" simulation, which is also the result of Proposition 2. The postgraduate wage in the "Low Cost" simulation fluctuates as much as the bachelor wage in the baseline. Another interesting pattern in Figure 1.3 is that the postgraduate wage in the "Low Cost" simulation is higher than that in the baseline simulation. So low adaptation costs shift the postgraduate wage up. In the 2nd to the last row of column "Low Cost" of Table 1.11, the postgraduate wage premium increases to 1.222 from 1.219 in the baseline. So once holding the level of adaptation costs equal, the postgraduate wage premium increases. As postgraduates have higher adaptation costs than bachelor graduates, they accept relatively lower wages, leading to a smaller wage premium.

1.6.3 Wage-tenure Profiles

Different levels of adaptation costs also have different implications for wage-tenure profiles. These implications can be summarized through plotting the wage-tenure profiles by education, which are displayed in Figure 1.4. The solid line depicts the average postgraduate wage against current job tenure, and the dashed line depicts the average bachelor wage. As each series is logged and demeaned, it shows the percentage

Table 1.13: Lower Adaptation Costs for Postgraduates

Moments	Baseline	Low Cost
Postgraduates		
Job separation rate	.005	**.010**
Job finding rate	.248	**.265**
Percent wage losses after displacement	-.176	**-.083**
Elasticity of median wage to GDP	.322	**.599**
Bachelor graduates		
Job separation rate	.009	.009
Job finding rate	.263	.263
Percent wage losses after displacement	-.089	-.089
Elasticity of median wage to GDP	.58	.58
Postgraduate wage premium (w_{PG}/w_{BA})		
Median	1.219	1.222
Elasticity to GDP	-.258	**.018**

Note: Baseline: baseline calibration; Low Cost: Postgraduates have the low level of adaptation costs of the bachelor graduates.

Figure 1.3: Effect of Adaptation Costs on Wage Cyclicality
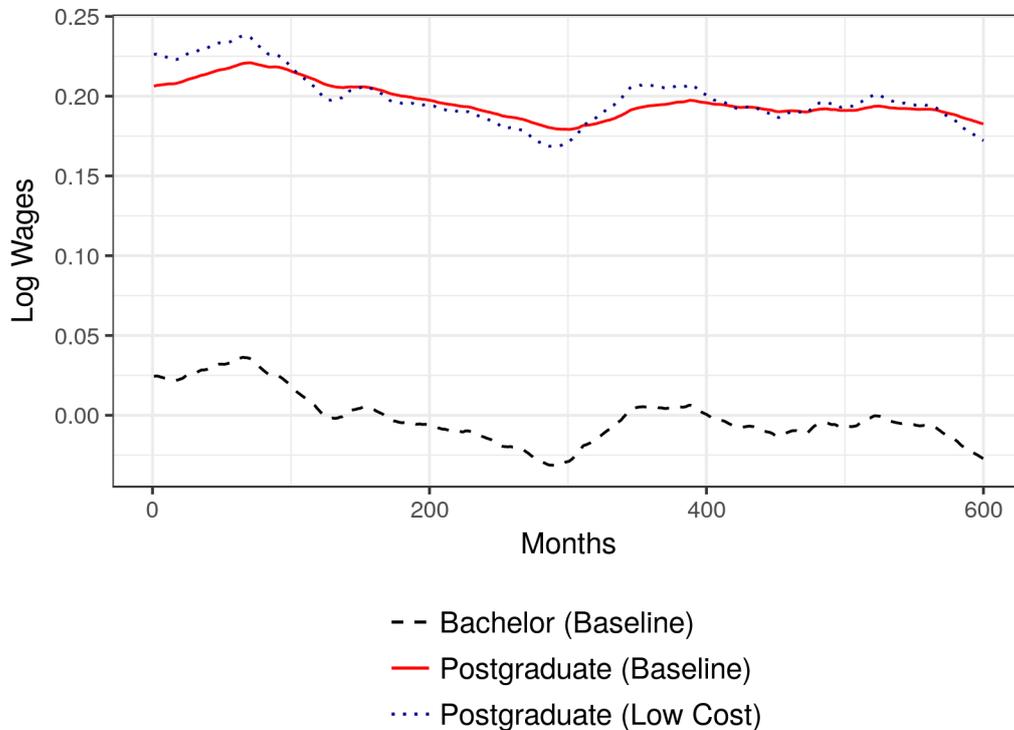
deviation from the mean. For both education groups, the wage-tenure profiles are upward sloping. The starting wage (wages that correspond to Month 1 of labour market tenure) of postgraduates is relatively lower than that of bachelor graduates. This can also be seen in the column "Baseline" Table 1.13, where the percent wage loss after displacement for postgraduates is -0.176, and that for bachelor graduates is about -0.089. The third row of column "Low Cost" of Table 1.13 shows that when postgraduates have the same low level of adaptation costs as bachelor graduates, the immediate wage loss after displacement changes from -0.176 to -0.083, which is almost the same to bachelor graduates.

Figure 1.4 also shows that wage growth is rapid during the early stage of employment, and is faster for postgraduates than that for bachelor graduates. In fact, the first year of job tenure raises the postgraduate wage by 7 percent and the bachelor wage by 5 percent, and the first 10 years (120 months) of job tenure raise the postgraduate wage by 21 percent and the bachelor wage by 11 percent[15]. Hence, as postgraduates have higher adaptation costs, their starting wage on a new job is relatively lower, but subsequent wage growth is faster.

1.7   Changes in Unemployment Insurance Policy

I analyze the effect of a 10% increase in the unemployment insurance replacement rate. The goal of such a policy is to give more generous social insurance when workers are unemployed. Firms respond to the policy change by adjusting contracts. I also compute the willingness to pay for such a policy for each education group. To define the willingness to pay, I write the lifetime expected utility of an individual as

$$\mathbb{E}_0 U_d = \mathbb{E}_0 \sum_{t=1}^{\infty} \beta^{t-1} \left(\frac{w_{dt}^{1-\gamma} - 1}{1 - \gamma} - c\left(e_{dt}\right) \right)$$

---

[15]Topel (1991) estimates that 10 years of job tenure raise the wage by 25%. Altonji and Williams (2005) place the tenure effect on wages at 11% per decade.

Figure 1.4: Compare Wage-tenure Profiles by Education
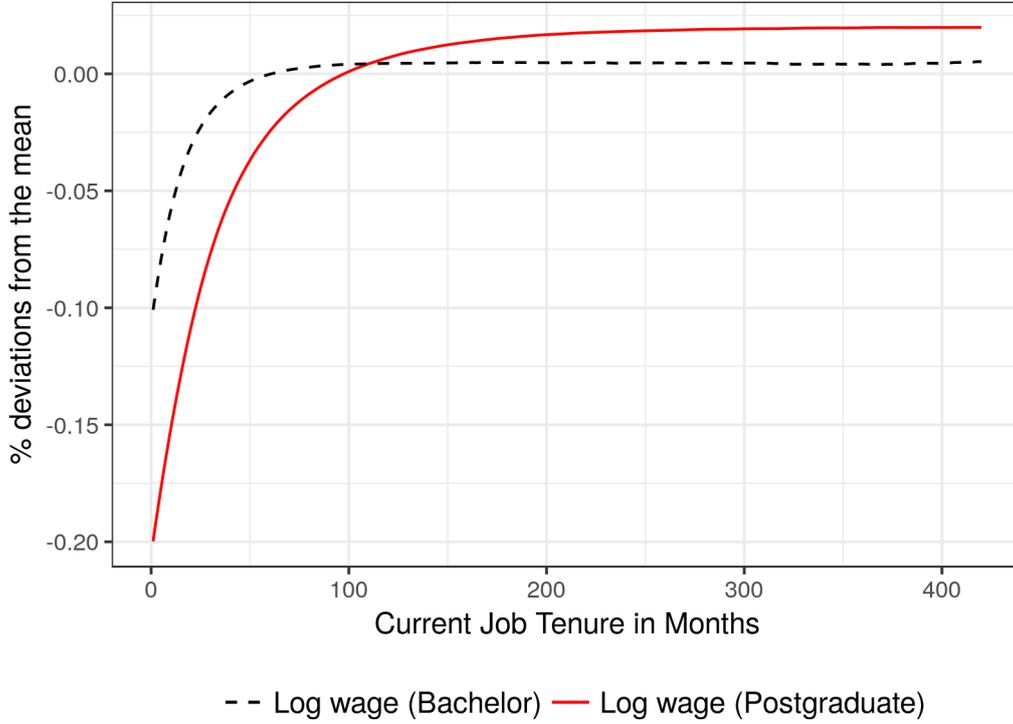
where the subscript d refers to the baseline economy ($d = 1$) or an alternative more generous economy ($d = 2$). Now define π as the proportion of consumption an individual is willing to pay to be indifferent between environment $d = 2$ and $d = 1$. This is implicitly defined by

$$\mathbb{E}_0 U_1 = \mathbb{E}_0 U_2|_\pi \equiv \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{\left((1-\pi)\, w_{2t}\right)^{1-\gamma} - 1}{1 - \gamma} - c\left(e_{2t}\right) \right)$$

$$\mathbb{E}_0 U_1 = (1-\pi)^{1-\gamma} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{w_{2t}^{1-\gamma}}{1 - \gamma} - \frac{1}{(1-\gamma)(1-\beta)} - \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t c\left(e_{2t}\right)$$

I can show that

$$\pi = 1 - \left[\frac{\mathbb{E}_0 U_1 + A + B}{\mathbb{E}_0 U_2 + A + B} \right]^{\frac{1}{1-\gamma}}$$

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Table 1.14: Raise UI replacement rate by 10%

Moments	Baseline	High UI	% change
Postgraduates			
Median wage	1.22	1.22	0%
Elasticity of median wage to GDP	.322	.36	12%
Willingness to pay π		.42%	
Bachelor graduates			
Median wage	1	1	0%
Elasticity of median wage to GDP	.58	.638	10%
Willingness to pay π		.72%	
Noncollege workers			
Median wage	.68	.68	0%
Elasticity of median wage to GDP	.574	.623	9%
Willingness to pay π		.74%	

Note: Baseline: baseline calibration; High UI: 10% increase in the unemployment insurance replacement rate; "% change": percentage change in values between "High UI" and "Baseline".

[16]where $A = \frac{1}{(1-\gamma)(1-\beta)}$ and $B = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t c(e_{2t})$.

I report the simulation results in the column "High UI" of Table 1.14. First, understanding that the government is providing more insurance, firms choose to pass on more of the aggregate shocks to their workers. The result is an increase in the wage cyclicality: the wage elasticity to GDP increases by 12% for the postgraduates, 10% for the bachelor graduates, and 9% for the noncollege workers. So the wage insurance provided by firms against aggregate shocks is crowded out by insurance provided by the government, but less for the lower educated.

In Table 1.14, I also report π, the willingness to pay for such a policy. For a 10% increase in the UI replacement rate, postgraduates are willing to pay 0.4% of their consumption, bachelor graduates and noncollege workers are willing to pay 0.7% of their consumption. Hence, lower educated workers have higher welfare gain than

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[16]

$$\pi = 1 - \left[\frac{\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{w_{2t}^{1-\gamma}}{1-\gamma} - c(e_{1t}) + c(e_{2t}) \right)}{\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{w_{2t}^{1-\gamma}}{1-\gamma}} \right]^{\frac{1}{1-\gamma}}$$

Figure 1.5: Detrended Real GDP and the Relative Supply of PG to BA
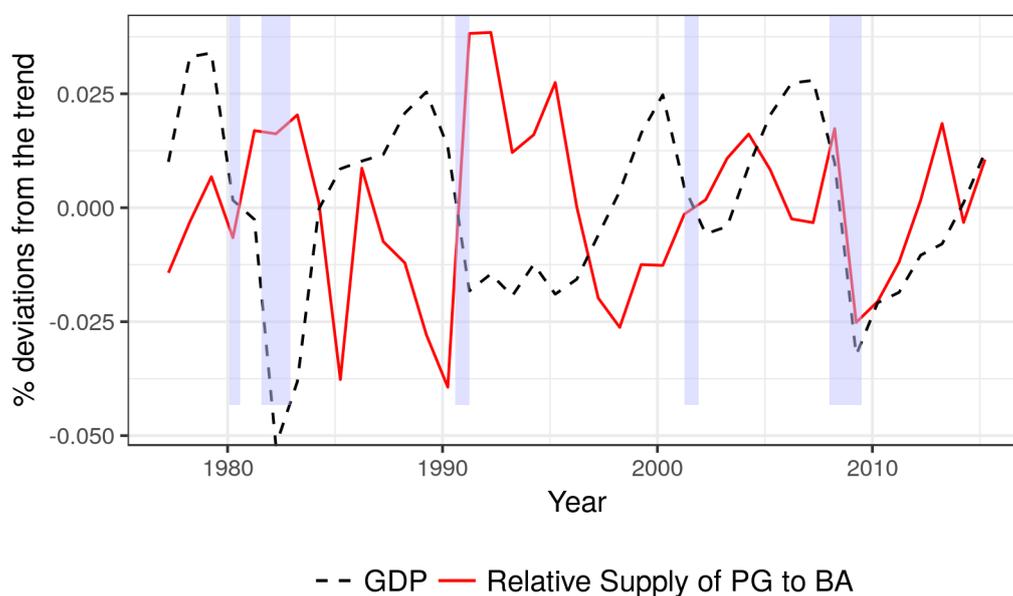
Notes: March CPS 1976–2016. Males 26–64. NBER recessions are shaded. Correlation between two series is -0.32. Series are logged and HP-filtered with parameter 100.

postgraduates from such a policy, which supports the argument for a regressive UI replacement rate schedule, i.e. unemployment insurance replacement rate should be lower for the postgraduates.

1.8 Evaluating Other Potential Explanations

This section evaluates the plausibility of other potential explanations for counter-cyclical postgraduate wage premium.

1.8.1 Relative Supply

One possibility why postgraduate wage premium is counter-cyclical is that the relative supply of postgraduates to bachelor graduates declines in recessions, and thus the postgraduate wage increases relative to the bachelor wage. So I test whether the relative supply of postgraduates to bachelor graduates is pro-cyclical.

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Figure 1.5 plot the detrended real GDP and the relative supply of postgraduates to bachelor graduates. I restrict the sample to male workers aged 26-64. To detrend, I use a Hodrick–Prescott (HP) filter with parameter 100. NBER dated recessions are shaded. The relative supply of postgraduates to bachelor graduates increases in all of the recessions except the recent Great Recession, and its correlation with real GDP is -0.32, indicating the relative supply of postgraduates to bachelor graduates is counter-cyclical.

1.8.2 Differences in the Profitability of Jobs

One possibility why postgraduates have smaller cyclical wage shocks might be related to the higher profitability of their jobs. In the terminology of search models, postgraduates might have a lower value of outside option, which is in turn governed by the flow income of unemployment. In my baseline simulation, I ruled out this possibility by assuming the proportionality between the flow income of unemployment and general skills across education groups in equation 1.10.

Here I relax the proportionality assumption between postgraduates and bachelor graduates. To test this hypothesis, first, I make postgraduates and bachelor graduates have the same level of adaptation costs. Then instead of assuming the flow income of unemployment for postgraduates as $b^{PG} = b * h_{PG} = 0.557 * 1.222 = 0.681$, I search for the value of b^{PG} that generates the empirical elasticity of postgraduate wage to GDP. I find $b^{PG} = 0.172$, which is smaller than the flow income of unemployment for postgraduates in the baseline. The simulation results, reported in the column "Profitability" of Table 1.15, indicate that postgraduates have smaller wage cyclicality than bachelor graduates. However, the model now counter-factually predicts higher job finding rates for postgraduates than bachelor graduates. Intuitively, since postgraduate jobs yield higher profit, firms are willing to post more vacancies in this segment of the labour market, leading in turn to higher labour market tightness and job finding rates.

Table 1.15: Other Potential Explanations

Moments	Data	Baseline	Profitability	Hiring Cost
Postgraduates				
Job separation rate	.005	.005	.005	.004
Job finding rate	.245	.248	**.351**	**.099**
Elasticity of median wage to GDP	.34	.322	.34	.34
Bachelor graduates				
Job separation rate	.009	.009	.009	.009
Job finding rate	.263	.263	.263	.263
Elasticity of median wage to GDP	.58	.58	.58	.58

1.8.3 Differences in Hiring Costs

Another possibility might be postgraduates have higher hiring costs. In my baseline simulation, I already assumed that the vacancy posting cost is growing proportionally with general skills in equation 1.11. However, it might understate the true differences in hiring costs between postgraduates and bachelor graduates.

To test this hypothesis, first, I make postgraduates and bachelor graduates have the same level of adaptation costs. Then instead of assuming the vacancy posting cost for postgraduates as $\eta^{PG} = \eta * h_{PG} = 7.324 * 1.222 = 8.95$, I search for the value of η^{PG} that generates the empirical elasticity of postgraduate wage to GDP. I find $\eta^{PG} = 516$, which is much bigger than the vacancy posting cost for postgraduates in the baseline. The simulation results, reported in the column "Hiring Cost" of Table 1.15, indicate that postgraduates have smaller wage cyclicality than bachelor graduates. However, the model now counter-factually predicts much smaller job finding rates for postgraduates than the data. Intuitively, since it is costlier to hire postgraduates, firms will post fewer vacancies in this labour market segments. As a result, their job finding rate drops.

1.9   Conclusion

I document a new fact that the postgraduate wage premium is counter-cyclical — postgraduates have smaller cyclical wage shocks than bachelor graduates. I also document that postgraduates have smaller labour market turnover rates. I argue the reason for this phenomenon is that postgraduates have higher adaptation costs than bachelor graduates. To support this argument, I provide following empirical evidence: First, postgraduates have longer adaptation duration; Second, postgraduates suffer larger wage losses from job displacement; Third, workers with longer tenures have larger differences in wage cyclicality between postgraduates and bachelor graduates.

To understand the effects of adaptation costs on wage cyclicality, I develop an equilibrium search model of imperfect monitoring, job adaptation, and aggregate shocks. The theoretical implication of the model is that workers with higher adaptation costs have lower outside options, and work harder to keep their jobs regardless of what firm offers. Thus, they have a lower degree of moral hazard and are better insured against aggregate wage shocks by firms. The model shows that differences in adaptation costs are an important driving force for differences in labour market turnover rates and wage cyclicality between postgraduates and bachelor graduates. The model also shows that postgraduates accept lower starting wages, but their subsequent wage growth is faster.

The paper implies that lower educated workers, even bachelor graduates, are unlikely to get much insurance from firms, hence, increasing the demand for social insurance among this group. I analyze the effect of an increase in the unemployment insurance replacement rate. I find such a policy crowds out implicit insurance provided by firms, but the effect is smaller for the lower educated. Lower educated workers have higher welfare gain than postgraduates from such a policy, which supports the argument for a lower UI replacement rate for postgraduates.

Chapter 2

Asymmetric Information, Durables, and Earnings Shocks

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2.1 Introduction

How do households accommodate shocks? A large literature has addressed precisely this question. In doing so it has considered formal and informal insurance arrangements as well as self-insurance, through holding assets. Since in industrialized countries there is little evidence of formal insurance channels, the literature has focused on savings. However, the structure of these asset holdings will affect the extent to which they can be used for consumption smoothing.

In practice, people save in liquid assets and in durable purchases, such as housing, cars and household appliances, all of which are characterized by important transaction costs. Liquid assets have the greatest insurance value. However, durables also store value offering resale opportunities and consumption streams. But transaction costs reduce insurance value. The key aim of the paper is to identify the transaction costs and the insurance value of durables.

There are two major durables: housing and cars. We focus on cars here because they are widely owned, even by lower-income people, which allows us to consider consumption smoothing effects of durables where it matters a great deal, namely at the lower end of the income distribution. Like most durables cars have the dual role as a consumption good and a store of value, which explains why people own cars. In principle, one could decouple these two roles by leasing cars instead of owning them. However, the leasing market is not well developed, at least over the time period we consider. Finally, cars are more liquid than housing, where obtaining a housing backed consumption loan can be expensive and take a substantial amount of time. So in some sense cars lie in between household appliances which often have no second-hand value and housing, which is a substantial store of value but is highly illiquid and is not as widely owned.

A general feature of secondary markets for cars is that there is asymmetric information about the quality of cars being traded between the buyer and the seller (Akerlof, 1970). Hendel and Lizzeri (1999) incorporate adverse selection into a dynamic

model and examine the interactions between new and used car markets. The adverse selection problem implies that the average quality of used cars on the market varies with the number of used cars flowing into the market which depends on preferences for quality and stochastic depreciation. The gain from buying a new car depends on the average quality of used cars on the market as well as the implied transaction costs if a need to sell the car arises. Thus the market for used and new cars are inextricably linked. The car market is thus subject to important adverse selection leading to an endogenous transaction cost - the lemons penalty.

To quantify the lemons penalty we specify and estimate a stochastic life-cycle general equilibrium model of car ownership, consumption and other asset accumulation. Individuals have the choice of buying new or second-hand cars, or old bangers, or no car at all. In our model dealers buy old cars from consumers without knowing their exact quality, fix them and sell them back to consumers. Car dealers are offered cars that on average are of lower quality than similar cars in the population. Dealers, therefore, pay a lower price than what they would have done if there was no asymmetric information and this difference is the lemons penalty. This introduces an endogenous transaction cost that reduces the insurance value of holding this durable asset.

We estimate the model using a population-wide high-quality administrative data set with complete information about car ownership for the period 1992-2009. The data is linked to longitudinal income-tax records of the owners with information about income and wealth of the owners as well as information on the second-hand prices for cars. We find that the 1-year-old car has the biggest lemons penalty, which is about 16% of a new car price. Then the lemons penalty declines as ownership duration increases. We also find that lemons problem strongly suppresses both used car sales and demands.

A significant amount of previous papers have modelled households ownership and replacement of cars and recognized that the car replacement decision is associated with transaction costs. Lam (1991), Eberly (1994), Attanasio (2000), Foote, Hurst, and Leahy (2000) presents Ss-models of car ownership where exogenous transaction

costs create inaction regions, or Ss-bands, within which the household does not up- or downgrade the car. Generally, Ss-models are concerned with the consumer decision and do not model the endogenous determination of prices in the second-hand market and hence do not provide a structural explanation of why transaction costs vary as the supply of cars to the secondary market changes. Another set of papers modelling partial equilibrium have shown how credit market imperfections affect the demand for cars, Attanasio, Goldberg, and Kyriazidou (2008) and Alessie, Devereux, and Weber (1997). By the nature of the partial equilibrium setup, these papers are not concerned with the determination of the lemons penalty. A strand of recent literature has focused on the effect of policies that can potentially affect the secondary market for cars, such as scrappage subsidies and gasoline prices. Schiraldi (2011) develops and estimates a structural dynamic model of consumer demand for new and used cars and use the estimated model to evaluate the impact of scrappage subsidies. He proposes a strategy for identifying transaction costs but assumes that the quality of used cars is common knowledge among agents, so that there is no adverse selection problem. Busse, Knittel, and Zettelmeyer (2013) model the effect of changing gasoline prices on equilibrium prices of new and used cars to learn about how consumers trade off capital costs and ongoing user costs of cars, but not how consumers change their valuation of new and used cars over the business cycle. Gavazza, Lizzeri, and Roketskiy (2014) develop an equilibrium model of the primary and secondary market for cars to learn about how differences in the characteristics of these markets can explain observed differences between the US and French car markets. Critical in relation to our study is that Gavazza, Lizzeri, and Roketskiy (2014) assume exogenous transaction costs in the market for used cars and therefore do not model how asymmetric information about the quality of cars in the secondary markets vary endogenously across the business cycle. Adda and Cooper (2000) model demand for new cars and how this interacts with the cost of replacing a used car with a new car and use the model to examine the effect of scrappage subsidies in France. They do not model trade in the secondary market for cars and hence ignore the issue of adverse selection in the market for used cars.

The papers cited are concerned with how primary markets interact with secondary markets and/or how specific policies, such as scrappage subsidies, affect the second-hand market and the primary market, but they do not model how the lemons penalty is endogenously determined. In this paper, we are interested in how variations in household resources affect the demand for cars and the relative importance of the primary and secondary market for cars. We explicitly model the demand and supply of cars to the secondary market while allowing for asymmetric information about the quality of used cars and estimate the key parameters of the model using very detailed data about household income fluctuations and car replacement decisions.

The next section presents the model and details about the solution method. Section 2.3 presents the data and provides initial descriptions of the data. Section 2.4 outlines the estimation technology, and section 2.5 and 2.6 presents the results and simulations. Section 2.7 concludes.

2.2 Model Setup

Individuals are life-cycle utility maximizers. They draw utility from consumption and cars, and they have an exogenous stream of income. Their choices involve choosing consumption, car purchases or sales and savings. Ours is a model of car ownership, income risk and transactions over the life cycle. One period in the model is one year.

We construct a model which consists of overlapping generations of risk-averse consumers whose lifespan is T. At any point in time there are T generations alive. Time is discrete and denoted by t.

2.2.1 Cars

A consumer can only own one car at a time[5]. Cars differ by their quality q_t and the ownership duration $z_t \in \{0, 1, \ldots, \bar{z}\}$. They are purchased new or second-hand at a fixed quality, normalized to 1. A car receives persistent quality shocks

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[5]In our data, 10% of households in Denmark hold more than one car.

$$q_{t+1} - q^b = d\epsilon_t \left(q_t - q^b \right)$$

Here quality can not be lower than the base quality q^b. d is the deterministic depreciation factor, which is common knowledge. $\epsilon \in [0,1]$ is the private depreciation factor, observable only by the owner, and is logit normally distributed — $\ln\left(\frac{\epsilon}{1-\epsilon}\right) \sim \mathcal{N}(\eta, 1)$.

A car can only be bought or sold using a dealer as an intermediary[6]. Dealers buy used cars from consumers and fix them to have quality 1 (the max), reset them to have ownership duration 0, but they still remain second-hand cars[7]. A used car of ownership duration z_t can be sold to a dealer at dealer price $p_{z_t}^d$. The dealer purchase price $\{p_1^d, p_2^d, \ldots, p_{\bar{z}}^d\}$ is endogenous and depends on the distribution of car quality among sellers. The price of fixed second-hand cars sold by dealers is p^u. As fixed second-hand cars are of quality 1, p^u can also be thought as the price for a unit of quality. Since Denmark doesn't produce cars, we assume an internationally set price for new cars p^n, and the supply of new cars are infinitely elastic. The difference between a new and used car is embodied in consumer preferences.

A "regular" car becomes a banger if it has been owned for more than $\bar{z}$ years, or if it suffers a "banger shock", which occurs with probability δ^r. A banger has base quality q^b and can either be sold or bought at price p^b. We assume bangers have no lemons issue. Noting that p^u is the price for a unit of quality, we have that $p^b = q^b p^u$. A banger is scrapped if it receives a "scrappage shock" with probability δ^b.

2.2.2 Preferences

The utility function is assumed to take the CRRA form

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[6]According to bilbasen.dk, the largest second-hand car website in Denmark, 90% of the second-hand car are sold by dealers. We think in reality car sold by dealers is fixed to its best quality and it comes with the quality guarantee. So there is no asymmetric information when dealers sell used cars. We focus on the asymmetric information when dealers buy used cars from consumers.

[7]This means the number of times a car is sold is irrelevant in the model, so ownership duration is equivalent to vintage. This assumption helps us to simplify the model so that we can focus on one type of second-hand car and figure out its lemon's problem.

$$u\left(c_t, n_t, q_t\right) = \frac{\left(c_t\left(1 + \theta\left(n_t\right)q_t\right)^{\alpha}\right)^{1-\gamma} - 1}{1 - \gamma}$$

Here α determines the utility penalty of owning a car. n_t indicates car type, and $\theta\left(n_t\right)$ determines the relative preference between car types

$$\theta\left(n_t\right) = \begin{cases} 0 & \text{if } n_t = 0, \text{ no car} \\ \theta^f & \text{if } n_t = 1, \text{ car bought as new} \\ 1 & \text{if } n_t = 2, \text{ car bought as used} \\ \theta^b & \text{if } n_t = 3, \text{ banger} \end{cases}$$

We think people have a higher evaluation in cars they bought as new. So we assume the utility penalty θ^f remains in the new car until it is sold to dealers.

A consumer holds liquid assets a_t at the beginning of period t. The evolution of the liquid asset is governed by:

$$a_{t+1} = (1 + r)\left[a_t + y_t - c_t - B_t p_B + S_t p_S\right]$$

Here $B_t = 1$ if she buys a car, and p_B is the buying price: $p_B = p^n$ if she buys a new car, $p_B = p^u$ if she buys a second-hand car, and $p_B = p^b$ if she buys a banger. $S_t = 1$ if she sells a car, and p_S is the selling price: $p_S = p^d_{z_t}$ if she sells a car held for z periods, and $p_S = p^b$ if she sells a banger[8].

If $a_{t+1} < 0$, the consumer borrows. The liquidity constraint takes the form

$$a_{t+1} \geq -p^d_{z_{t+1}} - \underline{a}$$

Uncolateralised debt is limited to a maximum of $\underline{a}$. Cars are a store of credit up to the expected resale value $p^d_{z_{t+1}}$.

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[8]If a car received a banger shock and became a banger, the owner gets an insurance payment which equals to the collateral value of the car. This is to insure owner from bankruptcy.

Income Process Individuals receive an uncertain flow of labour income y_t depending on their level of education being either high or low $s \in [H, L]$. y_t has the following form in logs

$$\ln y_t = b_0 + b_1 t + b_2 t^2 + v_t - \omega_t$$

$$v_t = v_{t-1} + e_t$$

$$\omega_t = (1 - U_t) \rho \omega_{t-1} + U_t \kappa_t$$

There are three key components to this process that affect behavior and are relevant to the way durables affect consumption smoothing. First, an age profile $b_0 + b_1 t + b_2 t^2$, which is important because people are liquidity constrained and are not able to reallocate life-cycle income at will. Second, a stochastic permanent component v_t evolving as a random walk as in Meghir and Pistaferri (2004), which is the key source of uncertainty. The initial shock v_0 is drawn from a Normal distribution with mean zero and variance $\sigma_{v_0}^2$. The shock e_t has mean 0, are Normally distributed with variances σ_e^2. Third, an exogenous shock ω_t that represent unemployment events and have an exponentially declining persistent effect on income, very much like in the literature on the scaring effects of unemployment. As the duration of unemployment in Denmark is typically shorter than 1 year, unemployment lasts for 1 period in the model. U_t is a dichotomous variable: $U_t = 1$ for the unemployed and $U_t = 0$ otherwise. Shock at unemployment κ_t takes a small value $\underline{\kappa}$ with probability $\underline{\delta^u}$, and a big value $\overline{\kappa}$ with probability $\overline{\delta^u}$. After re-employed, the scarring effect decreases at rate ρ.

2.2.3 Value Functions

Value functions are defined at the start of period t. The discrete decision facing a consumer gives rise to the value function

$$V_t (n_t, a_t, y_t, z_t, q_t) = \max \left\{ V_t^0, V_t^b, V_t^u, V_t^r \right\}$$

Here V_t^0 is the value if she decides to not own. V_t^b is the value if she decides to own a banger. V_t^u is the value if she decides to upgrade — buy a new car or a second-hand car. V_t^r is the value if she owns a standard (non-banger) car, and decides to keep the car. The state space includes: car type n_t, liquid asset a_t, income y_t, ownership duration z_t, and car quality q_t (accumulated shocks).

1. Consider a consumer who decides to not own in period t. At the beginning of period $t + 1$, her ownership type $n_{t+1} = 0$. Ownership duration z_t and quality q_t are not in the state space for non-owners.

$$V_t^0 (a_t, y_t, n_t, z_t, q_t) = \max_{c_t} \left\{ \frac{c_t^{1-\gamma} - 1}{1 - \gamma} + \beta \mathbb{E}_t V_{t+1} (0, a_{t+1}, y_{t+1}) \right\}$$

2. Consider a consumer who decides to own a banger in period t. At the beginning of period $t+1$, her ownership type $n_{t+1} = 3$, and the banger may become scrapped with probability δ^b. z_t and q_t are not in the state space for banger-owners.

$$V_t^b (a_t, y_t, n_t, z_t, q_t) = \max_{c_t} \left\{ \frac{\left(c_t \left(1 + \theta^b q^b \right)^\alpha \right)^{1-\gamma} - 1}{1 - \gamma} \right.$$
$$\left. + \beta \mathbb{E}_t \left[\left(1 - \delta^b \right) V_{t+1} (3, a_{t+1}, y_{t+1}) + \delta^b V_{t+1} (0, a_{t+1}, y_{t+1}) \right] \right\}$$

3. Consider a consumer who decides to upgrade in period t, either to a brand new car or a dealer-fixed car. At the beginning of period $t + 1$, the car may become a banger with probability δ^r.

$$V_t^u (a_t, y_t, n_t, z_t, q_t) = \max_{(c_t, n_{t+1})} \left\{ \frac{\left(c_t \left(1 + \theta \left(n_{t+1} \right) \right)^\alpha \right)^{1-\gamma} - 1}{1 - \gamma} \right.$$
$$\left. + \beta \mathbb{E}_t \left[(1 - \delta^r) V_{t+1} (n_{t+1}, a_{t+1}, y_{t+1}, z_{t+1}, q_{t+1}) + \delta^r V_{t+1} (3, a_{t+1}, y_{t+1}) \right] \right\}$$

4. Consider a consumer who owns a car at the beginning of period t, and decides to keep that car in period t. At the beginning of period $t + 1$, the car may become a

banger with probability δ^r.[9]

$$V_t^r\left(a_t, y_t, n_t, z_t, q_t\right) = \max_{c_t} \left\{ \frac{\left(c_t\left(1 + \theta\left(n_t\right)q_t\right)^{\alpha}\right)^{1-\gamma} - 1}{1-\gamma} \right.$$

$$\left. + \beta\mathbb{E}_t\left[\left(1-\delta^r\right)V_{t+1}\left(n_t, a_{t+1}, y_{t+1}, z_{t+1}, q_{t+1}\right) + \delta^r V_{t+1}\left(3, a_{t+1}, y_{t+1}\right)\right]\right\}$$

2.2.4 Determining Dealer Purchase Prices

We need to determine the $\bar{z}$ prices at which dealer buy cars from individuals. The first component we need is average quality of an offered car at each age

$$\bar{q}_z = \mathbb{E}\left(q_i | z, p^n, p^u, p^b, p_1^d, \ldots, p_{\bar{z}}^d\right)$$

that is, for any given set of prices, we can calculate the average quality of cars coming to the market. Adverse selection does not shut down the market — cars may be sold for upgrading to better quality or downgrading to access credit.

Dealers buy cars and repair cars to have quality 1. In reality, fixing a car is very expensive, including purchasing new car parts and paying mechanicians. As the fixing cost shouldn't be higher than selling price, we assume that the marginal cost of repairing is the price per unit of quality p^u. Then the cost to repair an average offered car is

$$p^u\left(1 - \bar{q}_z\right)$$

where $1 - \bar{q}_z$ is the depreciated quality. As the dealer can sell a second-hand car for p^u, the expected profit is

$$p^u - \left[p_z^d + p^u\left(1 - \bar{q}_z\right)\right] = \bar{q}_z p^u - p_z^d$$

In equilibrium, dealers make 0 profit, which implies

$$p_z^d = \bar{q}_z p^u \quad \text{for } z \in \{1, 2, \ldots, \bar{z}\} \tag{2.1}$$

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[9]If the existing car is of ownership duration $\bar{z}$, it becomes a banger in the following period for sure.

As p^u is the price for a unit of quality, $\bar{q}_z p^u$ is the expected value of an offered car of ownership duration z. So dealer purchase price equals the expected value of an offered car.

2.2.5 Equilibrium

Equilibrium in the market is defined by:

1. Consumers maximize utility.

2. Dealers make zero profit.

3. Dealers don't keep inventory: the number of second-hand cars sold by dealers equals the number of cars they bought from consumers.

4. The stock of cars is constant.

2.2.6 Algorithm

We want to estimate the model, and at the same time find the equilibrium defined in Section 2.2.5. First, we find a fixed point for dealer price p_z^d according to equation (2.1), so that equilibrium condition 2 is satisfied. Second, to satisfy equilibrium condition 3 and 4, we minimize dealer's inventory, and the difference between inflows and outflows for cars. We also estimate other unknown parameters to some data moments at the same time.

Specifically, We take the new car and fixed car prices as observed, noting that banger price is a fixed fraction of fixed car price.

1. An initial guess of parameter values.

2. Find a fixed point for the dealer purchase prices p_z^d using zero-profit condition (2.1).

3. Given p_z^d, estimate unknown parameters by the method of simulated moments. We also target equilibrium condition 3 and 4 at the same time.

4. Go back to step 2 until convergence

2.3 Data

The empirical analysis is based on Danish administrative data. The core data set is the Central Register of Motor Vehicles (CRMV) from which we have data covering the period 1992-2009. This register contains information about the entire population of cars registered with Danish number plates and holds information about the unique identity of all cars in the form of a serial number, the exact registration and de-registration dates and as well as information about the car brand, model and variant. These data are merged to data about prices of almost any type of new and used car on the market in the same period as is covered by the CRMV. It is possible to follow the price of any given brand-model-variant-vintage combination from when the car is new and until it is eight years old. The price data are collected by the Association of Danish Car Dealers (DAF) based on market analyses and reports from its members, and they reflect the price of cars in a "normal condition" depending on the age of the car. The CRMV also contains information about the identity of the owner of any given car at any given point in time, and this information is used for linking the car records to other administrative records of the owner. In particular, we link the CRMV with income tax records and a number of other administrative registers giving longitudinal information about income, wealth, labour market status, education, and family composition of the car owners. In this way, we are able to construct a longitudinal data set, where we can follow the population of Danish households in the period 1992-2009 and give a complete description of their income, wealth, car ownership. The wealth data can be divided into assets and liabilities, which can further be divided into a number of subcategories. Unfortunately, the definitions of these categories are not stable across the observation period. In particular, the definitions change almost yearly in the period 1992-1996, but from 1997 the definitions are stable, and it is possible to clearly identify financial wealth. Furthermore, the data are longitudinal, and this means that

we are able to track decisions about the sales and purchases of cars and how these decisions interact with savings decisions. In this way, we are able to examine how households use cars as an asset for smoothing adverse income shocks associated with unemployment events. To the best of our knowledge, no other data set collects longitudinal information about cars, income and wealth, and we are going to exploit these unique features of the data to inform the model.

2.3.1 Summary Statistics

We consider a 10% extract of the population register, and we include an observation only if the oldest person in the household is at least 30 years old and at most 60 years old. To these individuals, we add the partner if there is one, and we summarize all the remaining information at the household level. We are going to examine how households use cars to deal with adverse income shocks, and we therefore also consider a subsample consisting of observations for households who have been affected by an unemployment event and who owned at least one car in the year preceding the job loss. In the job-loss analysis, we are going to examine how people use car assets and financial wealth to smooth around the time of the job loss. As financial wealth is only consistently reported after 1997, we are going to include only individuals who experienced a job loss in 1999 or later, so that we can examine how financial wealth is adjusted when the unemployment event hits. Table 2.1 presents basic summary statistics for the gross sample and for the job-loss sample. For each of these samples, we provide summary statistics for two age groups, 30-40 and 41-60, as we are going to consider people in these age groups separately in the analysis. We group the summary statistics into three blocks providing information about car ownership, the financial situation of the household and demographics.

Car ownership is taxed in two ways in Denmark. There is an annual ownership tax, and there is a one-time tax associated with purchasing a new car. The latter, called the registration fee, is the most important amounting to up to 180% of the wholesale

price thus making Denmark one of the most expensive countries to purchase a new car in. As a consequence, 26-32% of the population depending on age does not own a car at any given point in time, cf. Table 2.1, column 1 and 3. Another consequence of new cars being expensive is that the average age of the car fleet is eight to nine years. The average level of disposable income is 309 thousand DKK (1 USD $\approx$6.5 DKK) for the young group and 323 thousand DKK for the middle-aged. A substantial fraction of the population in both age groups hold quite modest amounts of financial assets. This is witnessed by the fact that the median level of financial assets to income is 9 percent for the young group and 15 percent for the old group. In fact, around 50 percent of the households in both age groups hold financial assets worth less than one month of disposable income. These low-financial assets households also have little housing equity and are unlikely to be able to use that as a buffer. 60-67 percent of the households in this group have a car. Consequently, the value of the car stock makes up the overwhelming part of their assets. For the median household in this segment, the value of the car makes up 86 percent of their total financial and car assets.

Turning to the group of people holding financial assets amounting to more than one months worth of disposable income the picture looks different. A bigger fraction of the households is car owners and the ownership rate increases with age. The young households have little housing equity, but hold significant amounts of financial assets, so that the car only makes up about 34 percent of the sum of the car and financial assets. The middle-aged group in this segment has far more housing equity, and the car stock only makes up 34 percent of the sum of the car and financial assets. In other words, this group appears well-prepared for adverse events.

In Table 2.1, column 5-8 the corresponding numbers are shown for the job-loss sample[10]. In the data, we observe the fraction of the year that a person has been unemployed. We define an unemployment event to have taken place when the average

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[10]The job-looser sample includes observations for individuals who have been affected by unemployment events during the period 1999-2009. An unemployment event is defined to take place if the household is exposed to three months of full-time unemployment over the year. For two-adult households, it is defined to take place if the couple jointly experiences at least six months of unemployment within a calendar year.

fraction of the year in unemployment among the adult household members exceeds three months. We include in the job-loss sample only those households who had at least one car in the year preceding the job loss. The households in the job-loss sample, naturally, have a slightly lower level of income and the value of their car stock is also slightly lower. However, the value of the car stock out of the sum of financial and car assets is remarkably similar to the overall sample as is the amount of housing equity, and this is the case for both age groups.

We shall be calibrating/estimating the model to match moments in the general population. We will then examine how model households use the car stock and financial assets to deal with unemployment events and then compare with how households in the data deal with unemployment events.

2.4   Model Estimation

To be able to use the model for quantifying the lemons penalty, some of the model parameters will be calibrated or fixed at externally estimated values while others will be directly estimated. We start out describing fixed and externally estimated parameters and then turn to the parameters which are estimated by matching a set of moments simulated out of the model to corresponding moments in the data.

2.4.1   Fixed and Externally Estimated Parameters

The parameter values that are fixed or externally estimated are listed in Table 2.2.

Demographics   A period in the model is 1 year. Consumers enter the model at age 21, retire after age 61 and leave the model at age 79. In Denmark, a drivers license can be held from age 18 and is valid until the driver reaches 70 years of age. Further driving tests combined with medical examinations allows the driver to retake his license every two years after the age of 70.

Table 2.1: Summary Statistics

		Full sample				Job-loss sample			
		30-40		41-60		30-40		41-60	
Age group		Mean	Median	Mean	Median	Mean	Median	Mean	Median
Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Car									
Car owner		0.68	1	0.74	1	0.66	1	0.69	1
Age of car stock, car owner		8.89	9	8.35	8	10	10	9.44	9
Owner of regular car, car owner		0.92	1	0.93	1	0.90	1	0.90	1
Owner of banger, car owner		0.17	0	0.16	0	0.22	0	0.22	0
Income/wealth									
Disposable income (1000 DKK)		309	315	323	318	260	262	265	264
Financial assets / disposable income		0.31	0.09	0.56	0.15	0.31	0.09	0.57	0.14
1[financial assets < 1 months disp. income]		0.49	0	0.35	0	0.49	0	0.36	0
Car owner		0.65	1	0.67	1	0.62	1	0.62	1
Car value (1000 DKK), car owner		90	67	96	70	90	65	90	65
Car value / disposable income, car owner		0.27	0.21	0.28	0.22	0.32	0.24	0.32	0.24
Car value/(financial assets+Car value),car owner		0.70	0.86	0.71	0.86	0.79	0.88	0.78	0.88
Housing equity to house value (ETV),home owner		0.11	0.00	0.21	0.11	0.11	0.00	0.20	0.10
Housing equity to disposable income (ETI)		0.51	0.00	1.02	0.31	0.54	0.00	1.04	0.30
1[financial assets > 1 months disp. income]		0.51	1	0.65	1	0.51	1	0.64	1
Car owner		0.72	1	0.77	1	0.70	1	0.74	1
Car value (1000 DKK), car owner		113	87	118	94	109	80	110	83
Car value / disposable income, car owner		0.34	0.26	0.35	0.28	0.37	0.27	0.38	0.29
Car value/(financial assets+Car value),car owner		0.44	0.34	0.39	0.34	0.47	0.34	0.41	0.34
Housing equity to house value (ETV),home owner		0.22	0.15	0.44	0.44	0.22	0.14	0.43	0.41
Housing equity to disposable income (ETI)		1.11	0.46	2.29	1.55	1.14	0.45	2.28	1.52
Demographics									
Age		35	35	50	50	35	35	50	50
Married/cohabiting		0.71	1	0.75	1	0.66	1	0.70	1
Has children		0.61	1	0.47	0	0.62	1	0.45	0
Homeowner		0.50	1	0.61	1	0.52	1	0.62	1
College degree		0.26	0	0.21	0	0.23	0	0.17	0
Number of observations		1,452,171		2,559,063		466,426		678,752	

Notes: A regular car (banger) is a car aged <=15 (>15) years. Variables are CPI deflated to 2000 and are censored at 1% and 99% year by year. Financial assets include cash in banks, bonds and stocks. ETV and ETI are based on tax assessed house values. These variables are only available for 1997-2009.

Interest rate We calculate the interest rate using the interest rate of the two-year Danish government bonds adjusted by consumer price index in 1996-2009, which gives a rate of 1.6%.

Constructing car prices First, we want to impute the price of a second-hand car sold by dealers. In our model, dealers adjust second-hand car to the max quality. To reach a measure corresponding to this, we use the highest price of a second-hand car sold by dealers in the data: First, we pick cars bought as new and sold one year later and calculate the depreciation rate, which is 12.1 percent on average. The median book price of a new car in the data is 181 thousand DKK. So we set the price of a fixed second-hand car to $181 \times (1 - 0.121) \approx 159$ thousand DKK. We normalize all the prices and income by the price level of fixed-up second-hand cars. This implies that $p^u = 1$ and that the price of a new car i the model is $p^n = 1.14$.

We assume a car can be owned for 9 years, i.e. $\bar{z} = 9$. In the model, we assume that dealers can fix both deterministic and stochastic quality depreciation. However, in reality, dealers are only able to fix the stochastic depreciation. Even though the quality of cars sold by them are depreciated with deterministic age shocks, there is no asymmetric information in the price. So we use the year-to-year depreciation rate in the book price, which is 11.2 percent, as the deterministic depreciation rate in the model, i.e. the deterministic depreciation factor is $d = 1 - 0.11 = 0.89$.

We think of bangers as old cars that have no lemon's problem and not possible to fix up to the level of a regular used car. To quantify the value of a typical banger we observe that the weighted average of median book price of cars more than 15 years old is 20 thousand DKK, and we set the banger price in the model to $p^b = \frac{20}{159} = 0.13$. This defines the base quality $q^b = \frac{p^b}{p^u} = 0.13$, implying that a banger is worth 13 percent of a fixed second-hand car in terms of quality. We set the annual scrappage rate for bangers at $\delta^b = 0.073$, which is determined by the scrappage rate for cars more than 15 years old in the data.

Income process We estimate the parameters of the household income process using Danish income tax records in 1992-2009. (b_0, b_1, b_2) are parameters for deterministic age profile. $\sigma_{v_0}^2$ is the cross-sectional variance of the initial income shock, and σ_e^2 is the variance of the permanent shock. We normalize the income profile by p^u. We estimate the parameters for high (some college and above) and low education groups separately. The results in Table 2.2 show that the high education group has a lower variance in initial shock and a higher variance in permanent shocks than the low education group during the working lives. Income is not subject to risk after retirement.

Unemployment We impute the scarring effect of unemployment from differences in log household income of workers experienced unemployment. For the young, shock at unemployment takes a small value $\underline{\kappa} = 0.025$ with probability $\underline{\delta^u} = 0.047$, and a big value $\overline{\kappa} = 0.55$ with probability $\overline{\delta^u} = 0.005$. The unemployment shock for the young is purely transitory, so we set the persistence $\rho_{21-40} = 0$. For the old, shock at unemployment takes a small value $\underline{\kappa} = 0.049$ with probability $\underline{\delta^u} = 0.042$, and a big value $\overline{\kappa} = 0.457$ with probability $\overline{\delta^u} = 0.01$. The unemployment shock is persistent for the old, so we set the persistence $\rho_{41-60}\kappa = 0.8$.

Reducing liquidity We do include housing and pension wealth explicitly in the model — they are part of the liquid asset. In reality, such assets are not liquid. To take this into account, we prevent aggregate income from declining before retirement and assume that the retirement replacement rate is 100 percent. In this way, retirement income is taken into account without inducing people to save heavily for retirement during their working life.

Initial conditions We set the initial distribution of financial assets for the two education groups at age 21 to match the average in the data for people aged 20-26. Furthermore, individuals are randomly assigned with or without a car at age 21.

Utility function   The parameter for relative risk aversion γ is set to match the consumption elasticity of inter-temporal substitution of 0.7 (Attanasio and Weber, 1995), which corresponds to $\gamma = 1.43$.

Borrowing limit   In the benchmark calibration, we assume the lower bound of Uncolateralised debt is $\underline{a} = 0$.

Table 2.2: Exogenous Parameter Values

Parameter	Description	Value	Source
p^n	new car price	$1.14p^u$	DAF Car Data (181 DKK)
p^u	fixed car price	normalized to 1	DAF Car Data (159 DKK)
p^b	banger price	$0.13p^u$	DAF Car Data (20 DKK)
d	deterministic depreciation	0.89	DAF Car Data
δ^b	scrap rate for bangers	0.073	DAF Car Data
High education			
$\left(b_0^H, b_1^H, b_2^H\right)$	deterministic age profile	(-0.59, 0.063, -0.001)	Tax records
$\left(\sigma_{v_0 H}, \sigma_{eH}\right)$	initial and permanent std.	(0.388,0.174)	Tax records
Low education			
$\left(b_0^L, b_1^L, b_2^L\right)$	deterministic age profile	(-0.39, 0.026, -0.001)	Tax records
$\left(\sigma_{v_0 L}, \sigma_{eL}\right)$	initial and permanent std.	(0.457,0.145)	Tax records
Young			
$\left(\underline{\kappa}_y, \overline{\kappa}_y\right)$	Unemployment shock	(0.025,0.55)	Income process
$\left(\underline{\delta^u}_y, \overline{\delta^u}_y\right)$	Unem. shock arrival rate	(0.047,0.005)	Income process
ρ_y	persistence of scarring	0	Income process
Old			
$\left(\underline{\kappa}_o, \overline{\kappa}_o\right)$	Unemployment shock	(0.049,0.457)	Income process
$\left(\underline{\delta^u}_o, \overline{\delta^u}_o\right)$	Unem. shock arrival rate	(0.042, 0.01)	Income process
ρ_o	persistence of scarring	0.8	Income process
r	interest rate	0.016	Bond rate
γ	relative risk aversion	1.43	Attanasio and Weber (1995)

2.4.2 Estimated Parameter Values

Given the parameters above, we estimate remaining parameters using data for the household where the oldest person is aged 30-60 in the period 1992 to 2009. Our approach is to choose the parameters to minimize the relative deviations between moments calculated in the data and corresponding simulated moments. The moments we use are in the following.

1. the ownership rates of cars by age and by education [11]

2. the ownership rates of bangers by education

3. the fraction of people who buy new cars by age and by education

4. percentage of cars being sold after being owned for 2 years

5. average ownership duration of cars

6. the median financial asset to income ratio at age 55

We use the moments listed above to pin down 6 parameters: the discount factor β, the utility penalty of owning car α, the relative preference for cars bought as new θ^f, the relative preference for bangers θ^b, the arrival rate of banger shock δ^r, and the parameter for the private depreciation factor η. The dealer sales price, which we observe, capture the deterministic depreciation component d, and the private depreciation factor is then pinned down by the rate at which cars are put to the market by households, i.e. the ownership duration at the time where cars are sold from households to dealers. Parameter values from the estimation are in Table 2.4. Table 2.3 presents the moments from the data and the model. For equilibrium condition 3 and 4, we minimize dealer's inventory and the difference between inflows and outflows for cars. The relative deviation is 0.007 for the former and 0.077 for the latter.

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[11]Bangers are cars that are more than 15 years old.

We define 2 education groups, and people with high education are those with at least some college education, which is about 20% of the population.

Table 2.3: Fitted Moments

Moments		Data	Model
Ownership rate of regular cars			
Low Edu	Age 30 - 40	57.2%	55.8%
	Age 41 - 60	62.0%	61.8%
High Edu	Age 30 - 40	58.8%	60.0%
	Age 41 - 60	68.7%	64.3%
Ownership rate of bangers			
Low Edu	Age 30 - 60	20.4%	21.8%
High Edu	Age 30 - 60	18.3%	20.1%
% people buy new cars			
Low Edu	Age 30 - 40	3.9%	2.2%
	Age 41 - 60	5.4%	5.9%
High Edu	Age 30 - 40	5.0%	3.9%
	Age 41 - 60	6.4%	11.3%
Financial asset to income ratio at age 55		20%	20.9%
% of cars being sold after 2 years		32.6%	29.7%
Ownership duration of cars		4.2	3.9

Table 2.4: Calibrated Parameter Values

Description		Value
Discount factor	β	0.963
Preference for new car	θ^f	1.131
Preference for banger	θ^b	0.683
Utility benefit of owning car	α	0.371
$\ln\left(\frac{\epsilon}{1-\epsilon}\right) \sim \mathcal{N}(\eta, 1)$	η	2.064
arrival rate of banger shock	δ^r	0.101

From our estimation, the expected mean of private depreciation factor $\mathbb{E}(\epsilon) = 0.85$. The deterministic depreciation factor $d = 0.89$, and the overall expected depreciation factor $d\mathbb{E}(\epsilon) = 0.76$. Given the estimated utility parameters, consumers have a higher preference for new cars, and a lower preference for bangers. The negative value of α implies that cars and consumption are substitutes in utility, in the sense that the cross-partial derivative of utility with respect to c and q is negative. The discount factor $\beta = 0.963$ which lies within the range of values commonly assumed in dynamic discrete choice models (e.g. Rust (1987)). The arrival rate of banger shock for cars is smaller than the arrival rate of scrap shock for bangers.

2.5   The Lemons Penalty

Due to asymmetric information, the expected quality of cars that are offered to dealers is lower than the expected quality of cars that are owned. Dealers, therefore, will not pay the expected value of cars being owned to an offered car. They will ask for a price discount, which is the lemons penalty.

The first row of Table 2.5 shows the dealer prices, which equals the expected value of cars being sold, according to equation 2.1. The second row of Table 2.5 shows the expected value of cars being owned. The differences between them are the lemons penalty, which are showed in the third row. The 1-year-old car has the biggest lemons penalty, which is about 16% of a new car price. Then the lemons penalty declines overtime[12]. Panel (a) of Figure 2.1 plots the distribution of car value by ownership duration simulated from the model. The solid line is the distribution of car value conditional on being sold, the dashed line is the distribution of car value conditional on being owned, and the vertical line is the dealer price. Those owners whose cars are on the right of the dealer price make a loss when selling their cars, so very few of them sell their cars after one period. On the contrary, those owners whose cars are on the

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[12]Lemons penalty is a measure of endogenous transaction cost. One alternative reason why it decreases with ownership duration is that transaction cost is proportional to the price which decreases with the car's age. One one hand, our estimates show the decrease is non-linear which is particularly faster in the first few years, on the other hand, our model also builds a structural for the transaction cost.

Table 2.5: The Lemons Penalty

Ownership duration	1	2	3	4	5	6	7	8	9
Asymmetric information									
Dealer price	0.605	0.560	0.497	0.436	0.379	0.309	0.279	0.244	0.256
Expected car value (owned)	0.790	0.637	0.533	0.453	0.389	0.342	0.304	0.277	0.256
Lemons penalty	**-0.185**	**-0.077**	**-0.036**	**-0.017**	**-0.010**	**-0.033**	**-0.025**	**-0.033**	**0**
% of cars being sold	5.6%	29.7%	54.9%	71.0%	79.9%	80.9%	82.7%	83.0%	100%
Symmetric information									
Average Dealer price	0.800	0.589	0.477	0.413	0.378	0.396	0.352	0.373	0.246
Expected car value (owned)	0.790	0.614	0.508	0.430	0.374	0.329	0.293	0.266	0.246
% of cars being sold	74.7%	82.3%	86.5%	90.0%	92.7%	93.4%	94.3%	94.8%	100%
Symmetric information with market clearing									
Average Dealer price	0.828	0.638	0.502	0.428	0.386	0.406	0.361	0.385	0.255
Expected car value (owned)	0.819	0.643	0.527	0.445	0.385	0.341	0.303	0.277	0.255
% of cars being sold	71.9%	82.1%	85.8%	89.1%	92.0%	92.9%	93.9%	94.4%	100%

Notes: In the baseline asymmetric information case, the price that a dealer sells a second-hand car is set at $p^u = 1$. Given this price and the price that the dealer pays to private sellers, demand for second-hand cars equals supply, and 11% of the population buy a car in any given period. With symmetric information, the price that a dealer pays to private sellers is equal to the actual quality of that car. Given a dealer sale price of $p^u = 1$, there is an excess demand by households for second-hand cars bought from the dealer. This scenario is shown in the second panel where 29% of the population want to buy a second-hand car from a dealer, but only 25% are selling their cars to the dealer. In the third panel, we allow p^u to adjust so that demand equals supply: p^u increases to 1.038, and demand falls to 23% of the population in any given period.

left of the dealer price make a profit when selling their cars, so many of them sell their cars after one period. As a result, the average value of 1-year-old cars being sold is far less than the value of cars being owned, which gives rise the biggest lemons penalty. The 4th row of Table 2.5 shows the cumulative percentage of cars being sold. About 30% of cars are sold in the first two years. The interpretation is that a consumer will only get rid of her car quickly when it is a lemon.

2.5.1 Symmetric Information

To understand the lemons problem, we compare asymmetric information model with symmetric information model. In the symmetric information model, if a consumer has a car of quality q_t, she can sell it at its true value $q_t p^u$.

After eliminating asymmetric information from the model, the aggregate demand for fixed cars changes, and thus the fixed car price p^u changes. Then expected car value also changes, as it is proportional to p^u. To compare it with asymmetric information model, as a first step, we keep the fixed car price constant, i.e. $p^u = 1$, although this means aggregate demand of fixed cars is greater than aggregate supply. The 5th row of Table 2.5 shows the average dealer prices, and the 6th row shows the expected value of cars being owned in this case.

In the symmetric information model, cars are sold at their true quality — no one makes a loss or a profit. In the asymmetric information model, cars are sold at average quality of cars on the market. So good cars can be sold at a better price in the symmetric information model than in the asymmetric information model. In the asymmetric information model, dealer prices are much lower than the expected value of cars being owned, so only bad cars are sold. In the symmetric information model, average dealer prices are close to the expected value of cars being owned, so both good and bad cars are sold. Panel (b) of Figure 2.1 plots the distribution of car value simulated from the model with symmetric information. The solid line is the distribution of car value conditional on being sold, the dashed line is the distribution of car value conditional on

Figure 2.1: Distribution of Car Value Conditional on being Sold and being Owned by Vintage

(a) Asymmetric Information
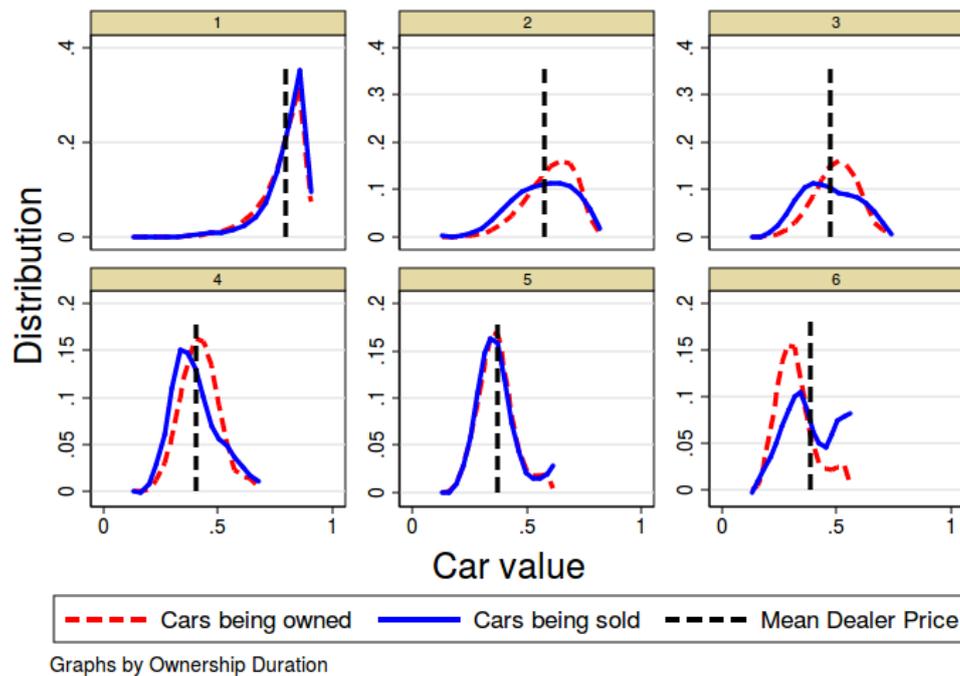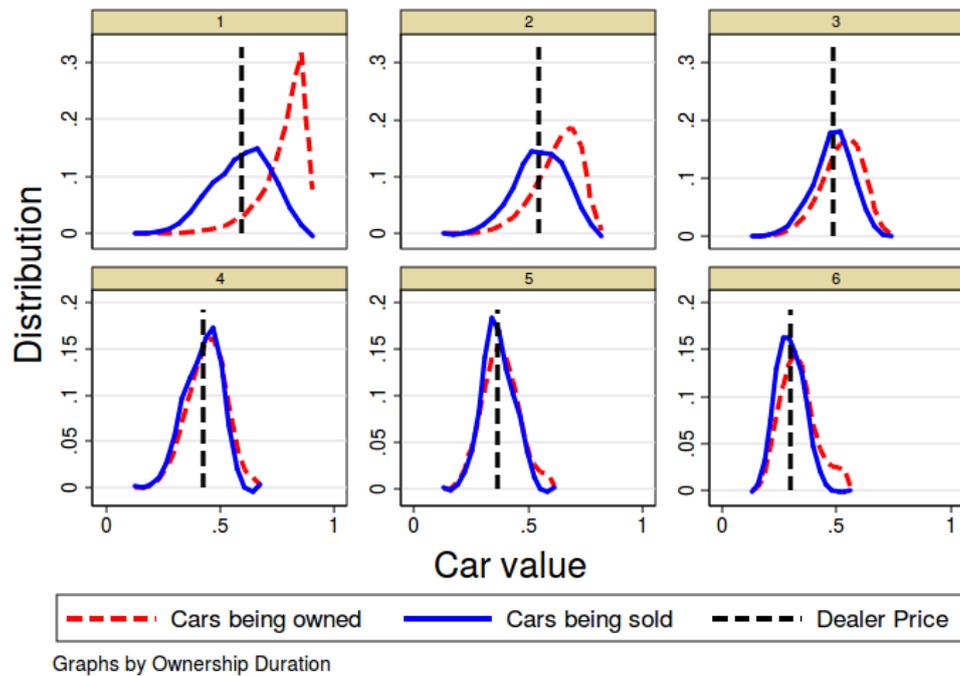
(b) symmetric information

being owned, and the vertical line is the average dealer price. The two distributions are very close to each other. The 7th row of Table 2.5 shows the percentage of cars being sold in this case. 82% of cars are sold in the first 2 years, comparing to only 30% in the asymmetric information model. Therefore, good cars are sold earlier in the full information model than in the asymmetric information model. It shows lemon's problem strongly suppresses used car sales.

Comparing the 1st and 5th row of Table 2.5, we find the average dealer prices of cars with ownership duration 1–2 are higher in the symmetric information model than the dealer prices in the asymmetric information model. As good cars are sold earlier, the quality of cars sold in young used car market is better in the full information model than in the asymmetric information model.

The rest of Table 2.5 show the simulated data for the symmetric information model after allowing p^u to change. As cars can be sold at a better price in the symmetric information model, consumers demand more cars: the total demand for fixed cars increases from 11% to 23% of the population. As a result, the fixed car price p^u increased by 3.8% from 1 to 1.038. So lemons problem also strongly suppresses used car demands.

2.6 Unemployment Events and Downgrading

The previous section has shown that within the context of the model the lemons penalty is significant and suppresses the car trade volume significantly. This has implications for how households can and will use car assets for self-insurance compared to other assets. To learn about the impact of lemons penalty for the car to act as a self-insurance device, this section presents an analysis of unemployment events on the probability of downgrading, i.e. selling a car and replacing with a banger or selling without buying. This analysis serves two purposes. First, it informs about how consumers can and will use cars assets to self insure against adverse income shocks following an unemployment event. Second, by comparing unemployment event data simulated from the model with the actual unemployment event data, which were not used for esti-

mating/calibrating the model, we get an impression about the appropriateness of the specification of the model.

2.6.1 Job Loss and Downgrading in the Data

In this section, we consider how households in the data and our model deal with unemployment events. For doing this, we focus on the job-loss sample and perform an event study where we consider how a number of outcomes change around the job loss. First, we consider how disposable income, y_{it}, changes. This is the resource loss that potentially can be smoothed by adjusting the wealth accumulated in the car stock, Z_{it}, or by adjusting financial assets, A_{it}, or debt, D_{it}. To measure how households deal with the job loss we measure how each of these components is adjusted around the job loss, and finally, we consider them jointly in order to see how total household-level spending is adjusted around the job loss. Spending is imputed by applying a simple accounting identity, $c_{it} = y_{it} - \Delta Z_{it} - \Delta (A_{it} - D_{it})_{it}$, where c_{it} is the spending of household i in period t. [13]

The event is defined to be the first job loss observed in the period 1999-2009. We include single adult households and households consisting of couples. For singles, we define a job loss to take place if the person has been out of the job for a total of at least 60 days during the year. For couples, we define the job loss to take place if the total unemployment accumulates to 120 days when summarized for both partners over the year. This is done to obtain shocks that are of comparable magnitude across singles and couples.

We start out considering the effect of the job loss on disposable income. Figure 2.2 shows the average change in disposable income at the household level around the year of the job loss. The figure is constructed by ordering observations according to the year

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[13]The imputation procedure was proposed by Browning and Leth-Petersen (2003). They matched at the household level data from the Danish Family Expenditure Survey (DES) for the years 1994-1996 to the administrative income/wealth tax records for the years around their DES survey year and directly compared the spending measure from the DES with the imputed spending measure based on administrative records. They found that the imputation provides a measure that performs quite well in terms of matching self-reported total expenditure of individual households.

Figure 2.2: Disposable Income around the Job Loss

(a) Income level
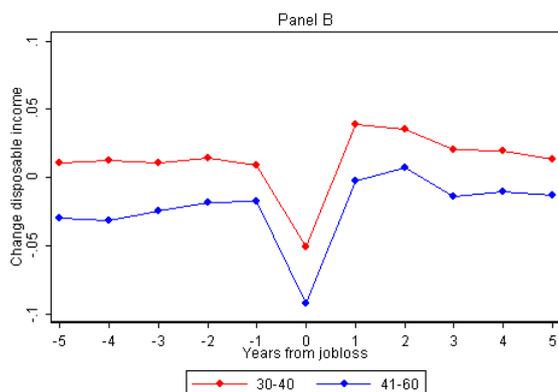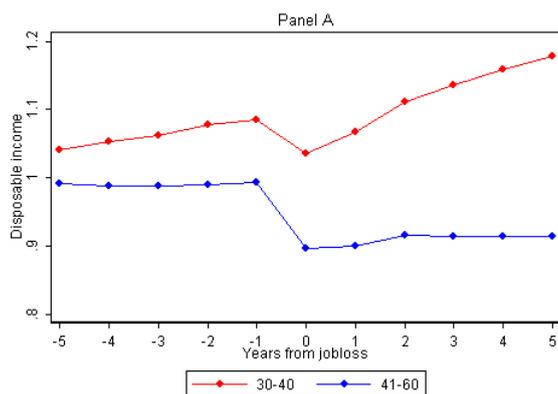
(b) Change in income

Notes: The event graphs are constructed by ordering observations according to the first year in the data period where households experience to be unemployed for at least three months on average across the adult household members. The red line covers households where the oldest person in the household was aged 30-40 at the time of the job loss. The blue line covers households where the oldest person in the household was aged 41-60 at the time of the job loss. Panel A shows the level of disposable income. Panel B shows the change in disposable income across the sample period. In both panels, the outcome is relative to the average level of disposable income for the same household across the sample period.

of the job loss, which is denoted period 0, and then following individuals from up to five years before the job loss and until up to five years after the job loss. As job losses happen at different points in time, the data will not be balanced along the event time scale, and the number of observations will decline when moving further away from the event year. Disposable income at any given point in time is normalized by the average disposable income of the individual across the sample period to get a stable normalization variable that is not affected by transitory fluctuations and is arguably a proxy for the level of permanent income.[14] We consider two age groups, 30-40 and 41-60. Figure 2.2, Panel A, shows how the level of disposable income develops from five years before the job loss to five years after the job loss. Income is steadily increasing for the young group, and the job loss appears to reduce disposable income only for two to three years following the job loss. For the mid-aged group, the picture is different. Here the job loss appears to lower the level of income permanently. Figure 2.2, Panel B plots the first differences. Here the impact of the unemployment event becomes very clear. The income growth of the younger group is positive in all years except the year of the job loss where it drops by about 5%. Already one year later it picks up, and in year three after the job loss, it is back on the growth level from before the job loss. For the mid-aged group, income growth is slightly negative in most years, and it takes a hit in the year of the job loss. Income growth rates never become positive for the mid-aged group reflecting the permanency of the income drop sparked by the job loss.

Figure 2.3 shows the propensity to downgrade the car stock, Panel A, and how total spending, Panel B, is adjusted. We define downgrading to take place when the household sells a car in period t and end up with a value of the car stock that is reduced to at least 60% of the value of the car stock in the previous period, i.e. $Z_t < 0.6\,Z_{t-1}$. Panel A shows that downgrading is generally increasing over the event window, and that the propensity to downgrade evolves roughly similar for the two age groups before the

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[14]By including leaded observations in this average we risk that this measure includes values of income that are potentially the result of the choices made as a consequence of the unemployment event or the spending/savings decision made by the household. In unreported analyses, we also tried to normalize on the average of lagged values disposable income. This did not affect the results in any important way.

Figure 2.3: Downgrading of the Car Stock and Adjustment of Total Spending

(a) Downgrading
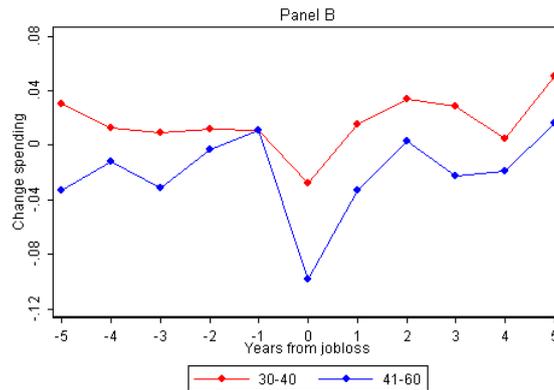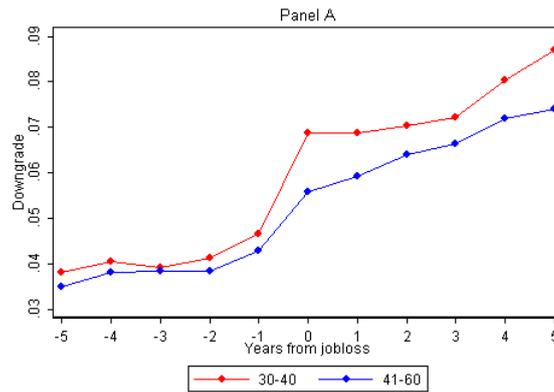
(b) Spending adjustment

Notes: The event graphs are constructed by ordering observations according to the first year in the data period where households experience to be unemployed for at least three months on average across the adult household members. The red line covers households where the oldest person in the household was aged 30-40 at the time of the job loss. The blue line covers households where the oldest person in the household was aged 41-60 at the time of the job loss. Panel A shows the fraction of households who downgrade their car stock. Downgrading takes place when a car is sold in period t and the value of the car stock in year t is at most 60% of the value of the car stock in year $t-1$. Panel B shows the change in spending where spending is relative to the average level of disposable income for the same household across the sample period.

Figure 2.4: Unemployment Event - Income

(a) Income level

(b) Change in income
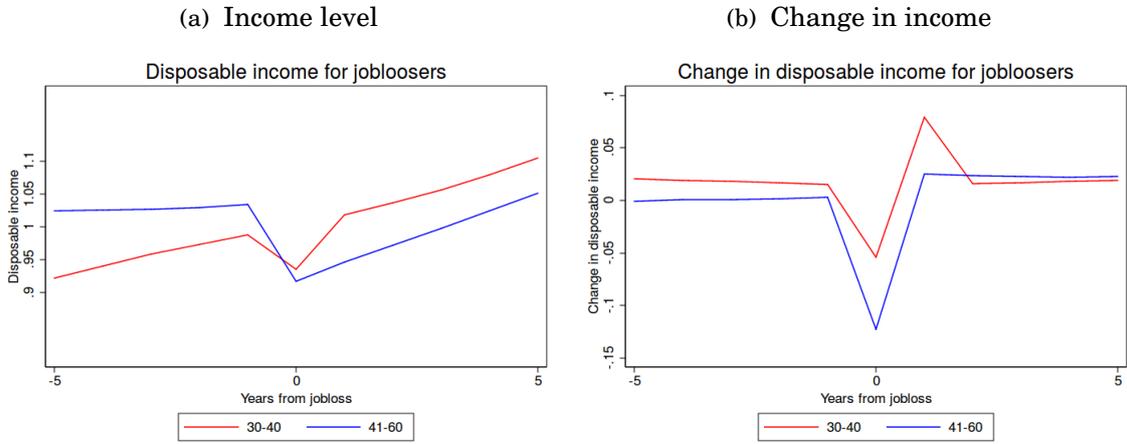
job loss. However, at the point of the job loss the propensity to downgrade increases discretely, about 3-4 percentage points, for the young group and less for the mid-aged group. Panel B shows how total spending develops. The mid-aged group adjust spending downwards at the time of the job loss, but the young group adjust their spending less.

We now perform a similar event study based on data simulated from the model. We start out considering income and then turn to the propensity to downgrade the car stock and the consumption adjustment. For these two outcomes, we consider both the asymmetric information case and the symmetric information case. The former corresponds to the event analysis based on the real data, and the comparison between the former and the latter will be informative about whether asymmetric information limits the use of car assets smoothing out the effects of adverse income shocks that we observe in the asymmetric information case.

We start out by considering how the model is able to reproduce the pattern of income around the job loss. Figure 2.4 plots the average change in income (as a fraction of life time income) around the time of the job loss based on data simulated from the model. It shows that the job loss generates an average drop in income of about 5% for the young and 12% for the old.

Figure 2.5: Unemployment Event - Downgrading and Consumption Adjustment

(a) Asymmetric information – Downgrading
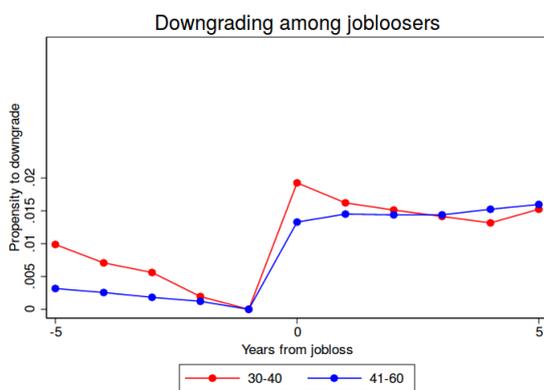
(b) symmetric information – Downgrading
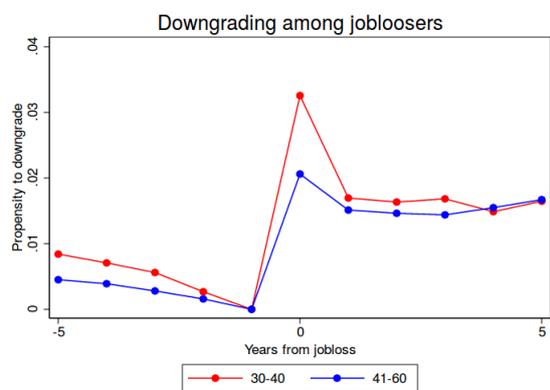
(c) Asymmetric infor. – Change in consumption
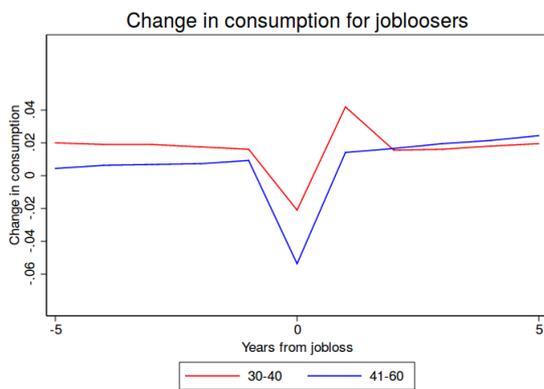
(d) symmetric infor. – Change in consumption
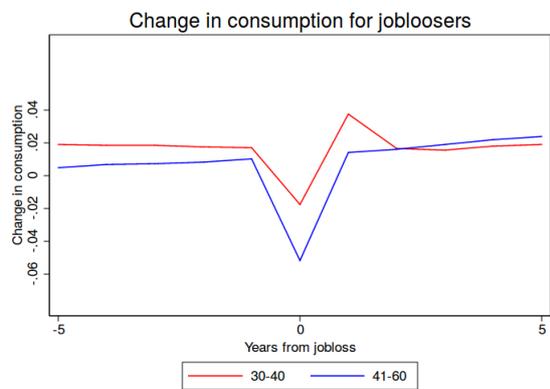
Figure 2.5 presents downgrading and spending adjustments for the asymmetric information case, panel 2.5a and 2.5c, and for the case with symmetric information, panel 2.5b and 2.5d. The propensity to downgrade under asymmetric information increases discretely by 1.9% for the young and 1.3% for the old. The discrete increase in the downgrading propensity is slightly smaller in the simulated data than in the real data, but the increase in the propensity to downgrade is bigger for the young group as it is in the real data. Also, the consumption drop at the job loss is smaller for the young than for the old sample as it is in the real data. It shows that the job loss generates an average drop in consumption of about 2.1% for the young and 5.4% for the old. The event study results based on the simulated data from the model with asymmetric information broadly match the results from the event study based on the actual data. Because these moments were not used for estimating/calibrating the model this leaves us with some faith that the model provides credible description of the household level car adjustment decision.

Figure 2.5, panel 2.5b and 2.5d, presents the same event study for the symmetric information case. It shows that at the point of unemployment, the propensity to downgrade increases to 3.3% for the young and 2.1% for the old. This means that when the information problem is removed, car stock becomes more liquid, and people use it as an insurance device against adverse income shock to a larger extent than they actually do in the case of asymmetric information. In fact, the propensity to downgrade increases 74% for the young and 85% for the old. The results also show that the job loss generates an average drop in consumption of about 1.8% for the young and 5.2% for the old, i.e. moving from asymmetric information to the full information regime reduces the consumption drop by 0.3 percentage points for young and 0.2 percentage points for the old.

2.7 Conclusion

In this paper, we formulate a stochastic life-cycle general equilibrium model of car ownership in which dealers buy old cars from consumers without knowing their exact quality, fix them and sell them back to consumers. Car dealers are offered cars that on average are of lower quality than similar cars in the population. Consumers selling above average quality cars, therefore, receive a lower payment than what they would have if there was no informational asymmetry about the quality of the car and this difference is the lemons penalty. The supply of cars into the used car market varies as households receive news about their income and this affect the average quality of cars entering the secondary market. This mechanism enables us to study how equilibrium prices and the flow of cars in and out of the market is characterized. We calibrate the model using a population-wide high-quality administrative data set with complete information about car ownership for the period 1992-2009. The data is linked to longitudinal income-tax records of the owners with information about income and wealth of the owners. We structurally estimate the model and use the estimated model to quantify the lemons penalty by comparing the observed market outcome with the counter-factual outcomes under symmetric information.

Our results show that the lemons penalty is significant at the beginning of the car ownership period and in particular for new cars. We show that the lemons penalty reduces the transaction volume quite significantly. Our results show that there are welfare gains to be harvested by reducing the magnitude of the lemons penalty and that there are potentially great advantages of instituting policies to alleviate asymmetric information problems in the second-hand car markets.

Chapter 3

The Impact of Unemployment Insurance on the Cyclicality of Labour Force Participation

3.1 Introduction

Should workers search more or less in recessions? During economic downturns, the returns of job search will likely fall because both the probability of obtaining a job and the expected income from a job are declining. So standard economic theories such as Veracierto (2008) and Tripier (2004), predict that workers should search less in recessions. This decline in job search should be observable in aggregate data as a decrease in labour market participation, which is the fraction of the population that wants to work and are actively searching. However, section 3.2 of this paper shows that while it is true the aggregate employment is procyclical, the labour force participation in the US is acyclical.

To explore why labour force participation is acyclical, it is important to examine the worker flows into and out of the labour force. I find that both of the worker flows from employment and unemployment into out-of-labour-force (OLF) are procyclical—decrease in recessions. This is counter-factual, as recessions depress job search, and there should be a higher proportion of workers from these two states drop out of the labour force. Krusell, Mukoyama, Rogerson, and Sahin (2016) documents similar patterns, and they suggest the procyclicality of the transition rate from unemployment to OLF is due to composition change that unemployed workers in recessions are of higher productivity, thus are less likely to drop out of the labour force. But this still can not explain why the transition rate from employment to OLF is procyclical, i.e. a lower proportion of employed workers separate into OLF in recessions. Figure 3.1 uses the 1979–2014 monthly US Current Population Survey (CPS) to plot the transition rate from employment to OLF (job separation rate into OLF). NBER dated recessions are shaded[1]. The sample is restricted to workers aged 25–59 years old. In all of the recent recessions, the transition rate from employment to OLF drop substantially, indicating it is procyclical.

To explain these data patterns, I look at unemployment insurance (hereafter, UI)

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[1] Two consecutive quarters of negative GDP growth

Figure 3.1: Transition Rates from Employment to OLF (E2O) and the Business Cycle
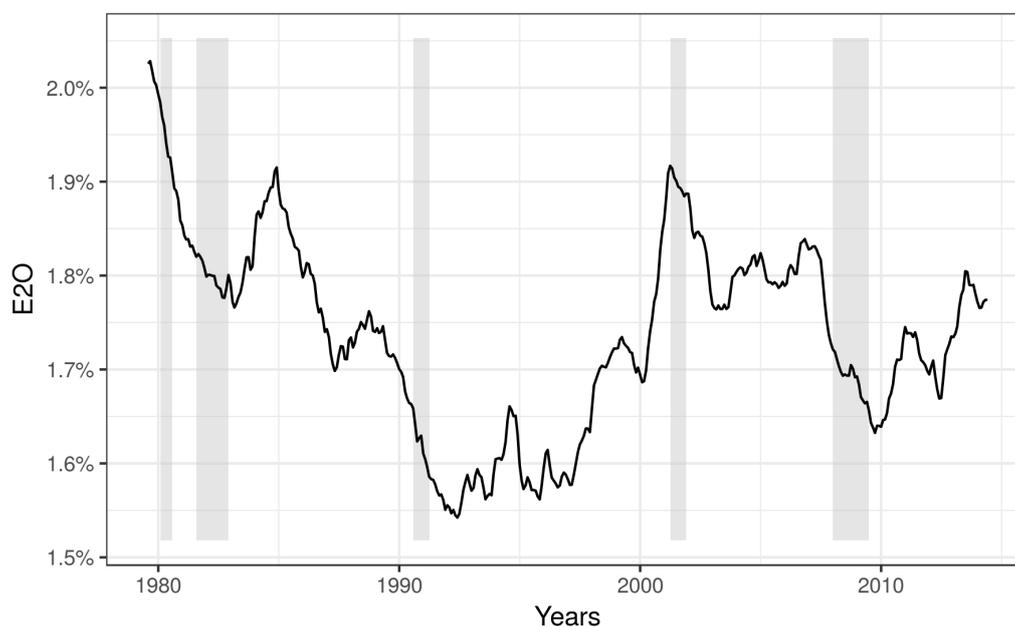
Note: Monthly CPS 1979–2014. Workers aged 25–59.
NBER dated recessions are shaded.

benefit. Empirical evidence shows that the level of UI increases more in recessions than in booms. My theory is that as UI is more generous in recessions, the unemployment state becomes more attractive relative to OLF, and thus workers are more likely to choose unemployment rather than OLF.

To evaluate this possible explanation, I develop an equilibrium search and matching model with aggregate productivity shocks and endogenous labour force participation. I model UI explicitly and labour force participation varies with the level of UI. I take the empirical correlation between GDP and UI and find that it can explain the acyclical labour force participation. The model also shows that counter-cyclical unemployment insurance has the effect of stabilizing the economy by reducing the variation in employment and GDP.

The next section presents the data on labour force participation. Section 3.3 describes the UI program and documents a new fact the level of UI is counter-cyclical. Section 3.4 presents the model. Section 3.5 and 3.6 outline the estimation technology

Table 3.1: Cyclical Properties of Aggregate Labour Market States

	E-pop	U-rate	LF
Mean	0.767	0.052	0.809
Std.	0.013	0.207	0.004
Corr. with log GDP	0.796	-0.827	0.129

Note: Date is Monthly CPS 1979–2014. Sample is workers aged 25–59.
"E-pop" is the employment population rate, "U-rate" is the unemployment rate, and
"LF" is the labour force participation rate.
The row labelled "mean" refers to the mean of levels, while the other rows refer to the
log of the variable in each column. Row series are seasonally adjusted using Census's
X13 procedure, and HP filtered with a smoothing parameter 10^5.

and present the results and simulations. Section 3.7 concludes.

3.2   Data

3.2.1   Labour Market States over the Business Cycle

To begin my analysis, table 3.1 presents summary statistics for the business cycle prop-
erties for the labour market states. I use monthly CPS for the years 1979 to 2014. The
sample is restricted to prime-age workers that is 25–59 years old. I use E-pop to de-
note the employment population rate, U-rate to denote the unemployment rate—total
number of unemployed over the number of employed and unemployed, and LF to de-
note the labour force participation rate—total number of employed and unemployed
over the population.

In the population, 81% of the people participate the labour force, 77% of the peo-
ple have a job, and the unemployment rate is about 5%. Among the three series, the
unemployment rate is the most volatile, and the labour force participation rate is the
least volatile. Regarding the cyclicality, employment is strongly procyclical, the un-
employment rate is strongly counter-cyclical, and the labour force participation rate is
acyclical.

Table 3.2: Transition Rates between the Labour Market States

	E2U	E2O	U2E	U2O	O2E	O2U
Mean	0.012	0.017	0.252	0.182	0.063	0.037
Std.	0.13	0.046	0.123	0.103	0.055	0.129
Corr. with log GDP	-0.749	0.551	0.785	0.625	0.792	-0.791

Note: "E2U" and "E2O" are the transition rates from employment to unemployment and to OLF. "U2E" and "U2O" are those from unemployment to employment and to OLF. "O2E" and "O2U" are those from OLF to employment and to unemployment.

3.2.2 Transition Rates from and into OLF

The labour force participation looks very stable across the business cycle. However, the labour force is not fixed. In fact, a great many workers move in and out of labour force each month, and there are large changes in these flows over the business cycle. Table 3.2 presents data for average monthly transition rates between the three labour market states: employment (E), unemployment (U), and OLF (O).

The transition rates into and out of labour force are very large. Each month, about 10% of the labour force nonparticipants enter the labour force in the subsequent month (O2E + O2U), and about 18% of unemployed workers enter OLF (U2O). The job separation rate into OLF (E2O) is 1.7% and is 40% higher than the job separation rate into unemployment (E2U). Besides, the variations of the transition rates into and from OLF are also very large, taking into account that the standard deviation of the labour force participation rate is only 0.004.

Before we turn to the cyclicality, according to the standard theory that recessions depress job search, you can imagine that the transition rates into the labour force should be procyclical, and the transition rates out of the labour force should be counter-cyclical. The last row of table 3.2 shows that, while it is true the O2E is procyclical, the other three transition rates are all counter-factual: O2U is counter-cyclical, and both E2O and U2O are procyclical.

The transition rate from OLF to unemployment (O2U) is counter-cyclical can be explained by the standard theory that the decrease in job finding rate in recessions

implies workers who have just entered the labour force are less likely to become employed, increasing the flow of these workers into unemployment. For the procyclicality of the transition rate from unemployment to OLF (U2O), Krusell, Mukoyama, Rogerson, and Sahin (2016) suggests that it is due to composition change that unemployed workers in recessions are of higher productivity, thus are less likely to drop out of the labour force. But this still can not explain why the job separation rate into OLF (E2O) is procyclical, i.e. a lower proportion of employed workers separate into OLF in recessions.

3.2.3 Adjustments for Classification Error

Calculating the transition rates using CPS is subject to classification error. That is, some workers are incorrectly categorized into a labour market state in a given month, which gives rise to spurious transitions. Imagine a respondent who is in fact employed for three consecutive surveys, but who is misclassified as OLF in the second survey. Then we would observe two spurious transitions, E2O and O2E, with no actual transition took place. Reinterviews with CPS respondents in the 1980s indicate that of all persons who should have been classified as employed, 1.03% were improperly classified as OLF (Abowd and Zellner, 1985).

In order to examine how job separation rate into OLF is affected by such classification errors, I recode those people who are observed to transit from employment to OLF in one month but return in the following month as consecutively employed, i.e., recode someone whose three-month trajectory is E-O-E as E-E-E [2].

Similar approaches have recently been used in the literature (see Rothstein (2011), Farber and Valletta (2013), and Elsby, Hobijn, and Sahin (2015)). By doing this, I only measure job separation rate into OLF for observations who leave the labour force for at least 2 consecutive months, and I inevitably will miss some genuine transitions. However, rather than providing a definitive correction of classification errors, the goal of the

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[2]Abowd and Zellner (1985) and Poterba and Summers (1986) indicate such classification errors are particularly important for transitions between unemployment and OLF. So I also recode U-N-U trajectories as U-U-U, and I recode N-U-N trajectories as N-N-N.

Table 3.3: E2O Adjusted for Classification Errors

	E2O	Adjusted E2O
Mean	0.017	0.013
Std.	0.046	0.046
Correlation with log GDP	0.55	0.524

Note: "E2O" is the transition rate from employment to OLF. The last column is E2O adjusted for classification error.

exercise is only to provide a robustness check whether the cyclicality of job separation rate into OLF is affected by eliminating reversal transitions.

Table 3.3 shows the E2O adjusted for classification errors. While the mean is adjusted down by one forth, the correlation with log GDP is almost the same (0.55 vs 0.524). Importantly for the focus of this paper, E2O appears robust to adjustment for classification errors.

3.2.4 Ratio of E2U to E2O

Figure 3.2 plots the ratio of E2U to E2O. The shaded regions are NBER recessions. The ratio increases in every recession, and decreases during booms. Its correlation with detrended GDP is -0.833. So E2O is procyclical because the proportion of newly separated workers entering OLF is lower in recessions than in booms. Why? The key object governing willingness to enter unemployment rather than OLF is the unemployment insurance benefit (UI). I will show that UI is counter-cyclical in the following.

3.3 Unemployment Insurance Benefits

I think UI benefit has a role to play in the cyclicality of job separation rate into OLF. In this section, I present evidence that the level of UI benefit is counter-cyclical: In recessions, it becomes more generous to provide a better social safety net. Then unemployment is more attractive comparing to OLF in recessions than in booms. So in recessions more labour force nonparticipants enter unemployment, and at the same

Figure 3.2: Ratio of E2U to E2O over the Business Cycle
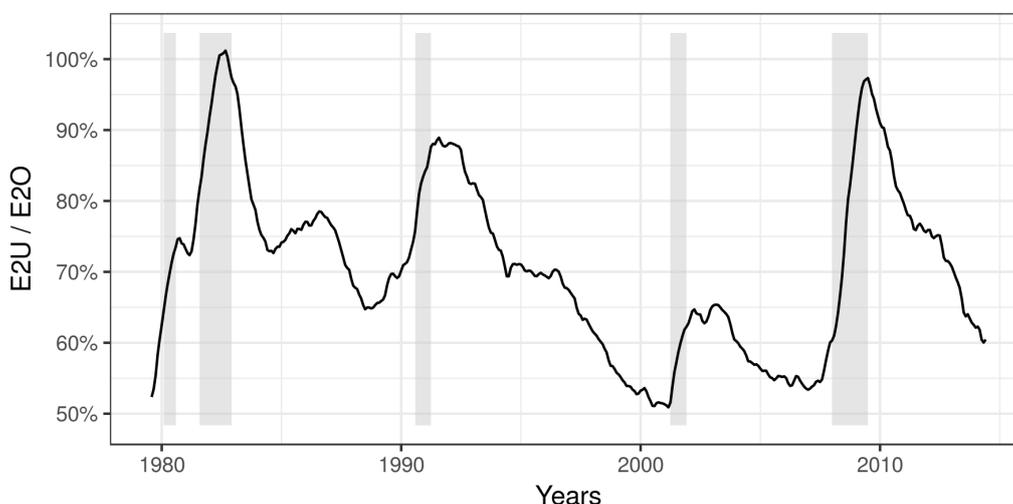
Note: NBER dated recessions are shaded.

time, new job losers are more likely to enter unemployment rather than OLF.

3.3.1   UI Program in the US

I first describe the UI Program based on the information from US Department of Labor.

Eligibility   Eligibility and benefits under the US UI Program are determined based on earnings or hours/weeks of work during a base period. Typically, this base period is the first four out of five completed calendar quarters that precede the filing of a claim. In order to be eligible for UI, applicants must meet minimum earnings or hours/weeks of work requirements that vary considerably by state.

Weekly Benefit Amount   Nearly all states have an explicit minimum weekly benefit amount. The minimum weekly benefit by state ranges from no minimum in Vermont to $106 per week in Washington.

The weekly benefit amount is also subject to a maximum imposed by each state. In 2002, the maximum weekly benefit amount (MWBA) ranges from a low of $190 in Alabama to a high of $512 in Massachusetts, although two-thirds of the states have

benefit maxima falling within the range of $250 to $350.

States replace, on average, 50% of worker's lost wages up to a maximum imposed by each state. There are significant differences in the weekly benefit schedules across states. Twelve states offer weekly allowances for dependents in addition to the basic weekly benefit. The allowances can be quite variable in size.

Waiting Period   Applicants for unemployment insurance benefits who are otherwise eligible must face a waiting period which is one week in duration in nearly all states.

Maximum Benefit Duration   Nine states have a uniform benefit duration of 26 weeks. The remaining states have benefit durations that can vary in length based on the applicant's earnings history.

3.3.2   Counter-cyclical UI Schedule

The previous section shows that the UI program in the U.S. is a federal program, but benefit levels are set by each state, and states can freely adjust these parameters over time. Fuller, Auray, and Lkhagvasuren (2013) finds 23% of those collecting UI are affected by the maximum weekly benefit amount (MWBA).

Figure 3.3 plots the detrended GDP, which is the dashed line, and state-average MWBA [3], which is the solid line. Both series are HP filtered with a smoothing parameter 100. The shaded regions denote NBER recessions. It shows that MWBA rises around every recession. The correlation between the cyclical part of GDP and MWBA is -0.623. So MWBA is strongly counter-cyclical, which also makes the level of UI benefit counter-cyclical. As UI is counter-cyclical, the unemployment state is more attractive relative to OLF in recessions, and thus workers are more likely to choose unemployment rather than OLF. In the following, I use a model to evaluate this possible explanation.

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[3]Next step, I will average it out weighted by the population in each state.

Figure 3.3: Detrended GDP and State-average Maximum UI Weekly Benefit Amount
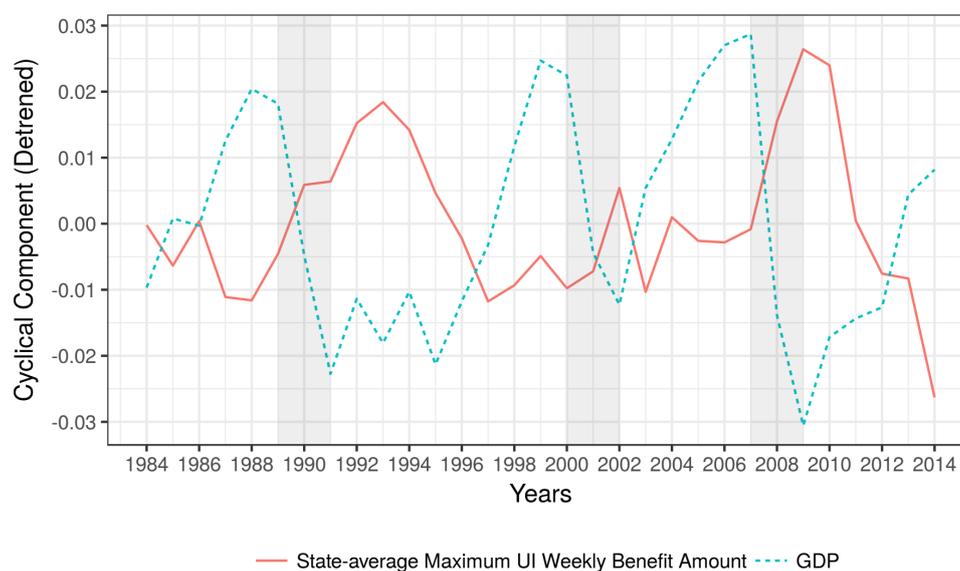
Note: NBER dated recessions are shaded. Both series are HP filtered with parameter 100.
Correlation between the two series is -0.623.

It might be optimal for the states to increase the unemployment insurance in recessions. A recession increased unemployment leads to less growth and a drop in consumer spending, affecting businesses, which lay off workers due to losses. A more generous UI can mitigate the business cycle shocks by reducing fluctuations in disposable income (Brown, 1955) or by redistributing funds towards individuals with higher propensity to consume than those who provide the funds (Blinder, 1975).

3.4   The Model

I present here an equilibrium search and matching mode with aggregate productivity shocks. The model is an extension of Robin (2011) allowing for endogenous job finding rate and endogenous labour force participation. Idiosyncratic shocks on worker's home productivity generate flows into and out of labour force.

3.4.1 Preliminaries

Time is discrete and denoted by t. The aggregate productivity is denoted by z_t, which is a Markov chain with transition probability $\pi(z_t, z_{t+1})$. The economy is populated by a unit mass of workers who are heterogeneous in 3 ways:

1. Labour market state (either employed, unemployed, or out-of-labour-force)

2. Permanent ability x

3. Stochastic home productivity ϵ

All firms are identical. They have access to a production technology

$$p_t(x) = z_t x$$

which combines the aggregate productivity z and worker's ability x. An employed worker is paid a wage w and searches on-the-job. A production match can be separated by an exogenous shock arriving at rate δ. It may also be terminated voluntarily if the match surplus becomes negative.

A worker who is out-of-labour-force (OLF) works at home. His home productivity is ϵ[4], which follows a Markov process with transition probability $\tau(\epsilon_t, \epsilon_{t+1})$. She searches for a job at a lower intensity comparing to an unemployed worker.

An unemployed worker actively searches for a job. She receives unemployment benefit $b(x, z)$ which is the minimum between the raw benefit amount $R(x)$ and the maximum benefit amount $B(z)$

$$b(x, z) = \min\{R(x), B(z)\}$$

I assume the raw benefit amount $R(x)$ is proportional to worker's ability x, which

---

[4]It is possible that home productivity is correlated with ability. This is a very interesting empirical topic, which requires data on time use. For this project, what's important is the relative value of UI benefit to home productivity. Let's assume home productivity is positively correlated with ability. As UI benefit is proportional to ability up to a cap, workers with higher ability get a constant UI and increasing home productivity. So workers with higher ability more prefer OLF than unemployment.

equals to her long-term income. The maximum benefit amount $B(z)$ is affected by aggregate productivity z. An unemployed worker works at home for a shorter time comparing to a worker who is in OLF, so she gets only part of the home production $\gamma \epsilon$. The flow value of an unemployed worker is

$$h(x, \epsilon, z) = b(x, z) + \gamma \epsilon$$

3.4.2 Value Functions

Let $W_t(w, x, \epsilon)$ denote the present value of a wage w for an employed worker of type (x, ϵ). The effect of aggregate shock z_t on the value function is captured in the time subscript t. Let $\Pi_t(w, x, \epsilon)$ denote the expected profit to the firm that employs the worker. Under the assumption of free entry, the value of a vacancy is 0 in equilibrium due to the competition between firms.

Let $U_t(x, \epsilon)$ denote the present value of an unemployed worker of type (x, ϵ), and let $H_t(x, \epsilon)$ denote the present value of a worker who is OLF. Assume no cost of switching between unemployment and OLF, a worker that is not employed decides whether to stay unemployment or OLF considering

$$N_t(x, \epsilon) = \max\{U_t(x, \epsilon), H_t(x, \epsilon)\}$$

where $N_t(x, \epsilon)$ can be thought as the present value of non-employment.

The Match surplus is defined in the same way as Robin (2011). It equals to the sum of the surplus to the worker and the surplus to the firm being matched

$$S_t(w, x, \epsilon) = W_t(w, x, \epsilon) - N_t(x, \epsilon) + \Pi_t(w, x, \epsilon)$$

Proposition 3. *(Lise and Robin, 2016) Under the assumption of transferable utility, the match surplus is not changed by the wage, and it depends on time only through the*

aggregate state z_t, i.e.

$$S_t(w, x, \epsilon) = S_t(x, \epsilon) = S(x, \epsilon, z_t)$$

I will first assume this equation holds, and verify that the match surplus indeed does not depend on w in section 3.4.5. The model has a block recursive structure that allows us to solve for decision rules regarding labour mobility without requiring knowledge of the entire distributions of the labour force. I can then simulate the evolution of these distributions using the realized sequence of z_t and the decision rules implied by $S(x, \epsilon, z_t)$.

3.4.3 Wage Contract

The wage is determined in the same way as Postel-Vinay and Robin (2002). Firms have full bargaining power. Workers hired from non-employment are given their reservation value $N_t(x, \epsilon)$. Employed workers always search on-the-job which may trigger Bertrand competition between firms. As firms are identical, the wage is raised until the worker extracts the whole surplus from the match. I assume the worker moves to the poaching firm with probability 0.5.

A non-employed worker are thus hired at wage $\underline{w}$ which solves

$$W_t(\underline{w}, x, \epsilon) - N_t(x, \epsilon) = 0 \tag{3.1}$$

When an employed worker is poached by an outside firm, she extracts the whole surplus from the match. Thus her wage $\bar{w}$ solves

$$W_t(\bar{w}, x, \epsilon) - N_t(x, \epsilon) = S_t(x, \epsilon) \tag{3.2}$$

A wage contract can be renegotiated to ensure the incentive-compatibility constraints are satisfied for both the worker and the firm.

$$0 \leq W_t(w, x, \epsilon) - N_t(x, \epsilon) \leq S_t(x, \epsilon)$$

$$0 \le \Pi_t\left(w, x, \epsilon\right) \le S_t\left(x, \epsilon\right)$$

3.4.4 Evolution of the Labour Distribution

Within each period, events happen in this order

- Time 1: The aggregate productivity shock and idiosyncratic home productivity shock realize.

- Time 2: Job separation and labour force participation take place. Vacancies are created.

- Time 3: Matching takes place.

Time 1

Let $l(x, \epsilon)$ denotes the measure of workers of type (x, ϵ) in the economy. At the beginning of period t, $e_t(x, \epsilon)$ is the measure of employed workers of type (x, ϵ), $u_t(x, \epsilon)$ is the measure of unemployed workers, and $o_t(x, \epsilon)$ is the measure of workers in OLF. Hence

$$u_t(x, \epsilon) + e_t(x, \epsilon) + o_t(x, \epsilon) = l(x, \epsilon)$$

Then the aggregate state changes from z_{t-1} to z_t, and each household receives a new realization of home productivity ϵ_t. The measure of employed workers of type (x, ϵ)changes to

$$\tilde{e}_t\left(x, \epsilon\right) = \int e_t(x, \epsilon')\tau(\epsilon', \epsilon)\mathrm{d}\epsilon$$

which is the aggregate of all employed workers of ability x whose new home productivity is ϵ.

Time 2

All matches with negative surplus $S_t\left(x, \epsilon\right) < 0$ are destroyed endogenously, and a fraction δ of viable matches, with $S_t\left(x, \epsilon\right) \ge 0$, are destroyed exogenously. The measure of

employed workers of type (x, ϵ) after shocks are

$$e_{t+}(x, \epsilon) = (1 - \delta)\mathbf{1}\{S_t(x, \epsilon) > 0\}\tilde{e}_t(x, \epsilon)$$

Non-employed workers, including those newly separated from their jobs, decide whether to enter unemployment or OLF. Workers choose unemployment if the flow value of unemployment is greater than that of OLF

$$h_t(x, \epsilon) > \epsilon$$
$$b_t(x) + \gamma\epsilon > \epsilon$$
$$b_t(x) > (1 - \gamma)\epsilon$$

i.e. unemployment insurance from unemployment must be larger than the extra home production from OLF. Then at intermediate stage $t+$, the measure of unemployed workers of type (x, ϵ) equals

$$u_{t+}(x, \epsilon) = [l(x, \epsilon) - e_{t+}(x, \epsilon)]\,\mathbf{1}\{b_t(x) > (1 - \gamma)\epsilon_t\}$$

The rest enter OLF

$$o_{t+}(x, \epsilon) = l(x, \epsilon) - e_{t+}(x, \epsilon) - u_{t+}(x, \epsilon)$$

The search intensity of the unemployed workers is normalized to 1. Relative to the unemployed, the search intensities of the employed and nonparticipants are s_e and s_o respectively. They together produce effective search effort

$$L_t = \iint [u_{t+}(x, \epsilon) + s_e e_{t+}(x, \epsilon) + s_o o_{t+}(x, \epsilon)]\,\mathrm{d}x\mathrm{d}\epsilon$$

which equals the aggregate of the measure of workers multiplied by corresponding search intensities. Firms observe the new state and decide to post V_t vacancies.

Time 3

Then the total number of new matches in period t is

$$M_t = L_t^{1-\alpha} V_t^{\alpha} \tag{3.3}$$

The derivation of matches is in Appendix B.1. Define $\lambda_{u,t} = \frac{M_t}{L_t}$ as the probability an unemployed worker meets a vacancy in period t, and $\lambda_{o,t} = s_o \frac{M_t}{L_t} = s_o \lambda_{u,t}$ as the probability a nonparticipant meets a vacancy. A worker is hired if $S_t(x, \epsilon) \geq 0$. So the measure of new matches of type (x, ϵ) from unemployment is

$$u_{t+}(x, \epsilon)\lambda_{u,t}\mathbf{1}\left\{S_t(x, \epsilon) \geq 0\right\}$$

and that from OLF is

$$o_{t+}(x, \epsilon)\lambda_{o,t}\mathbf{1}\left\{S_t(x, \epsilon) \geq 0\right\}$$

Then after the matching, the measure of employed workers is augmented by the new matches

$$e_{t+1}(x, \epsilon) = e_{t+}(x, \epsilon) + \left[u_{t+}(x, \epsilon)\lambda_{u,t} + o_{t+}(x, \epsilon)\lambda_{o,t}\right]\mathbf{1}\left\{S_t(x, \epsilon) \geq 0\right\}$$

which continues to the beginning of next period. The measure of unemployed workers and nonparticipants becomes

$$u_{t+1}(x, \epsilon) = u_{t+}(x, \epsilon)\left(1 - \lambda_{u,t}\mathbf{1}\left\{S_t(x, \epsilon) \geq 0\right\}\right)$$

$$o_{t+1}(x, \epsilon) = o_{t+}(x, \epsilon)\left(1 - \lambda_{o,t}\mathbf{1}\left\{S_t(x, \epsilon) \geq 0\right\}\right)$$

3.4.5 Derivation of Match Surplus

The value of Non-employment

Consider a worker of type (x, ϵ) who is unemployed for the whole period t. During that period, she gets unemployment benefit $b_t(x)$ and part of the home production $\gamma\epsilon$. In period $t + 1$, she will meet a vacancy with probability $\lambda_{u,t}$. Hence

$$U_t(x, \epsilon) = b_t(x) + \gamma\epsilon + \frac{1}{1+r}\mathbb{E}_t\left[(1 - \lambda_{u,t})N_{t+1}(x, \epsilon') + \lambda_{u,t}\max\left\{W_t(\underline{w}, x, \epsilon'), N_{t+1}(x, \epsilon')\right\}\right]$$

Reminding that firms offer workers from non-employment their reservation wages (equation 3.1), the continuation value is always the value of non-employment in period $t + 1$, $N_{t+1}(x, \epsilon')$. Hence

$$U_t(x, \epsilon) = b_t(x) + \gamma\epsilon + \frac{1}{1+r}\mathbb{E}_t N_{t+1}(x, \epsilon') \tag{3.4}$$

Similarly, for a worker who is in OLF for the whole period t, her value is

$$H_t(x, \epsilon) = \epsilon + \frac{1}{1+r}\mathbb{E}_t N_{t+1}(x, \epsilon') \tag{3.5}$$

Then the value of non-employment is

$$N_t(x, \epsilon) = \max\left\{b_t(x) + \gamma\epsilon, \epsilon\right\} + \frac{1}{1+r}\mathbb{E}_t N_{t+1}(x, \epsilon')$$

The value of employment

Consider a worker of type (x, ϵ) who is employed at wage w for the whole period t. In period $t + 1$, she will become unemployed or remain employed. If she remains employed, she will be contacted by another firm with probability $\lambda_{e,t+1}$. Hence the value

of employment is

$$W_t \left(w, x, \epsilon \right) = w + \frac{1}{1+r} \mathbb{E}_t \max \left[\left[\mathbf{1} \left\{ S_{t+1} \left(x, \epsilon' \right) < 0 \right\} + \delta \mathbf{1} \left\{ S_{t+1} \left(x, \epsilon' \right) \geq 0 \right\} \right] N_{t+1} \left(x, \epsilon' \right) \right.$$

$$+ \left(1 - \delta \right) \mathbf{1} \left\{ S_{t+1} \left(x, \epsilon' \right) \geq 0 \right\} \left[\lambda_{e,t+1} W_{t+1} \left(\bar{w}, x, \epsilon' \right) \right.$$

$$\left. \left. + \left(1 - \lambda_{e,t+1} \right) \left[N_{t+1} \left(x, \epsilon' \right) + \min \left\{ \max \left\{ W_{t+1} \left(w, x, \epsilon' \right) - N_{t+1} \left(x, \epsilon' \right), 0 \right\}, S_{t+1} \left(x, \epsilon' \right) \right\} \right] \right] \right]$$

According to wage equation (3.1) and (3.2), the surplus to a worker employed at wage w is

$$W_t \left(w, x, \epsilon \right) - N_t \left(x, \epsilon \right) = w - \max \left\{ b_t \left(x \right) + \gamma \epsilon, \epsilon \right\} + \frac{1}{1+r} \mathbb{E}_t \max \left[\left(1 - \delta \right) \mathbf{1} \left\{ S_{t+1} \left(x, \epsilon' \right) \geq 0 \right\} \right.$$

$$\left. \times \left[\lambda_{e,t+1} S_{t+1} \left(x, \epsilon' \right) + \left(1 - \lambda_{e,t+1} \right) \min \left\{ \max \left\{ W_{t+1} \left(w, x, \epsilon' \right) - N_{t+1} \left(x, \epsilon' \right), 0 \right\}, S_{t+1} \left(x, \epsilon' \right) \right\} \right] \right]$$

$$(3.6)$$

The value of a filled job

Consider a firm who is matched with a worker of type (x, ϵ) and pays wage w. During that period, the firm produces $p_t \left(x \right)$. In period $t + 1$, the firm can still earn a profit if the match is not terminated and the worker is not poached by another firm. Hence the value of a filled job is

$$\Pi_t \left(w, x, \epsilon \right) = p_t \left(x \right) - w + \frac{1}{1+r} \mathbb{E}_t \max \left[\left(1 - \delta \right) \mathbf{1} \left\{ S_{t+1} \left(x, \epsilon' \right) \geq 0 \right\} \right.$$

$$\left. \times \left(1 - \lambda_{e,t+1} \right) \min \left\{ \max \left\{ \Pi_{t+1} \left(w, x, \epsilon' \right), 0 \right\}, S_{t+1} \left(x, \epsilon' \right) \right\} \right] \quad (3.7)$$

The match surplus

Making use of equation (3.6) and (3.7), the match surplus is

$$S_t \left(x, \epsilon \right) = W_t \left(w, x, \epsilon \right) - N_t \left(x, \epsilon \right) + \Pi_t \left(w, x, \epsilon \right)$$

$$= p_t \left(x \right) - \max \left\{ b_t \left(x \right) + \gamma \epsilon, \epsilon \right\}$$

$$+ \frac{1}{1+r} \mathbb{E}_t \max \left[\left(1 - \delta \right) \mathbf{1} \left\{ S_{t+1} \left(x, \epsilon' \right) \geq 0 \right\} \left[\lambda_{e,t+1} S_{t+1} \left(x, \epsilon' \right) + \left(1 - \lambda_{e,t+1} \right) S_{t+1} \left(x, \epsilon' \right) \right] \right]$$

which simplifies to

$$S_t\left(x,\epsilon\right) = p_t\left(x\right) - \max\left\{b_t\left(x\right) + \gamma\epsilon, \epsilon\right\} + \frac{1-\delta}{1+r}\mathbb{E}_t\max\left\{S_{t+1}\left(x,\epsilon'\right), 0\right\} \tag{3.8}$$

So the surplus depends on time only through z_t. There exists a deterministic solution $S_t\left(x,\epsilon\right) = S\left(x,\epsilon,z_t\right)$ to that equation:

$$S\left(x,\epsilon,z\right) = p\left(x,z\right) - \max\left\{b\left(x,z\right) + \gamma\epsilon, \epsilon\right\} + \frac{1-\delta}{1+r}\mathbb{E}[S\left(x,\epsilon',z'\right)^+ |\epsilon, z]$$

$$= p\left(x,z\right) - \max\left\{b\left(x,z\right) + \gamma\epsilon, \epsilon\right\} + \frac{1-\delta}{1+r}\iint S\left(x,\epsilon',z'\right)^+ \tau\left(\epsilon,\epsilon'\right)\pi(z,z')\mathrm{d}\epsilon'\mathrm{d}z'$$

where $S^+ = \max\left\{S, 0\right\}$.

3.5 Estimation

3.5.1 Parameter Specification

A period is a month. I set the real interest rate $r = 0.048$ annually, which is the average of the 3-month Treasury Bill in 1979-2014. I assume the discount factor β is the inverse of the real interest rate, i.e. $\beta = \frac{1}{1+r}$. I assume worker's ability x is beta distributed, s.t.

$$\left(x - \frac{\eta_\beta}{\eta_\alpha + \eta_\beta}\right) \sim \text{Beta}\left(\eta_\alpha, \eta_\beta\right)$$

where the mean $\mathbb{E}\left(x\right) = 1$. The aggregate productivity shock z is log-normal distributed

$$\log z \sim \mathcal{N}(-\frac{\sigma_z^2}{2}, \sigma_z^2)$$

where the mean $\mathbb{E}\left(z\right) = 1$. The i.i.d home productivity shock ϵ is also log-normal distributed

$$\log \epsilon \sim \mathcal{N}(\log\mu_\epsilon - \frac{\sigma_\epsilon^2}{2}, \sigma_\epsilon^2)$$

where the mean $\mathbb{E}\left(\epsilon\right) = \mu_\epsilon$. The Markov transition probability $\tau(\epsilon_t, \epsilon_{t+1})$ and $\pi(z_t, z_{t+1})$ are constructed using Gaussian copula with parameter ρ_ϵ and ρ_z respectively. Using

JOLTS data, Robin (2011) finds that the job arrival rate for the employed is 12% of that for the unemployed. So I set $s_e = 0.12$. Following Shimer (2005), the elasticity of the matching function $\alpha = 0.28$, which was estimated from data on vacancies and unemployment.

Unemployment insurance benefit is the minimum between the raw benefit amount $R(x)$ and the maximum benefit amount $B(z)$

$$b(x,z) = \min\{R(x), B(z)\}$$
$$R(x) = b_1 x$$
$$B(z) = \begin{cases} b_2 & \text{if } z \geq \tilde{z} \\ b_2 + b_3(\tilde{z} - z) & \text{if } z < \tilde{z} \end{cases}$$

Here the raw benefit amount $R(x)$ is proportional to worker's ability x, where b_1 is the replacement rate and equals to 0.5. I assume there is a threshold $\tilde{z}$. If the aggregate productivity z is above $\tilde{z}$, the maximum benefit amount equals b_2. If the aggregate productivity falls below $\tilde{z}$, the government will raise the maximum benefit amount to $b_2 + b_3$.

3.5.2   Data Moments

Given the parameter specifications above, there are 14 parameters to be estimated:

$$b_2, b_3, \tilde{z}, \gamma, \rho_z, \sigma_z, \mu_\epsilon, \rho_\epsilon, \sigma_\epsilon, c, s_o, \delta, \eta_\alpha, \eta_\beta$$

I estimate the model by the method of simulated moments. The data moments I target in estimation are listed in Table 3.5. I target at following 22 moments:

- Standard deviation and auto-correlation of log GDP;

- Standard deviation of maximum weekly benefit amount (MWBA); Correlation between GDP and MWBA; Ratio of MWBA to mean wage;

- Mean, standard deviation, and GDP correlation of the employment population rate, unemployment rate, and labour force participation rate;

- GDP correlation of job separation rate into unemployment and OLF.

- Mean and GDP correlation of transition rates between employment, unemployment, and OLF

Although all parameters are determined simultaneously, I can describe the identification in a heuristic way:

- The parameters of the aggregate productivity shock, ρ_z and σ_z, are identified by the standard deviation and auto-correlation of log GDP.

- The parameters of maximum benefit amount, b_2, b_3 and $\tilde{z}$, are identified by the moments of maximum weekly benefit amount.

- The proportion of home production when unemployed γ and the mean of the home productivity μ_ϵ are identified by the level of employment population rate, unemployment rate, and labour force participation rate.

- The persistence and standard deviation of home productivity, ρ_ϵ and σ_ϵ, are identified by the standard deviation and cyclicality of labour force participation rate.

- The parameters of the ability distribution, η_α and η_β, are identified by the standard deviation and cyclicality of the employment population rate and unemployment rate.

- The mobility parameters, δ, c and s_o, are identified by the transition rates.

Please note, I only match the GDP correlation of transition rates out of employment (E2U and E2O). I reserve the GDP correlation of other transition rates (U2E, U2O, O2E and O2U) for out of sample analysis. I construct these from Current Population Survey 1979~2014. As GDP is only provided on a quarterly frequency, I take the quarterly average for all monthly series. Then I log and HP filter the data with smoothing parameter 10^5 to produce business cycle statistics.

Table 3.4: Parameter Estimates

Description	Param.	Value
Unemployment Insurance	b_2	0.432
$B(x, z) = \min\{0.5x, b_2 + b_3 \mathbf{1}\{z < \tilde{z}\}\}$	b_3	0.013
	$\tilde{z}$	0.988
Proportion of home production when unemployed	γ	0.406
Aggregate productivity shock z	ρ_z	0.977
	σ_z	0.027
Home productivity shock ϵ	μ_ϵ	0.750
	ρ_ϵ	0.944
	σ_ϵ	0.109
Vacancy posting cost	c	7.927
Search intensity in OLF	s_o	0.207
Exogenous separation	δ	0.036
Worker ability $x \sim \text{Beta}(\eta_\alpha, \eta_\beta)$	η_α	2.246
	η_β	4.608

Note: MWBA is maximum weekly benefit amount; E-pop is the employment population rate; U-rate is the unemployment rate; LF is the labour force participation rate; E denotes employment; U denotes unemployment; O denotes OLF.

3.5.3 Estimation Results

The parameter estimates are displayed in Table 3.4. The level of maximum benefit amount during normal times is estimated to be 0.432. In recessions that z fells below 0.988, maximum benefit amount increases by 0.013, which is about 3%. The proportion of home production when unemployed is 0.4. The monthly aggregate productivity shock has a standard deviation of 0.027 and persistence of 0.977. The i.i.d home productivity shock ϵ has a mean of 0.75, standard deviation of 0.1 and persistence of 0.944. The cost of posting a vacancy is 7.9. Relative to active search in unemployment, the intensity of passive search in OLF is 0.2. The monthly exogenous job separation rate is 0.036. The ability $x \sim \text{Beta}(2.2, 4.6)$, which is skewed to the left.

The data moments and their model simulations are shown in columns "Data" and "Base" of Table 3.5. Overall the model fits the moments very well. One success of the model is that it can match the transition rates. For example, it improves the fit of the transition rate from unemployment to OLF (U2O) in Krusell, Mukoyama,

Rogerson, and Sahin (2016). Another success is that it can match the acyclicality of labour force participation rate, which is very high in standard search models (Tripier, 2004). Besides, the model can successfully generate the observed cyclicality of the job separation rate into OLF (E2O) and the job separation rate into unemployment (E2U) in the data.

3.6 Results Analysis

3.6.1 Constant Unemployment Insurance

To examine the importance of counter-cyclical UI, I run the counter-factual simulation where the UI is constant over the business cycle. Specifically, I set the cyclical change in maximum benefit amount $b_3 = 0$. Then I adjusted the level of maximum benefit amount during normal times b_2, so that the government expense on UI is the same as that in the baseline. Then b_2 is raised from 0.432 to 0.438.

The result is showed in the column labelled "UI Constant" of table 3.5. By definition, it does not produce dispersion in maximum benefit amount. As you can see, constant UI policy doubles the standard deviation of employment and increases the procyclicality of employment by 17%. Besides it also increases the standard deviation of GDP by 50%. So a counter-cyclical UI policy, as we have in reality, has the effect of stabilizing the economy by reducing the variation in employment and GDP.

On the other hand, with constant UI, labour force participation becomes strongly procyclical. What's more, the job separation rate into OLF (E2O) also changes from procyclical to counter-cyclical. So counter-cyclical UI is important in explaining the acyclicality of labour force participation.

3.6.2 Cutoff Margins and Acyclical Labour Force Participation

To explain the acyclical labour force participation, let me define two cutoff margins (x_s, ϵ_s) and (x_q, ϵ_q) where x and ϵ are worker's ability and home productivity respec-

Table 3.5: Model Fit

Moments	Data	Base	UI Constant
$\mathbb{E}\left(E-pop\right)$	0.767	0.754	0.753
$\mathbb{E}\left(U-rate\right)$	0.052	0.052	0.052
$\mathbb{E}\left(LF\right)$	0.809	0.795	0.795
$\mathbb{E}\left(E2U\right)$	0.012	0.011	0.011
$\mathbb{E}\left(E2O\right)$	0.017	0.021	0.021
$\mathbb{E}\left(U2E\right)$	0.252	0.252	0.252
$\mathbb{E}\left(U2O\right)$	0.182	0.154	0.152
$\mathbb{E}\left(O2E\right)$	0.063	0.067	0.067
$\mathbb{E}\left(O2U\right)$	0.037	0.040	0.040
$\mathbb{E}\left(MBA\right)/\mathbb{E}\left(wage\right)$	0.55	0.570	0.573
$\mathbf{sd}\left(E-pop\right)$	0.013	0.008	0.017
$\mathbf{sd}\left(U-rate\right)$	0.207	0.129	0.066
$\mathbf{sd}\left(LF\right)$	0.004	0.008	0.013
$\mathbf{sd}\left(MBA\right)$	0.012	0.012	Na
$\mathbf{sd}\left(GDP\right)$	0.024	0.024	0.035
$\mathbf{autocorr}\left(GDP\right)$	0.954	0.938	0.960
$\mathbf{corr}\left(E-pop,GDP\right)$	0.796	0.840	0.981
$\mathbf{corr}\left(U-rate,GDP\right)$	-0.827	-0.828	-0.993
$\mathbf{corr}\left(LF,GDP\right)$	0.129	0.129	0.977
$\mathbf{corr}\left(E2U,GDP\right)$	-0.749	-0.766	-0.999
$\mathbf{corr}\left(E2O,GDP\right)$	0.551	0.551	-0.456
$\mathbf{corr}\left(MBA,GDP\right)$	-0.528	-0.731	Na

Note: "MBA" is the maximum benefit amount; "E-pop" is the employment population rate; "U-rate" is the unemployment rate; "LF" is the labour force participation rate; "E" denotes employment; "U" denotes unemployment; "O" denotes OLF.
"Base": baseline simulation. "UI Constant": maximum benefit amount is constant over the business cycle, and its level is adjusted so that the government expense on UI is the same as that in the baseline.

tively

$$H_t\left(x_s, \epsilon_s\right) = U_t\left(x_s, \epsilon_s\right) \tag{3.9}$$

$$S_t\left(x_q, \epsilon_q\right) = 0 \tag{3.10}$$

The first indifference condition 3.9 defines an active search margin (x_s, ϵ_s), a level of individual characteristics at which the worker is indifferent between active search (unemployment) and passive search (OLF). According to Equation 3.4 and 3.5, the active search margin yields

$$(1 - \gamma)\,\epsilon = b\left(x, z\right)$$

This states that the forgone value of home production must be compensated by an equivalent gain in unemployment benefit. Then I have

$$(1 - \gamma)\,\epsilon = \min\left\{R\left(x\right), B\left(z\right)\right\}$$

$$\epsilon = \frac{1}{1 - \gamma}\min\left\{b_1 x, B\left(z\right)\right\} \tag{3.11}$$

This equation defines ϵ as a linear function of x, up to a maximum $B\left(z\right)$ depending on aggregate state z. On a graph with x on the x-axis and ϵ on the y-axis, equation 3.11 defines (x_s, ϵ_s) as a straight line from the origin, while the value of z changes the maximum.

The second indifference condition 3.10 defines an endogenous quit margin (x_q, ϵ_q), a level of individual characteristics at which any job match with the worker has 0 surplus. Below this level, an employed worker endogenously quits from her job. Equation 3.8 yields

$$S_t\left(x, \epsilon\right) = 0 = p_t\left(x\right) - \max\left\{b_t\left(x\right) + \gamma\epsilon, \epsilon\right\} + \frac{1 - \delta}{1 + r}\mathbb{E}_t \max\left\{S_{t+1}\left(x, \epsilon'\right), 0\right\}$$

$$\max\left\{b_t\left(x\right) + \gamma\epsilon, \epsilon\right\} = z_t x + \frac{1 - \delta}{1 + r}\mathbb{E}_t \max\left\{S_{t+1}\left(x, \epsilon'\right), 0\right\}$$

It states that the marginal worker at the endogenous quit margin has the flow value of

non-employment equals to output plus expected match surplus. As $\max\left\{S_{t+1}\left(x,\epsilon'\right),0\right\}$ is not negative, the flow value in non-employment for the marginally indifferent worker is greater or equal to the output. Similar to 3.11, this equation also defines (x_q, ϵ_q) as a line between ϵ and x. As $\mathbb{E}_t \max\left\{S_{t+1}\left(x,\epsilon'\right),0\right\}$ increases in x and decreases in ϵ, (x_q, ϵ_q) is not a straight line.

I plot (x_s, ϵ_s) and (x_q, ϵ_q) on the same coordinate axes using estimated parameters in Figure 3.4. The x-axis is ability x, and the y-axis is the stochastic home productivity shock ϵ, and each point on the graph is an individual state (x, ϵ). The active search margin (x_s, ϵ_s) is the solid line in the lower part of the graph. The dotted line on the top is the endogenous quit margin (x_q, ϵ_q). The graph is partitioned into three areas:

1. In the area above the endogenous quit margin (x_q, ϵ_q), one finds only workers in OLF who have negative match surplus. They do not work even job opportunities are presented.

2. In the area between (x_q, ϵ_q) and (x_s, ϵ_s), one finds either employed workers or workers in OLF. They all have positive match surplus, but their forgone value of home production is greater than unemployment benefit. For the employed workers, they will drop out of the labour force if their jobs terminate. For the workers in OLF, they desire work but their search intensity is only 20% of the unemployed workers ($s_o = 0.2$). Following Jones and Riddell (1999), they are called marginally attached workers.

3. In the area below the active search margin (x_s, ϵ_s), one finds either employed workers or unemployed workers. Their forgone value of home production is smaller than unemployment benefit. For the employed workers, they will stay in labour force if their jobs terminate.

Figure 3.5 shows the same graph across the business cycle. The solid line is the endogenous quit margin in a boom, and the dashed line is the same margin in a reces-

Figure 3.4: Active Search Margin and Endogenous Quit Margin
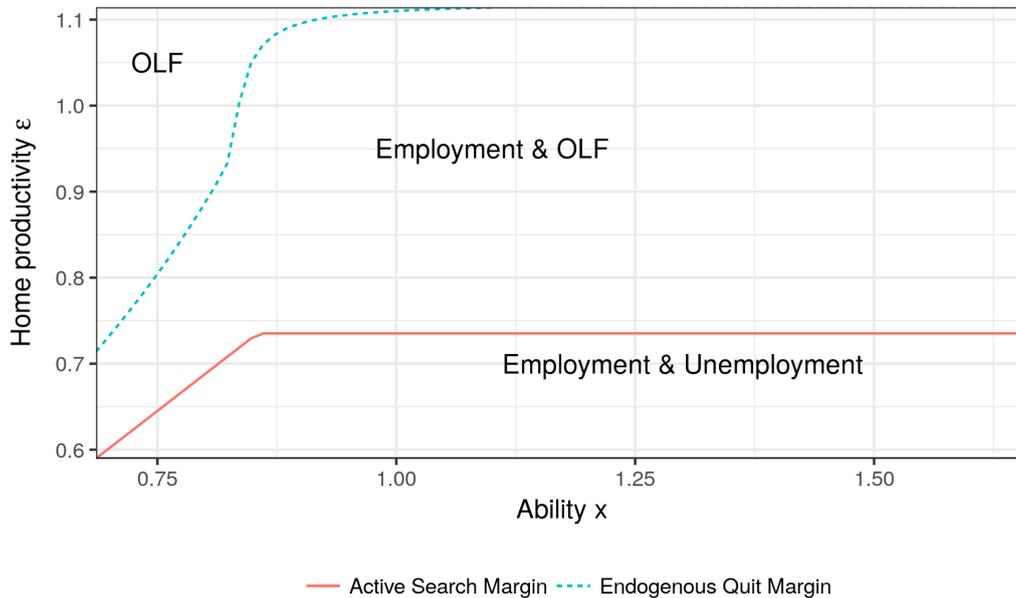
sion. The Boom shifts the endogenous quit margin upwards comparing to the recession, which means more workers have a positive surplus and workers expand the set of individual characteristics in which they want to work. That's why standard theory predicts the labour force participation should increase in booms.

Why is labour force participation acyclical in the data? In Figure 3.5, the line dotted by round points is the active search margin in a boom, and the line dotted by triangles is the same margin in a recession. Equation 3.11 shows that an increase in aggregate state z (boom) reduces maximum benefit amount $B(z)$ and unemployment insurance. So the boom shifts the active search margin downwards comparing to the recession. It means workers reduce the set of individual characteristics in which they want to work. I call it the offset force that reduces the procyclicality of labour force participation.

3.6.3 Transition Rates between the Labour Force States

Table 3.6 shows the cyclicality of transition rates between three labour force states from the data and from the model. Only GDP correlations of E2O and E2U are targeted

Figure 3.5: Cutoff Margins in Boom and Recession

Legend:
- Boom Active Search Margin
- Recession Active Search Margin
- Boom Endogenous Quit Margin
- Recession Endogenous Quit Margin
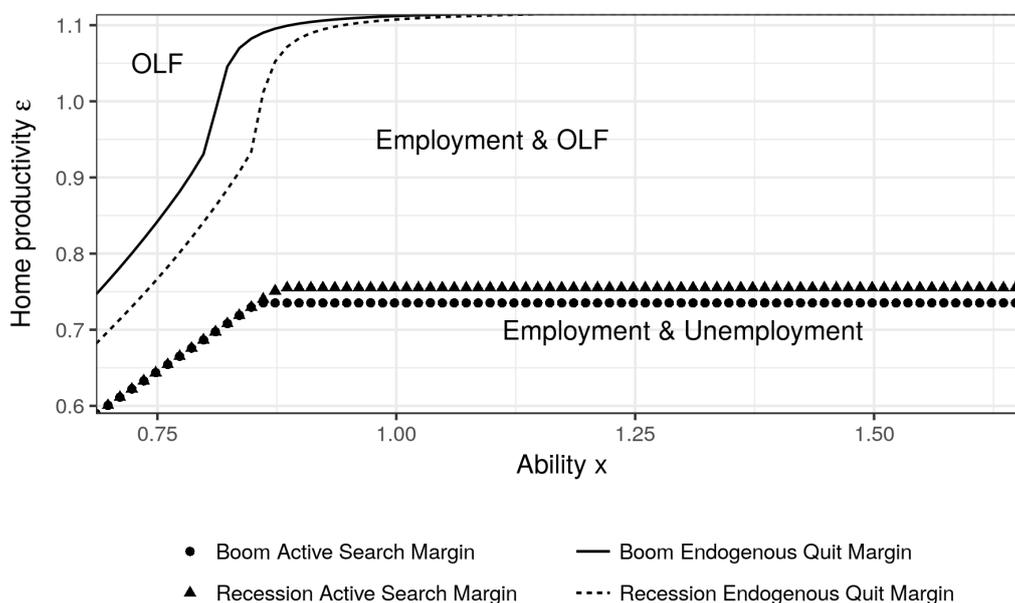
Table 3.6: Cyclicality of Transition Rates between the Labour Force States

Corr. with log GDP	E2U	E2O	U2E	U2O	O2E	O2U
Data	-0.749	0.551	0.785	0.625	0.792	-0.791
Model	-0.766	0.551	0.920	0.475	0.907	-0.398

Note: "E2U" and "E2O" are the transition rates from employment to unemployment and to OLF. "U2E" and "U2O" are those from unemployment to employment and to OLF. "O2E" and "O2U" are those from OLF to employment and to unemployment. Only E2U and E2O are targeted in the estimation.

in the estimation. GDP correlations of the other transition rates are used to provide an out-of-sample fit of the model. I find that the model reasonably captures the cyclicality of the other four transition rates as well.

The most counter-intuitive pattern in the data is the job separation rate into OLF (E2O) is procyclical, i.e. a larger proportion of employed workers drop out of the labour force in booms. This is striking as workers should want to work more in booms. I find the procyclicality of E2O is connected with the counter-cyclicality of E2U. According to Figure 3.5, active search margin shift downwards in booms, which means non-

employed workers expand the set of individual characteristics in which they want to be OLF rather than unemployed in booms. So employed workers hit by job separation shock are more likely to enter OLF than unemployment. So conditional on leaving employment, E2O is higher in booms, and E2U is lower in booms. Similarly, due to the downward shift of active search margin in booms, some unemployed workers drop out of the labour force, which could explain procyclicality of transition from unemployment to OLF (U2O).

The transition rates from unemployment to employment (U2E) is procyclical, because the endogenized job finding probability is procyclical. The transition rates from OLF to employment (O2E) is procyclical, not only due to the procyclicality of job finding probability, but also the upward shift of the endogenous quit margin in booms in Figure 3.5. It shows that nonparticipants expand the set of individual characteristics in which they want to work in booms. The procyclicality of O2E helps to explain the counter-cyclicality of OLF to unemployment (O2U): conditional on entering the labour force, nonparticipants are more likely to find a job and become employed rather than become unemployed.

3.7 Conclusion

In this paper, I study why labour market participation is acyclical. Standard theories of labour market predict that workers should search less when the returns to search are low, yielding the counter-factual prediction that labour market participation should be strongly pro-cyclical — decrease in recessions. I argue that the unemployment insurance benefit (UI) is the reason for this pattern. I find that the Maximum UI Weekly Benefit Amount is negatively correlated with the business cycle,

I embed this feature into an equilibrium search model with aggregate shocks and endogenous labour force participation. Using this model, I show that counter-cyclical UI makes unemployment more attractive in recessions, leading fewer workers to drop out of the labour force. This model can capture the key features of the cyclical move-

ments in labour market stocks and gross worker flows. Although the cyclical variation in the level of UI is small, it plays an important role in shaping fluctuations in the participation rate. The model also shows that counter-cyclical UI has the effect of stabilizing the economy by reducing the variation in employment and GDP.

Note on Co-authored Work

Note on the joint work in Ran Gu's thesis "Asymmetric Information, Durables, the Business Cycle, and the Labour Market".

Chapter 1, "Adaptation Costs, Asymmetric Information, and the Business Cycle Effects on the Postgraduate Wage Premium", is single-authored by Ran Gu.

Chapter 2, "Asymmetric Information, Durables, and Earnings Shocks", is co-authored between Richard Blundell, Ran Gu, Soren Leth-Petersen, Hamish Low and Costas Meghir. Each author contributed equally to the paper.

Chapter 3, "The Impact of Unemployment Insurance on the Cyclicality of Labour Force Participation" is single-authored by Ran Gu.

Bibliography

ABOWD, J., AND A. ZELLNER (1985): "Estimating gross labor-force flows," *Journal of Business & Economic Statistics*, 3(3), 254–283.

ADDA, J., AND R. COOPER (2000): "Balladurette and Juppette: A Discrete Analysis of Scrapping Subsidies," *Journal of Political Economy*, 108(4), 778–806.

AKERLOF, G. A. (1970): "The Market for "Lemons": Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 84(3), 488–500.

ALESSIE, R., M. DEVEREUX, AND G. WEBER (1997): "Intertemporal consumption, durables and liquidity constraints: A cohort analysis," *European Economic Review*, 41, 31–59.

ALTONJI, J. G., AND N. WILLIAMS (2005): "Do wages rise with job seniority? A reassessment," *Industrial and Labor Relations Review*, 58(3).

ATTANASIO, O. P. (2000): "Consumer Durables and Inertial Behaviour: Estimation and Aggregation of (8 , s) Rules for Automobile Purchases," *The Review of Economic Studies*, 67(4), 667–696.

ATTANASIO, O. P., P. K. GOLDBERG, AND E. KYRIAZIDOU (2008): "Credit Constraints in the Market for Consumer Durables," *International Economic Review*, 49(2), 401–436.

ATTANASIO, O. P., AND G. WEBER (1995): "Is consumption growth consistent with

intertemporal optimization? Evidence from the consumer expenditure survey," *Journal of Political Economy*, 103(6), 1121–1157.

AZARIADIS, C. (1975): "Implicit Contracts and Underemployment Equilibria," *Journal of Political Economy*, 83(6), 1183–1202.

BAILY, M. N. (1974): "Wages and Employment under Uncertain Demand," *Review of Economic Studies*, 41(1), 37–50.

BECKER, G. (1962): "Investment in Human Capital : A Theoretical Analysis," *Journal of Political Economy*, 70(5), 9–49.

BLATTER, M., S. MUEHLEMANN, AND S. SCHENKER (2012): "The costs of hiring skilled workers," *European Economic Review*, 56(1), 20–35.

BLINDER, A. S. (1975): "Distribution Effects and the Aggregate Consumption Function," *Journal of Political Economy*, 83(3), 447.

BLUNDELL, R., L. PISTAFERRI, AND I. PRESTON (2008): "Consumption inequality and partial insurance," *American Economic Review*, 98(5), 1887–1921.

BROWN, E. C. (1955): "The Static Theory of Automatic Fiscal Stabilization," *Journal of Political Economy*, 63(5), 427–440.

BROWNING, M., AND S. LETH-PETERSEN (2003): "Imputing consumption from income and wealth information," *Economic Journal*, 113(488).

BUSSE, M. R., C. R. KNITTEL, AND F. ZETTELMEYER (2013): "Are Consumers Myopic ? Evidence from New and Used Car Purchases," *American Economic Review*, 103(1), 220–256.

CAIRÓ, I., AND T. CAJNER (2016): "Human capital and unemployment dynamics: why more-educated workers enjoy greater employment stability," *Economic Journal*, 44, 1–40.

CHAPMAN, B. J., AND H. W. TAN (1980): "Specific Training and Inter-Industry Wage Differentials in U. S. Manufacturing," *The Review of Economics and Statistics*, 62(3), 371–378.

CHERNOZHUKOV, V., AND H. HONG (2003): "An MCMC approach to classical estimation," *Journal of Econometrics*, 115(2), 293–346.

CHODOROW-REICH, G., AND L. KARABARBOUNIS (2016): "The Cyclicality of the Opportunity Cost of Employment," *Journal of Political Economy*, 60637(June), 1–27.

EBERLY, J. C. (1994): "Adjustment of Consumers' Durables Stocks: Evidence from Automobile Purchases," *Journal of Political Economy*, 102(3), 403–436.

ELSBY, M. W. L., B. HOBIJN, AND A. SAHIN (2015): "On the Importance of the Participation Margin for Labor Market Fluctuations," *Journal of Monetary Economics*, 72(C), 64–82.

FARBER, H. S., AND R. G. VALLETTA (2013): "Do Extended Unemployment Benefits Lengthen Unemployment Spells? Evidence from Recent Cycles in the US Labor Market," .

FOOTE, B. C., E. HURST, AND J. LEAHY (2000): "Testing the (S , s) Model," *American Economic Review*, 90(2).

FULLER, D. L., S. AURAY, AND D. LKHAGVASUREN (2013): "Unemployment Insurance Take-up Rates in an Equilibrium Search Model," *Working Paper*.

GAVAZZA, A., A. LIZZERI, AND N. ROKETSKIY (2014): "A Quantitative Analysis of the Used Car Market," *American Economic Review*, (April), 1–39.

GUVENEN, F., S. OZKAN, AND J. SONG (2014): "The Nature of Countercyclical Income Risk," *Journal of Political Economy*, 122(3), 621–660.

HEATHCOTE, J., K. STORESLETTEN, AND G. L. VIOLANTE (2010): "The Macroeconomic Implications of Rising Wage Inequality in the United States," *The Journal of Political Economy*, 118(4), 681–722.

HECKMAN, J. J. (1979): "Sample Selection Bias as a Specification Error," *Econometrica*, 47(1), 153–161.

HENDEL, I., AND A. LIZZERI (1999): "Adverse Selection in Durable Goods Markets," *American Economic Review*, 89(5), 1097–1115.

HUDOMIET, P. (2015): "The role of occupation specific adaptation costs in explaining the educational gap in unemployment," *Working Paper*.

JONES, S. R. G., AND W. C. RIDDELL (1999): "The measurement of unemployment: an empirical approach," *Econometrica*, 67(1), 147–161.

KEANE, M., AND E. PRASAD (1993): "Skill Levels and the Cyclical Variability of Employment, Hours, and Wages," *Staff Papers (International Monetary Fund)*, 40(4), 711–743.

KRUSELL, P., T. MUKOYAMA, R. ROGERSON, AND A. SAHIN (2016): "Gross Worker Flows over the Business Cycle," .

LAGAKOS, D., AND G. ORDONEZ (2011): "Which Workers Get Insurance Within the Firm?," *Journal of Monetary Economics*, 58.

LAM, P.-S. (1991): "Permanent Income, Liquidity, and Adjustments of Automobile Stocks: Evidence from Panel Data.," *The Quarterly Journal of Economics*, 106(1), 203–230.

LAMADON, T. (2017): "Productivity Shocks, Dynamic Contracts and Income Uncertainty," *Working Paper*.

LINDLEY, J., AND S. MACHIN (2016): "The Rising Postgraduate Wage Premium," *Economica*, 83(330), 281–306.

LINDQUIST, M. J. (2004): "Capital-skill complementarity and inequality over the business cycle," *Review of Economic Dynamics*, 7(3), 519–540.

LISE, J., AND J.-M. ROBIN (2016): "The Macro-dynamics of Sorting between Workers and Firms," *Manuscript*, (December), 1–36.

MACLEOD, W. . B., AND J. M. MALCOMSON (1995): "Turnover Costs, Efficiency Wages and Cycles," *Annales d'Economiques et Statistique*, 37/38, 55–74.

MEGHIR, C., AND L. PISTAFERRI (2004): "Income variance dynamics and heterogeneity," *Econometrica*, 72(1), 1–32.

MORTENSEN, D. T., AND C. A. PISSARIDES (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61(3), 397–415.

MOULTON, B. R. (1986): "Random Group Effects and the Precision of Estimates," *Journal of Econometrics*, 32, 385–397.

MOULTON, B. R. (1990): "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units," *The Review of Economics and Statistics*, 72(2), 334–338.

PISSARIDES, C. A. (2000): *Equilibrium unemployment theory*.

POSTEL-VINAY, F., AND J.-M. ROBIN (2002): "Equilibrium wage dispersion with worker and employer heterogeneity," *Econometrica*, 70(6), 2295–2350.

POTERBA, J., AND L. H. SUMMERS (1986): "Reporting errors and labor market dynamics," *Econometrica*, 54(6), 1319–1338.

ROBIN, J.-M. (2011): "On the Dynamics of Unemployment and Wage Distributions," *Econometrica*, 79(5), 1327–1355.

ROTHSTEIN, J. (2011): "Unemployment Insurance and Job Search in the Great Recession," *Brookings Papers on Economic Activity*, 2011(2), 143–213.

RUST, J. (1987): "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher," *Econometrica*, 55(5), 999–1033.

SCHIRALDI, P. (2011): "Automobile replacement: a dynamic structural approach," *The RAND journal of economics*, 42(2), 266–291.

SHIMER, R. (2005): "The cyclical behavior of equilibrium unemployment and vacancies," *Annual Review of Economics*, 95(1), 25–49.

SPEAR, S. E., AND S. SRIVASTAVA (1987): "On Repeated Moral Hazard with Discounting," *The Review of Economic Studies*, 54(4), 599.

SWANSON, E. T. (2007): "Real Wage Cyclicality in the Panel Study of Income Dynamics," *Scottish Journal of Political Economy*, 54(5).

TOPEL, R. (1991): "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99(1), 145–176.

TRIPIER, F. (2004): "Can the labor market search model explain the fluctuations of allocations of time?," *Economic Modelling*, 21(1), 131–146.

VERACIERTO, M. (2008): "On the cyclical behavior of employment, unemployment and labor force participation," *Journal of Monetary Economics*, 55(6), 1143–1157.

Appendix A

Appendix for Chapter 1

A.1 Data Appendix

A.1.1 Aggregate Cyclicality of Wage Premium for Females

Table A.1 shows the cyclical properties of hourly wages and wage premium for females. Although females have lower wages than males in all education groups, values of wage premium between education are similar to males. For females, the college wage premium $\frac{w_{BA}}{w_{NC}}$ is not cyclical at all, and the postgraduate wage premium $\frac{w_{PG}}{w_{BA}}$ is significantly counter-cyclical in the median. So the bachelor wage is more pro-cyclical than the postgraduate wage over the business cycle for females, but the effect is not as robust as that for males.

A.1.2 Robustness for Regression of Individual Wage on Degree Interaction

This section shows the robustness check of regression 1.1, and the results are in Table A.2.

Table A.1: Cyclical Properties of Wage Premium for Females

	w_{PG}	w_{BA}	w_{NC}	$\frac{w_{PG}}{w_{BA}}$	$\frac{w_{BA}}{w_{NC}}$
Mean	22	17.5	11.8	1.26	1.48
Std	.027	.023	.016	.024	.016
Corr. with URATE	-.09	-.24	-.33	.12	-.01
Corr. with GDP	.23	.40	.51	-.12	.05
Regress on GDP (Elasticity)					
Mean	.31	.46***	.42***	-.15	.04
	(.21)	(.17)	(.11)	(.2)	(.13)
Median	.13	.36**	.40***	-.23*	-.04
	(.18)	(.16)	(.12)	(.13)	(.13)
Top 25%	.33*	.46***	.38***	-.14	.09
	(.19)	(.15)	(.12)	(.16)	(.11)

Note: Data is March CPS 1976–2016. Sample is females aged 26–64 in the private sector.

"PG" refers to postgraduates, "BA" refers to bachelor graduates, and "NC" refers to the non-college workers. "URATE" refers to the unemployment rate. The row labelled "mean" refers to the levels. The other rows refer to the log of the variable in each column, which are also HP filtered with a smoothing parameter 100. Standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Detrending, Median, and GDP

In column (2) of Table A.2, I detrend the aggregate unemployment rate using a cubic time trend and find that when the unemployment rate goes up by 1 percentage point, postgraduates face a 0.7% increase in their real wage relative to that of bachelor graduates. In column (3), I regress on the median wage instead and find similar results. In column (4), I use log real GDP as an indicator of the business cycle and run the following regression which is similar to regression 1.1

$$\ln W_{it} = X_{it}\beta + \alpha \ln \mathrm{GDP}_t + \gamma \mathrm{PG}_i \times \ln \mathrm{GDP}_t + \varepsilon_{it}$$

While a positive estimate of α would imply that the bachelor wage is pro-cyclical, a negative estimate of γ would indicate that the postgraduate wage is less pro-cyclical than the bachelor wage. Column (4) shows that when real GDP increases 1%, bachelor graduates face a 1.16% increase in their real wage, and postgraduates face a 0.52% increase in their real wage.

Age Groups and Time Periods

In Columns (5)~(7) of Table A.2, I cut the baseline sample into 3 age groups and find that differences in the wage cyclicality between bachelor graduates and postgraduates are significant in all age groups and are particularly larger for elder workers. In Columns (8)~(9), I cut the baseline sample into 2 time periods. It shows that wages are less cyclical after 1995, but the difference in the wage cyclicality between bachelor graduates and postgraduates are significant in both time periods.

Participation

If a time-varying unobserved productivity component (reflected in high or low values of ε_{it}) was correlated with the unobserved time-varying component that affected the individual's probability of employment, I would be faced with a typical selection bias

problem. For instance, the business cycle causes workers with systematically high or low value of the ε_{it} to enter or leave employment. The effect of changes in average labour force quality resulting from the inflow or outflow of high or low productivity workers would then bias the coefficient. If, also, the magnitude of this effect differed by education level, γ would have a bias. To eliminate such systematic selection, I use a maximum likelihood version of Heckman (1979) self-selection model. This model estimates a wage equation jointly with probit choice equation that determines whether a worker is employed. The model is written as follows:

$$\ln W_{it} = X_{it}\beta + \alpha U_t + \gamma \mathbf{PG}_i \times U_t + \varepsilon_{it},$$

$$\text{observed iff } P_{it} = 1,$$

$$\text{where} \quad P_{it}^* = Z_{it}\beta_0 + \delta U_t + \eta \mathbf{PG}_i \times U_t + \omega_{it},$$

$$P_{it} = \begin{cases} 1 & \text{if } P_{it}^* \geq 0 \\ 0 & \text{if } P_{it}^* < 0 \end{cases}$$

Here P_{it}^* is the latent index of a probit employment equation that determines whether worker i is employed at time t. Z_{it} is a vector of individual-specific regressors that affect the probability of employment. Typically, it contains elements that enter into X_{it} as well as some additional variables that may affect labour supply propensity but not worker productivity. The additional variables are: number of own children in the household, number of own children under age 5 in the household, and age of youngest own child in the household. The error terms ε_{it} and ω_{it} are assumed to have a bivariate normal distribution with correlation ρ and respective standard deviations σ_ϵ and 1. The latter variance is normalized to one for identification of the probit choice equation. Column (10) of Table A.2 presents the results. I find that the coefficient γ does not change.

It might be true that the estimated counter-cyclical postgraduate wage premium

reflects bachelor graduates are more likely to be unemployed and find a low paying job. So I run the regression (1.1) for workers who stayed in the same job last year, had no stretch of looking for work, and worked for 52 weeks. You can think this as comparing average postgraduates with good bachelor graduates, so the estimated coefficient should be smaller. Column (11) of Table A.2 presents the results. I find that the coefficient γ on $\text{PG}_i \times U_t$ is 0.007 (s.e. 0.003). So job separation can explain at most a small amount of the counter-cyclical postgraduate premium.

A.1.3 Importance of Occupations and Industries

To check whether the different wage cyclicality of occupations and industries are important determinants of the counter-cyclical postgraduate wage premium. A necessary condition for this argument to hold is that occupations and industries are strong predictors of counter-cyclical postgraduate wage premium. To test this condition, I ran the following regression

$$\ln W_{it} = X_{it}\beta + \sum_{j=1}^{J} \left(\kappa_j I_{ijt} + \alpha_j I_{ijt} \times U_t \right) + \gamma \text{PG}_i \times U_t + \varepsilon_{it} \qquad \text{(A.1)}$$

where $I_{ijt} = 1$ if worker i locates in industry or occupation j at time t. I_{ijt} is interacted with the unemployment rate. The interesting question is by how much coefficient γ shrinks after I control for the interaction between the unemployment rate and I_{ijt}. The more it shrinks, the more industries and occupations can explain, in a regression sense, the counter-cyclicality postgraduate wage premium.

Table A.3 shows the regressions results. Column 1 shows baseline without controlling for industries or occupations. When I control for 1-digit occupations using 10 categories dummies in column 2, the coefficient γ shrinks slightly to 0.0079. As I include more dis-aggregated occupation dummies (381 categories) in column 3, the coefficient γ shrinks 37% to 0.0057. When I include 42 industry dummies in columns 4, the coefficient γ shrinks slightly to 0.0084. In columns 5, I include interactions between 10 occupation dummies and 42 industry dummies, and the coefficient γ shrinks 26% to

Table A.2: Robustness – Regression of Real Hourly Wage on Degree Interaction

lnWage	(1) Base	(2) Cubic Detrend	(3) Median	(4) ln GDP
U_t (α)	-.0117***	-.009***	-.009***	1.16***
	(.0013)	(.001)	(.001)	(.092)
$PG_i \times U_t$ (γ)	.0090***	.007***	.005***	-.65***
	(.0028)	(.002)	(.002)	(.18)
$\alpha + \gamma$	-.0026	-.002	-.004**	.52***
	(.0021)	(.002)	(.002)	(.13)

	(5) 26~30	(6) 31~49	(7) 50~64
U_t (α)	-.019***	-.0081***	-.014***
	(.003)	(.002)	(.002)
$PG_i \times U_t$ (γ)	.006	.007*	.011**
	(.004)	(.004)	(.004)
$\alpha + \gamma$	-.013***	-.002	-.002
	(.004)	(.003)	(.004)

	(8) Before 1995	(9) After 1995	(10) Heckman	(11) Job Stayers
U_t (α)	-.022***	-.013***	-.011***	-.01***
	(.003)	(.002)	(.001)	(.002)
$PG_i \times U_t$ (γ)	.017***	.011***	.009***	.007**
	(.004)	(.004)	(.003)	(.003)
$\alpha + \gamma$	-.005	-.001	-.003	-.003
	(.003)	(.003)	(.002)	(.002)

Note: (1) Baseline regression: March CPS 1976–2016, and Males aged 26–64 in the private sector; (2) Unemployment rate is detrended by cubic trend; (3) Median regression; (4) Use Log real GDP as an indicator of the business cycle; (5) Aged 26~30; (6) Aged 31~49; (7) Aged 50~64; (8) Years before 1995; (9) Years after 1995; (10) Heckman selection model with first-stage employment choice. (11) Workers had only 1 employer, no stretch of looking for work, and worked for 52 weeks.
Controls: postgraduate degree, state, race, marriage dummies, a quadratic age trend, and a quadratic time trend. Standard errors are clustered at the state level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table A.3: Controlling for interaction between unemployment rate and I_{ijt}

$\ln \text{Wage}_{it}$	(1)	(2)	(3)	(4)	(5)
αU_t	-.0117***				
	(.0013)				
$\gamma \text{PG}_i \times U_t$	.0090***	.0079***	.0057***	.0084***	.0067***
	(.0028)	(.0022)	(.0021)	(.0023)	(.0022)
10 Occupations		✓			
381 Occupations			✓		
42 Industries				✓	
10 Occ. * 42 Ind.					✓

Controls: postgraduate degree, state, race, marriage dummies, a quadratic age trend, and a quadratic time trend. Standard errors are clustered at the state level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

0.0067. So industries and occupations can only explain part of the counter-cyclicality of postgraduate wage premium.

A.2 Model Appendix

A.2.1 Proof of Proposition 1

I will prove the proposition without subscript s and h, as it is identical across skill type and education. The maximization problem of an employed worker is (Equation 1.3)

$$\max_e u(w) - c(e) + \beta(1-e)\mathbb{E}_{z'}U_{z'} + \beta e W$$

I define the utility return to the worker for choosing effort e as

$$r(z, W) = \max_e -c(e) + \beta(1-e)\mathbb{E}_{z'}U_{z'} + \beta e W$$

which uniquely defines the policy function for effort $\tilde{e}(z, W)$, and the associated utility return is $\tilde{r}(z, W)$. Applying the envelope theorem, I have

$$\frac{\partial \tilde{r}(z, W)}{\partial W} = \beta \tilde{e}(z, W) \tag{A.2}$$

The firm's maximization problem is

$$\Pi(z, V) = \max_{w, W, W_{z'}} y - w + \beta \tilde{e}(z, W) \mathbb{E}_{z'} \Pi(z', W_{z'})$$

s.t.

$$V = u(w) + \tilde{r}(z, W)$$

$$W = \mathbb{E}_{z'} W_{z'}$$

Then I formulate the Lagrange function using ρ and μ as the multipliers

$$L(z, w, W, W_{z'}) = y - w + \beta \tilde{e}(z, W) \mathbb{E}_{z'} \Pi(z', W_{z'}) + \rho(u(w) + \tilde{r}(z, W) - V) + \mu\beta(\mathbb{E}_{z'} W_{z'} - W)$$

Applying the envelope theorem to the Bellman equation, I have

$$\frac{\partial \Pi(z, V)}{\partial V} = \frac{\partial L}{\partial V} = -\rho \tag{A.3}$$

The first order condition for w is

$$\frac{\partial L}{\partial w} = -1 + \rho u_w(w) = 0$$

Combining with equation A.3, I have

$$\frac{\partial \Pi(z, V)}{\partial V} = -\rho = -\frac{1}{u_w(w)} \tag{A.4}$$

The first order condition for W is

$$\frac{\partial L}{\partial W} = \beta \frac{\partial \tilde{e}(z, W)}{\partial W} \mathbb{E}_{z'} \Pi(z', W_{z'}) + \rho \frac{\partial \tilde{r}(z, W)}{\partial W} - \mu\beta = 0$$

Using equation A.2, I have

$$\beta \frac{\partial \tilde{e}(z, W)}{\partial W} \mathbb{E}_{z'} \Pi(z', W_{z'}) + \rho \beta \tilde{e}(z, W) - \mu \beta = 0 \qquad \text{(A.5)}$$

The first order condition for $W_{z'}$ is

$$\frac{\partial L}{\partial W_{z'}} = \beta \tilde{e}(z, W) \frac{\partial \Pi(z', W_{z'})}{\partial W_{z'}} + \mu \beta = 0 \qquad \text{(A.6)}$$

By eliminating β and μ from equation A.5 and equation A.6, I have

$$\frac{\partial \tilde{e}(z, W)}{\partial W} \mathbb{E}_{z'} \Pi(z', W_{z'}) + \rho \tilde{e}(z, W) + \tilde{e}(z, W) \frac{\partial \Pi(z', W_{z'})}{\partial W_{z'}} = 0$$

Divide both sides by $\tilde{e}(z, W)$

$$\frac{\partial \tilde{e}(z, W) / \partial W}{\tilde{e}(z, W)} \mathbb{E}_{z'} \Pi(z', W_{z'}) + \rho + \frac{\partial \Pi(z', W_{z'})}{\partial W_{z'}} = 0$$

Using equation A.4, I have

$$\frac{\partial \tilde{e}(z, W) / \partial W}{\tilde{e}(z, W)} \mathbb{E}_{z'} \Pi(z', W_{z'}) + \frac{1}{u_w(w)} - \frac{1}{u_w(w')} = 0$$

$$\frac{\partial \tilde{e}(z, W) / \partial W}{\tilde{e}(z, W)} \mathbb{E}_{z'} \Pi(z', W_{z'}) = \frac{1}{u_w(w')} - \frac{1}{u_w(w)}$$

$$\frac{\partial \ln \tilde{e}(z, W)}{\partial W} \mathbb{E}_{z'} \Pi(z', W_{z'}) = \frac{1}{u'(w')} - \frac{1}{u'(w)}$$

A.2.2 Recursive Pareto Form

Following Lamadon (2017), I seek to write recursively the following function

$$\Gamma(z, \rho) = \max_V \Pi(z, V) + \rho V$$

I start by substituting in Π and V to get:

$$\Gamma\left(z,\rho\right) = \max_{w,W,W_{z'}} y - w + \beta\tilde{e}\left(z,W\right)\mathbb{E}_{z'}\Pi\left(z',W_{z'}\right) + \rho\left(u\left(w\right) + \tilde{r}\left(z,W\right)\right)$$

and then I add the period constraints

$$\mu\beta\tilde{e}\left(z,W\right)\left(\mathbb{E}_{z'}W_{z'} - W\right)$$

then I recombine to get

$$\Gamma\left(z,\rho\right) = \min_{\mu}\max_{w,W,W_{z'}} y - w + \beta\tilde{e}\left(z,W\right)\mathbb{E}_{z'}\Pi\left(z',W_{z'}\right) + \rho\left(u\left(w\right) + \tilde{r}\left(z,W\right)\right) + \mu\beta\tilde{e}\left(z,W\right)\left(\mathbb{E}_{z'}W_{z'} - W\right)$$

$$\Gamma\left(z,\rho\right) = \min_{\mu}\max_{w,W,W_{z'}} y - w + \rho\left(u\left(w\right) + \tilde{r}\left(z,W\right)\right) - \mu\beta\tilde{e}\left(z,W\right)W + \beta\tilde{e}\left(z,W\right)\mathbb{E}_{z'}\left[\Pi\left(z',W_{z'}\right) + \mu W_{z'}\right]$$

$$\Gamma\left(z,\rho\right) = \min_{\mu}\max_{w,W} y - w + \rho\left(u\left(w\right) + \tilde{r}\left(z,W\right)\right) - \mu\beta\tilde{e}\left(z,W\right)W + \beta\tilde{e}\left(z,W\right)\mathbb{E}_{z'}\left[\max_{W_{z'}}\Pi\left(z',W_{z'}\right) + \mu W_{z'}\right]$$

$$\Gamma\left(z,\rho\right) = \min_{\mu}\max_{w,W} y - w + \rho\left(u\left(w\right) + \tilde{r}\left(z,W\right)\right) - \mu\beta\tilde{e}\left(z,W\right)W + \beta\tilde{e}\left(z,W\right)\mathbb{E}_{z'}\Gamma\left(z',\mu\right)$$

F.O.C. μ

$$W = \frac{\partial\mathbb{E}_{z'}\Gamma\left(z',\mu\right)}{\partial\mu}$$

So I am left with only looking for μ. For each $\left(z,\rho\right)$ I iterate over μ and try to minimize the objective value. F.O.C. w

$$\rho = \frac{1}{u_w\left(w\right)}$$

From the solution of this equation, we can reconstruct the lifetime utility of the worker, and the profit function of the firm

$$V\left(z,\rho\right) = \frac{\partial\Gamma\left(z,\rho\right)}{\partial\rho}$$

$$\Pi\left(z,V\right) = \Gamma\left(z,\rho^*\left(z,v\right)\right) - \rho^*\left(z,v\right)v$$

Appendix B

Appendix for Chapter 3

B.1 The Derivation of Matches

Define the aggregate market tightness as

$$\theta_t = \frac{V_t}{L_t} \tag{B.1}$$

Using matching function (3.3), I obtain the meeting probabilities of the unemployed $\lambda_{u,t}$ as a function of θ_t

$$\lambda_{u,t} = \frac{M_t}{L_t} = \left(\frac{V_t}{L_t}\right)^\alpha = \theta_t^\alpha \tag{B.2}$$

Then I define the meeting probabilities of the firm q_t as a function of $\lambda_{u,t}$

$$q_t = \frac{M_t}{V_t} = \frac{\lambda_{u,t} L_t}{V_t} \tag{B.3}$$

As free entry is assumed, firms are optimal to post vacancies up to the point where the expected profit of creating an additional vacancy is equal to its cost

$$cV_t = q_t V_t \iint \frac{[u_{t+}(x,\epsilon) + s_o o_{t+}(x,\epsilon)]}{L_t} S_t(x,\epsilon)^+ \mathrm{d}\epsilon \mathrm{d}x$$

where c is the vacancy posting cost. Dividing both sides by L_t and use equation (B.1)–(B.3), I have

$$c\theta_t = \lambda_{u,t} \iint \frac{[u_{t+}(x,\epsilon) + s_o o_{t+}(x,\epsilon)]}{L_t} S_t(x,\epsilon)^+ \mathbf{d}\epsilon \mathbf{d}x$$

$$c\theta_t = \lambda_{u,t} J_t$$

$$c\theta_t = \theta_t^\alpha J_t$$

$$\theta_t = \left(\frac{J_t}{c}\right)^{\frac{1}{1-\alpha}}$$

where J_t is the expected value of a new match.