Université de Montréal

Essays on the macroeconomics of labor market and firm dynamics

Par
GOUDOU Félicien Jesugo

Département de sciences économiques
Faculté des arts et sciences

Thèse présentée à la Faculté des études supérieures
en vue de l'obtention du grade de Philosophiæ Doctor (Ph.D.)
en sciences économiques

Août, 2023

Université de Montréal
Faculté des Études Supérieures et Postdoctorales

Cette thèse intitulée :

Essays on the macroeconomics of labor market and firm dynamics

présentée par

GOUDOU Félicien Jesugo

a été évaluée par un jury composé des personnes suivantes :

Davide Alonzo, président rapporteur

Immo Schott, directeur de recherche

Josh Lewis, membre du jury

Alain Delacroix, examinateur externe

Thèse déposée en Août 2023

A ma mère, mon épouse et mes champions GOUDOU Axel et Gildas

Remerciements

J'ai une profonde gratitude envers mon directeur de recherche Immo Schott pour sa présence continue, sa patience, ses multiples conseils en tout genre, son implication et sa contribution. Merci de m'avoir encouragé et d'avoir cru en moi tout au long de cette thèse. Merci infiniment pour tout.

Je remercie infiniment Jonathan Créchet, pour son soutien, son aide et pour sa disponibilité surtout durant les deux dernières années de ma thèse. Il m'a inpiré pour être un "*Jonathan*" pour les futures générations de doctorants. Je remercie également Baris Kaymak et Joao Galindo da Fonseca pour leur disponibilité, leur commentaires et support surtout sur le marché du travail. Je n'oublie pas l'ensemble des professeurs, chercheurs ainsi que le personnel administratif du département de sciences économiques de l'Université de Montréal et du CIREQ.

J'exprime également ma reconnaissance à mes collègues étudiants des Friday-Group avec notre directeur: Siwe Guy Leonel, Alex Nguebou, Adom Marius et Juste Djabakou. Leur pertinent commentaires lors des présentations ont été d'une aide précieuse. Je remercie particulièrement mes amis Stephane N'dri et Souleymane Zerbo pour leur soutien et leur disponibilité continue. Je ne saurai oublier tous les étudiants de doctorat du département de sciences économiques de l'Université de Montréal dont les discussions enrichissantes m'ont permis d'approfondir mes connaissances et d'améliorer le contenu de cette thèse.

Mes pensées et ma reconnaissance vont sprécifiquement à mon épouse DONHOUEDE Stéphanie pour le soutien moral et encouragement. C'est grâce à toi que j'ai parcouru tout ce chemin. A tout mes amis et toutes personnes non-citées recevez mes sincères remerciements.

Contents

List of Tables

List of Figures

Résumé

Cette thèse contribue à la compréhension des frictions sur le marché de travail et comment ces frictions affectent les agrégats macroéconomiques comme le chômage et la productivité. Elle jette également un regard critique sur les politiques environnementales telles que la taxe carbone et le financement vert.

Le premier chapitre examine comment les contrats de non-competition signés entre employeurs et employés affectent le chômage, la productivité et le bien-être des agents dans l'économie. Ces contrats stipulent que l'employé travaillant sous ceux-ci ne doit en aucun cas travailler pour un employeur concurrent; et ce pour une période déterminée allant de un à deux ans après séparation avec son premier employeur. Ce type de contrat est récurrent aux Etats-Unis et affecte au moins un employé sur cinq dans ce pays. Les résultats des analyses montrent qu'une forte incidence effective de ces contrats peut non seulement comprimer les salaires mais générer du chômage. Ceci est essentiellement dû au fait que certaines personnes ayant signé ce contrat ont du mal à se trouver un nouvel emploi après s'être séparées de leur premier travail. L'article propose de baisser la durée des restrictions d'emploi de ces contrats dans le but d'amoindrir leur effets sur les travailleurs. Cependant, il est à noter que ces contrats sont en partie bénéfiques du fait de l'incitation pour les employeurs de former les employés sur le marché du travail, augmentant la productivité totale.

Parlant de contrats d'emploi, le deuxième chapitre évalue les implications de la coexistence de contrats dits temporaires (contrat à durée déterminée) et permanents (contrat à durée indéterminée) sur le flux des travailleurs entre chômage, emploi et non-participation au marché du travail durant le cycle de vie des agents. Cette analyse revêt une importance particulière du fait des effets de ces flux de travailleurs sur l'emploi agrégé et les salaires durant le cycle de vie des agents. Il en ressort que les transitions des individus d'un emploi permanent au chômage sont le plus important facteur expliquant l'emploi agrégé durant le cycle de vie des agents. Toute politique visant à augmenter l'emploi devrait cibler ce flux de travailleurs. Par ailleurs, la transition des individus d'un emploi temporaire vers le chômage se révèle être significatif dans l'explication du faible emploi

des jeunes dans les pays européens comme la France, surtout pour ceux ayant un niveau d'éducation élevé. l'article va plus loin en construisant un model qui explique les profils de transitions observés durant le cycle de vie des agents et analyse comment les effets associés aux réformes de protection de l'emploi dans les pays européens sont distribués entre les travailleurs selon leur niveau d'éducation et âge.

Enfin, le troisième chapitre jette un regard critique sur les politiques environnementales comme la taxe sur les émissions générées par les unités de production et le financement vert. L'article montre qu'en dépit de leur efficacité dans la réduction des émissions, ces politiques peuvent impacter négativement l'allocation des ressources comme le capital entre les firmes, réduisant la productivité agrégée. Ceci provient du fait que certaines entreprises très productives mais financièrement contraintes peuvent avoir des difficultés à investir dans la technologie de réduction de leurs émissions carbone alors que d'autres moins productives que les premières mais très riches, investissent plus facilement. Le poids du fardeau fiscal lié aux emissions force les premières à quitter le marché réduisant la productivité. Ceci suggère que d'autres politiques comme celle de subventions vertes sont importantes pour réduire ces potentielles distortions.

Mots clés: Contrats de non-compétition, chômage, emploi, salaires, bien-être, contrat d'emploi temporaire, contrat d'emploi permanent, politiques environnementales, mauvaise allocation, productivité agrégée.

Abstract

This thesis contributes to understanding labor market frictions and how these frictions impact macroeconomic aggregates such as unemployment and productivity. It also critically examines environmental policies such as carbon taxes and green financing.

The first chapter examines how non-compete contracts signed between employers and employees affect unemployment, productivity, and welfare in the economy. These contracts stipulate that the employee, while under contract, cannot work for a competing employer for a specified period, typically ranging from one to two years after separation from their initial employer. This type of contract is widespread in the United States and affects at least one in five employees in the country. Results show that a high enforceable incidence of these contracts can compress wages and generate unemployment. This is primarily due to the fact that some individuals who have signed such contracts face difficulties in finding new employment after separating from their initial job. The article proposes reducing the duration of the post-employment restrictions of these contracts to mitigate their effects on workers. However, it is worth noting that these contracts partially benefit employers by incentivizing them to invest in employee training, thereby increasing overall productivity.

Speaking of employment contracts, the second chapter evaluates the implications of the coexistence of temporary contracts (fixed-term contracts) and permanent contracts (indefinite-term contracts) on worker flows between unemployment, employment, and labor force non-participation over the life-cycle. This analysis is particularly important due to the effects of these flows on aggregate employment and wages over the life-cycle. It is found that transitions of individuals from permanent employment to unemployment are the most significant factor explaining aggregate employment over the life-cycle. Any policy aimed at increasing employment should target this flow of workers. Moreover, the transition of individuals from temporary employment to unemployment is significant in explaining the low employment of young individuals in European countries like France, especially for those with higher levels of education. The article goes further by constructing a model that explains the observed transition profiles during agents' life-cycle and

analyzes how the effects linked to employment protection reforms in European countries are distributed among workers based on their level of education and age.

Finally, the third chapter provides a critical assessment of environmental policies such as emissions taxes on production units and green financing. The article shows that despite their effectiveness in reducing emissions, these policies can negatively impact resource allocation, such as capital, among firms, thus reducing aggregate productivity. This is because some highly productive but seriously financially constrained firms may struggle to invest in emission reduction technology, while less productive but wealthy entrepreneurs invest more easily. The burden of emissions-related fiscal measures forces the former to exit the market, thereby reducing productivity. This suggests that other policies, such as green subsidies, are important to mitigate these potential distortions.

Keywords: Non-compete contracts, unemployment, employment, wages, welfare, temporary employment contract, permanent employment contract, environmental policies, misallocation, aggregate productivity.

Chapter 1

The Employment Effects of Non-compete Contracts: Job Creation versus Job Retention*

1.1 Introduction

Interest in a general reduction in competition among firms is pronounced, and this interest has shifted the balance of bargaining power toward employers (Furman and Orszag (2018)). Barriers to competition tend to reduce efficiency and lead to lower output, employment, and wage growth. Among impediments to competition, non-compete agreements (hereafter, NCAs) in employment contracts and their labor market implications have become the focus of heated controversy in the US media and political arena (Krueger and Ashenfelter (2018)). These contracts, which prevent an employee from joining rival firms for a defined duration, have spread throughout the US labor market. Indeed, a survey conducted by Prescott et al. (2016) shows that about 20% of US workers were bound by NCAs in 2014. Moreover, data from the National Longitudinal Survey of Youth reveal that about 17% of the active young population ages 33-34 were constrained by NCAs in 2017. Often justifiable for protecting firm investments (Shi (2022); Garmaise (2011); Meccheri (2009); Long (2004)), NCAs are now surprisingly used even for lower-paying jobs[1]. Evidence of the disagreement over the benefit of such contracts is reflected through

*A new version of this paper is in preparation for resubmission as revision requested at *Labour Economics*. In this new version I endogenize the supply of NCAs contract.

[1]Dave Jamieson, "Jimmy John's makes Low-Wage Workers Sign 'Oppressive' Noncompete Agreements", Huffington Post, October 13, 2014, https://www.huffingtonpost.ca/entry/jimmy-johns-non-compete_n_5978180?ri18n=true

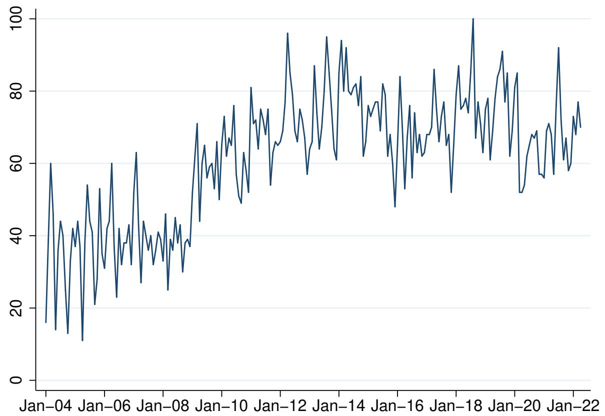


Figure 1.1: Google Trends results for the keyword search 'Non compete agreement' in the US.

a call for the reform of NCAs by the Obama administration in 2016 and ongoing support for this reform by the Biden administration [2]. Similar debates exist in Austria and Canada, with Ontario becoming the second jurisdiction in North America, after California, to prohibit NCAs.[3].

Despite these ongoing and important debates, research on the equilibrium and welfare effects of NCAs is still at an early stage. One reason is that detailed data on these labor contracts have only recently become available. The rare attempts at taking a structural approach toward understanding the equilibrium effects of NCAs for informed policy design have focused particularly on the managerial labor market (Shi (2022)) or the low-wage labor market (Potter et al. (2022)). This paper seeks to understand the pros and cons of NCAs based on a frictional labor-market model. It takes into account two important (different but complementary) dimensions of the provision of NCAs: their incidence and enforceability. My research is motivated by the significant correlations between the incidence of NCAs and aggregate labor market outcomes. Using data from the Longitudinal Employer-Household Dynamics (LEHD) and the Current Population Survey (CPS), I document that the transition rate from employment to unemployment is particularly low in US states that are experiencing a high incidence of NCAs. This relationship still holds at the national level across industries, suggesting that, on average, an employed worker experiences longer job tenure when she is more prone to sign non-compete agreements.

[2] For details, see "State Call to Action on Non-Compete Agreements," https://obamawhitehouse.archives.gov/sites/default/files/competition/noncompetes-calltoaction-final.pdf. See also "Fact Sheet: Executive Order on Promoting Competition in the American Economy," The White House, July 9, 2021, https://www.whitehouse.gov/briefing-room/statements-releases/2021/07/09/fact-sheet-executive-order-on-promoting-competition-in-the-american-economy/

[3] See Ontario's Bill 27, October 25, 2021

More interestingly, the same pattern is observed for the transition rate from unemployment to employment, implying that, on average, job seekers are less likely to find jobs in an environment in which most employment contracts that are signed include non-compete clauses. Formally, I estimate that a ten percentage point (p.p.) increase in the incidence of NCAs significantly lowers the job-finding rate and the transition rate of job separation to unemployment by 1.6 p.p. and 0.25 p.p., respectively, ceteris paribus.

As a robustness check, I take advantage of the enforcement reform of NCAs across the US during the period 1992-2010, as reflected in various state NCAs enforcement indexes (See Garmaise (2011)). Indeed, non-compete agreements are more likely to be popular among companies whose employees work in states that allow the inclusion of NCAs. I mainly focus on Florida, with its change in NCAs enforcement in 1996 as a case study. Indeed, Florida's 1996 strengthening of NCAs enforcement offers an attractive case study compared with legal changes in other states. The reasons for choosing this case study, and highlighted in Kang and Fleming (2020), are twofold: (*i*) the legislation in Florida focused purely on restrictive covenants, notably NCAs, (*ii*) Florida has had a four-decade history with the laws governing non-competes, such that employers and employees were probably accustomed to them. The outcome variables considered in this paper are the job destruction and job creation rates from the Business Statistics Dynamics provided by the US Census Bureau. The analysis relies on the synthetic control method developed by Abadie et al. (2015) using the other states as a control group. As expected, the job flow rates drop after the NCAs reform. This finding suggests that more highly enforceable NCAs contribute toward reducing the labor market dynamism brought about by a fall in both job creation and job destruction rates.

To understand the underlying mechanism, I develop a job search model encompassing the signing of non-compete contracts at the hiring stage and in which firms optimally invest in worker human capital. In the model economy, the ex-ante homogeneous job seeker population becomes heterogeneous with respect to NCAs constraints after transitioning from employment to unemployment. In this model, there is no on-the-job search[4]. I describe the model mechanism as follows. Since NCAs restrain workers' job opportunities, an unemployed worker who is bound by NCAs has a lower job-finding rate relative to the unconstrained worker. Moreover, since NCAs encourage firm investment by lengthening job tenure, they are attractive to firms and induce them to open vacancies in the economy that have a higher probability of including non-competition clauses in

[4]Since our focus here is to explain the role of NCAs in the flow of workers into and out of unemployment but not to explain their effects on wage dynamics, the abstraction of on-the-job search is meaningful in this context.

their contracts. Hence, the average job-finding rate increases with the incidence of NCAs and their enforceability through greater labor market tightness. Conversely, a higher incidence of enforceable NCAs increases the proportion of job seekers who are constrained by NCAs, which makes filling vacancies more difficult. Therefore, the average job-finding rate drops through decreasing labor market tightness. The model calibrated to the US economy implies a decreasing job-finding rate with the incidence of NCAs, consistent with the evidence found in the data. This fact appears as a trade-off for a lower job separation rate and higher firm investment in worker human capital implied by a higher incidence of NCAs. In equilibrium, the model predicts a higher unemployment rate associated with a higher incidence of enforceable NCAs in the economy.

Moreover, the NCAs employment trade-off translates to the one between the enhancement of aggregate productivity and an efficient level for the unemployment rate, making it theoretically ambiguous to predict the efficiency of NCAs. Our analysis suggests that a low level of incidence of NCAs is desirable. The inefficiency arises in our model economy mainly because too few jobs are created in an environment with a high incidence of enforceable NCAs. To reduce this inefficiency, this paper proposes a cap on the duration of NCAs post-employment. One advantage of this policy is its simplicity and transparency (i.e., it is easily verifiable without cost for both workers and firms).[5]. Results show that an average duration of NCAs capped at six months leads to steady state welfare gains of about 6.8%. The gain is greater in a regime with a high level of NCAs enforcement.

This paper is complementary to the literature on the implications of NCAs in employment contracts on both the worker and firm side. On the firm side, non-compete contracts encourage firms to invest in employees' human capital or training and hence facilitate innovation (Garmaise (2011); Meccheri (2009); Long (2004); Callahan (1985)). This paper contributes theoretically to this literature by showing that NCAs partially help to lessen the hold-up problem. However, unlike in Shi (2022)), which considers Bertrand competition between three parties (incumbent employer, employee, and new potential employer) à la Cahuc et al. (2006), this paper relies on the higher job tenure incentive that NCAs generate. However, NCAs may also affect a firm's activities. In this sense, Starr et al. (2017), relying on the variation in the intensity of NCAs enforcement across the US, found that NCAs have an ambiguous effect on start-up activity. Two mechanisms are underlined here. The first one is referred to as a "*screening effect*": A greater degree of enforcement lowers the expected returns to spin-off activity by raising the probability of losing a lawsuit over violating the terms of a non-competition agreement. The second mechanism refers to the potential « *investment protection effect* »

[5] See Shi (2022) for the same consideration

of NCAs, which potentially stimulates start-up activity and employment growth. This paper embraces the same idea in the search and matching framework, showing that job creation relies on the training motive effect of NCAs (leading to higher job creation) and the proportion of job seekers constrained by NCAs (leading to lower job creation). First, as an empirical contribution, I show that the second effect dominates because the job-finding rate decreases in an environment with a higher incidence of enforceable NCAs. Second, the DMP model calibrated to the US economy and relying on the mechanism above delivers qualitatively the same result. *On the worker side*, Starr et al. (2019), using worker-level data, argues that NCAs, through their chilling effect on worker mobility, slow wage dynamics in the labor market. This paper finds that the incidence of enforceable NCAs has an ambiguous effect on wages because of the opposing effects on outside options and training in our DMP setup.
Since NCAs lead to a low separation rate and low probability of finding a job, they generate two opposite effects on unemployment. To the best of my knowledge, this paper is the first to study the equilibrium effect of NCAs on the unemployment rate in the context of a search and matching model.
Finally, in terms of an efficiency analysis of the provisions of NCAs, my work is closely related to Shi (2022) and Potter et al. (2022). My results align with the former, suggesting that a cap at NCAs duration is welfare enhancing, whereas they are in opposition with Potter et al. (2022)'s finding in terms of the job creation effect of NCAs. I show that the trade-off associated with NCAs and employment leans toward the negative side. Nevertheless, comparatively speaking, my findings have broader relevance.

The rest of the paper is organized as follows. Section 2 documents the relationship between the incidence of highly enforceable NCAs on aggregate job flow rates. Section 3 introduces the model. Section 4 provides a theoretical analysis of the effect of the incidence of enforceable NCAs on aggregate labor market outcomes. Section 5 presents a quantitative evaluation of the impact of a higher incidence of NCAs on job flow rates, investment, and the equilibrium unemployment rate. Section 6 highlights an efficiency analysis, followed by a policy evaluation, of NCAs. Sections 7 and 8 discuss and conclude.

1.2 Empirical evidence

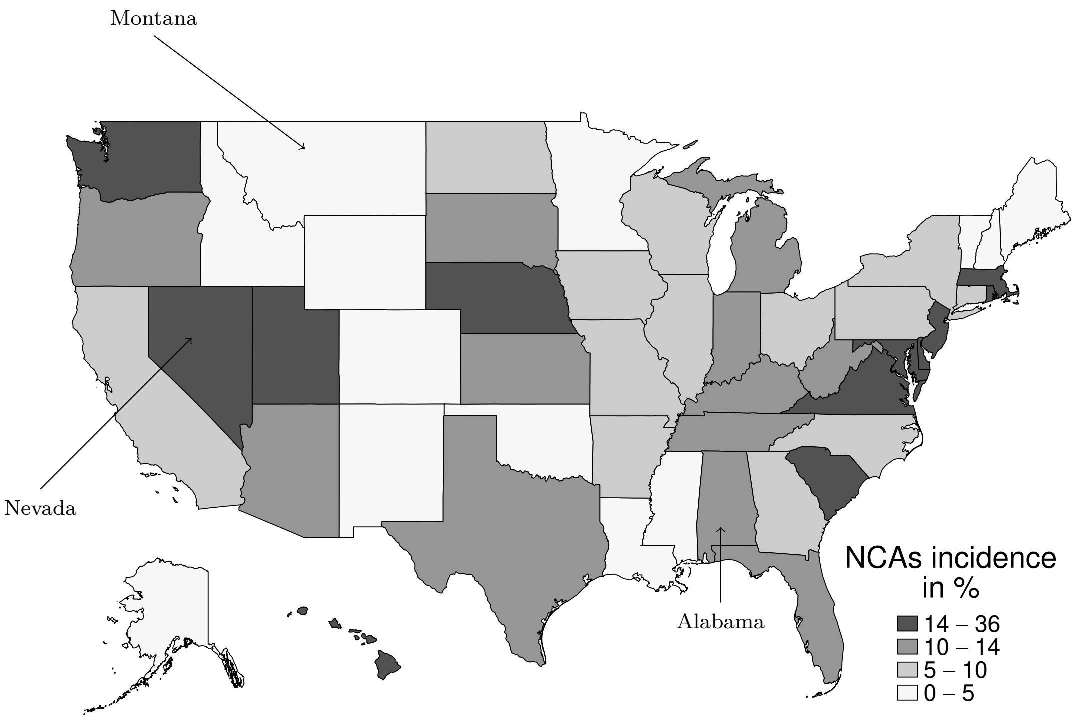
This section presents empirical evidence on the NCAs and their impact on the labor market. More precisely, we study the intertwined relationship between NCAs incidence and transition rates into and from employment.

Data on NCAs incidence comes from the Non-compete survey in the US (Starr et al.

(2021)). The survey was designed in 2014 to shed light on the use of NCAs in the US labor market. The data are representative of the US workforce and cover people aged between 18 to 75 who are either unemployed or employed in the private sector or a public healthcare system. It is, at this date, the only representative survey informing on the use of NCAs in the US. The final sample contains 11,505 respondents from all states, industries, occupations, and other demographic categories. I focus on the incidence of NCAs, defined as the proportion of workers bound by an NCAs contract and measured at the state or industry level. The data report heterogeneity in the use of NCAs across States, industries, and education levels in the US. Figure 1.2 maps State level NCAs incidence in the US for the survey's year (2014). Darker shades encode higher NCAs incidence. It highlights that States with NCAs incidence above 15% or below 5% can be found throughout the country. The cross-sectional standard deviation is 2.3 percentage points.

In addition to Non-compete survey data, I collect the NCAs enforceability index across

Figure 1.2: NCAs incidence across US States



States. The index scores the enforceability of the NCAs contracts based on legislation and case law. In other words, It measures, across states, the degree to which the Non-compete clauses effectively constrain workers who signed them, with a higher score indicating strong

NCAs enforcement. The NCAs enforceability index widely used in the literature comes from Bishara (2011)[6]. Nevertheless, I borrow the state-level weighted index constructed by Starr (2019) and built on Bishara (2011) index for the year 2009 [7].
Data on the job flow rates come from the Longitudinal Employer-Household Dynamics (LEHD) program. I supplement those data with the Current Population Survey data to obtain the micro-level transition rates between unemployment and employment monthly over time. I truncate the CPS data to the same period covered by the Non-compete survey. I depict the empirical evidence into two facts:

FACT 1: *On average, the job separation rate decreases with NCAs incidence*

The panel (a) in Figure 1.3 shows a scatter plot of the proportion of workers bound by NCAs, named NCAs incidence (x-axis) and transition rate from employment to non-employment (y-axis) across states and industries in 2014. The plots show a decreasing pattern between the incidence of NCAs and job separation rates. The correlation coefficient is -0.51 with a standard error (s.e.) of 0.12 across States. This negative correlation is stronger across industries at the aggregate level (See panel (b)) with a correlation coefficient equal to -0.65 and an associated standard error of 0.20.
To formally test the relationship, I embed data on the State-industry combination of NCAs incidence into the CPS data and exploit its panel dimension. The panel version of the CPS data is constructed following Shimer (2012). More precisely, I match individuals over two consecutive months in the CPS basic monthly files following Albert (2021) to compute job flow rates. As stressed before, NCAs incidence in State-industry combination data come from the Non-compete survey (Prescott et al. (2016))[8]. The exercise here is to understand how likely employed workers are to lose their job or transition to unemployment in a State-industry combination with a high incidence of NCAs.

I run the following linear probability specification:

$$y_{isjot} = \alpha(\text{NCA incidence})_{sj} + X_i\beta + \eta_s + \varepsilon_{isjot} \tag{1.1}$$

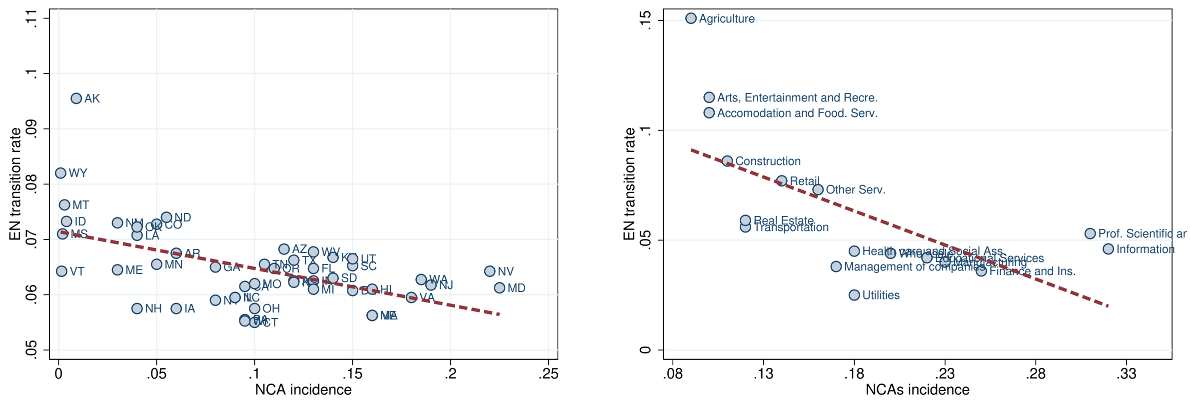
where y_{isjot} is a dummy variable that equals one if EU transition occurs for worker i

[6] Bishara (2011) looks at the following dimensions across jurisdictions: whether a State statute of general enforceability exists, the scope of employer's protectable interest, plaintiff's burden of proof, consideration provisions, modification of overly broad contracts, and enforceability upon firing.

[7] 2009 is the most recent year for which the index is constructed. Despite some recent changes in 2015 and 2016, which I view as non-significant, 2009 measures are a good proxy for the level of enforceability in 2014 (See Starr et al. (2019) for the same consideration)

[8] I thank Evan Starr for making these data available to me

Figure 1.3: NCAs incidence and job Separation rate in US, 2014



(a): States

(b): Industries

Notes: Panel (a) shows the relationships across States. Panel (b) highlights it across industries at 2-digit code using NAICS 2017. Across States, the correlation coefficient is -0.51 (s.e. 0.12) and -0.65 (s.e. 0.20) across industries. EN data come from LEHD, 2014 and NCAs incidence from Non-competes survey, 2014 (Starr et al. (2021)).

and 0 otherwise, in State s, industry j and occupation o happened in period t. It could also be a dummy variable that equals one if UE transition occurs and 0 otherwise. X includes worker demographics controls such as gender, race, education level, age, age squared, and immigrant status. The specification also controls for state, industry, and state-by-occupation fixed effects to ensure that any of those heterogeneities between workers explaining the transitions is a driving force. A period is a month, but I restrict the sample period years to 2012-2014 since the NCAs incidence measure comes from a survey realized in 2014 [9]. Table 1.1 reports the regression results for the job separation rate. It shows that a ten percentage point increase in NCAs incidence (about one standard deviation in the State-industry NCAs incidence in our sample) lowers the job separation rate by 0.25 p.p, after controlling for state fixed effects and covariates. The result is statistically significant at 1% level. Columns 4 and 5 of the table 1.1 report that the negative and significant effects hold even after controlling for industry and State-occupation fixed effects.

However, what matters is not the incidence of NCAs per se but the incidence of enforceable NCAs. Hence, I interact the NCAs incidence with the index of NCAs enforcement across States. I normalized the index to California at 0 (lowest NCAs enforcement regime) and Florida at 1 (highest enforcement regime). Results are reported in table A1 in appendix A.1. It shows that the magnitude of the negative effect between NCAs incidence and the job separation rate is larger in higher-enforcement states. Particularly, in a

[9] the results are robust to change of this period (only 2014 or 2013-2014)

high-enforcement state like Florida, job separation decline amounts to 0.29 percentage points monthly compared to a low-enforcement State like California. In sum, on average, an employed worker experiences longer job tenure when performing in an environment with a higher probability of signing an enforceable non-compete contract. This fact is in

Table 1.1: NCAs incidence and job separation rate

	(1)	(2)	(3)	(4)	(5)
NCAs incidence	-0.026^{***}	-0.019^{***}	-0.025^{***}	-0.012^{***}	-0.006^{**}
	(0.0043)	(0.0038)	(0.0054)	(0.0021)	(0.0028)
Demographics	No	Yes	Yes	Yes	Yes
Year/state FE	No	No	Yes	Yes	Yes
State by occupation FE	No	No	No	Yes	Yes
Industry FE	No	No	No	No	Yes
N. Obs.	250876	250876	250876	250402	250402

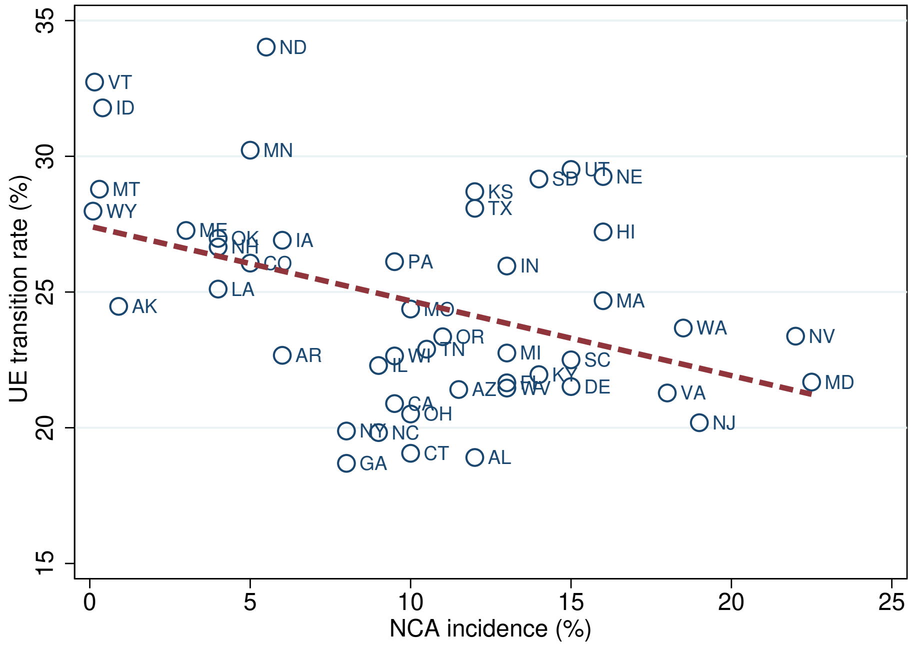
Note.- Dependent variable is the probability of an EU transition. Data come from the CPS monthly basic files 2012-2014. Demographic controls include *gender, race, age and age squared, education level, and immigrant status*. Standard errors in parenthesis, clustered at state level.
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

line with previous studies (Shi (2022), Starr et al. (2019)) and consistent with the nature and patterns of Non-compete agreements which are to impede worker mobility.

FACT 2: *On average, the job-finding rate declines with NCAs incidence*

I next examine the relationship between job finding rate and NCAs incidence. Figure 1.4 shows a scatter plot of the job-finding rate against NCAs incidence across US states in 2014 using the panel dimension of CPS data as explained above. As we can see, NCAs incidence seems to affect not only the job separation rate but also the rate at which job seekers find a job. The correlation coefficient is -0.48 with a standard error (s.e.) of 0.13 in raw data. The result suggests that job seekers in states with a high NCAs incidence have, on average, a low probability of finding a job. I formally test the correlation as in fact 1, using the same specification as in equation 1.1 and controls. Table 1.2 reports the regression results. It shows that a ten percentage point increase in NCAs incidence (about one standard deviation in the State-industry NCAs incidence in our sample) lowers the job-finding rate by 1.6 p.p, after controlling for State fixed effects and covariates. The result is statistically significant at 1% level. The interaction with the strength of NCAs enforcement reveals in table A1 in appendix A.1 that the magnitude of the NCAs incidence is larger in higher-enforcement states. Particularly,

Figure 1.4: NCAs incidence and job finding rate across States, 2014



Note.-. Across States, the correlation coefficient is -0.48 (s.e. 0.13). UE data come from CPS, 2014, and NCAs incidence from Non-competes survey, 2014 (Starr et al. (2021)).

in a high-enforcement state like Florida, the job-finding rate decline amounts to 1.55 percentage points monthly compared to a low-enforcement State like California, after one standard deviation increase in NCAs incidence (about 10%). In sum, on average, job seekers are less likely to find a job in an environment where most employment contracts signed include Non-compete clauses. This fact is consistent with the theory that the incidence of NCAs contracts might inhibit the entry of new firms (See House (2016), Nunn (2016)).

1.2.1 Robustness

Given that the NCAs incidence data is cross-sectional, one key concern from the previous results is the persistence of the findings presented above over time. To mitigate that issue, I study the change in job creation and destruction rates following an NCAs enforcement reform. To do so, I take advantage of the NCAs enforcement reform across States during the period 1992-2010 materialized in variation in State NCAs enforcement index (See Garmaise (2011)). Indeed, it is more likely that NCAs are popular among companies with employees working in States where they are allowed. I mainly focus on Florida

Table 1.2: NCAs incidence and job finding rate

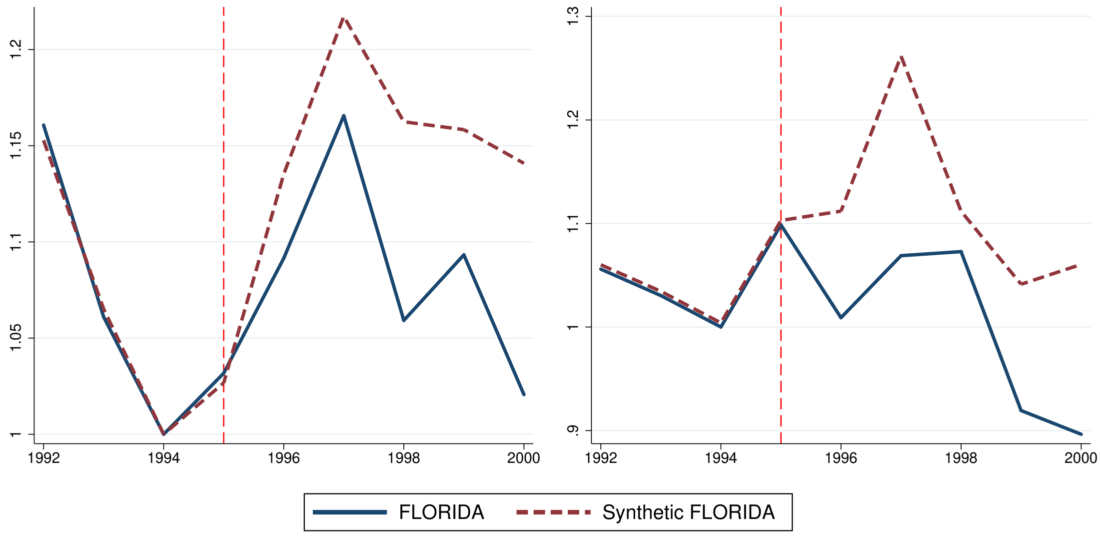
	(1)	(2)	(3)	(4)	(5)
NCAs incidence	-0.136^{***}	-0.122^{***}	-0.160^{***}	-0.093^{*}	-0.142^{*}
	(0.0376)	(0.0349)	(0.0321)	(0.0533)	(0.0845)
Demographics	No	Yes	Yes	Yes	Yes
Year/state FE	No	No	Yes	Yes	Yes
State by occupation FE	No	No	No	Yes	Yes
Industry FE	No	No	No	No	Yes
Observations	19141	19141	19141	18500	18500

Note.- Dependent variable is the probability of an EU transition. Data come from the CPS monthly basic files 2012-2014. Demographic controls include *gender, race, age, age squared, education level, and immigrant status.* Standard errors in parenthesis, clustered at state level.
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

State's change in NCAs enforcement in 1996 as a case study. A fundamental change in Florida's NCAs law was the introduction of a presumption of injury to a firm when a non-compete agreement is violated. Florida's 1996 strengthening of NCAs enforcement offers an attractive case study compared to law changes in other states. Indeed, Florida provides a close to the ideal site because (*i*) the legislation focused purely on restrictive covenants, notably NCAs, (*ii*) it was intended to strengthen enforcement in the state, and (*iii*) Florida has had a four-decade history with the laws governing non-competes, such that employers and employees were probably familiar with and accustomed to NCAs.
By assumption, the facts found above imply that conditional on the unemployment rate, the job creation (JCR) and job destruction (JDR) rates would fall after 1996 Florida's NCAs reform, making them more enforceable. I focus on the job creation rate from establishment births over the last 12 months or, clearly, the job creation from establishments with firm age equal to zero. The reason is that for those firms, it is more likely that they are in a growing stage and would like to hire, an incentive that the strengthening of NCAs might chill. For a more robustness check, I do the same exercise on high-growth firms, predominantly young firms with 65% less than ten years old according to Haltiwanger (2015). I consider firms aged ten years or less, and the results here still hold (See figure A1 in appendix A.1). The analysis uses data from the Business Statistics Dynamics provided by the U.S. Census Bureau. It relies on the synthetic control method developed by Abadie et al. (2015) using the other States as a control group. The synthetic control method is well-known and requires little description. The idea is to find a combination of comparison units (here, the other States except for Florida) named synthetic unit that better reproduces the characteristics of the interested unit (here,

Figure 1.5: Effect of NCAs enforcement strengthening on job flow rates in Florida

(a) : Job Destruction Rate (b) : Job Creation Rate



Florida) in terms of the outcomes (here, job flows rates) predictors before the reform. Synthetic controls are more suitable when the units of analysis are aggregate entities such as counties, States, regions, and countries. They are attractive because of their simple interpretability and transparency. Here, the States' characteristics that I matched are the unemployment rate, the GDP growth rate, the logarithm of the population aged 16 years or more, and the black population ratio. Figure 1.5 shows the results obtained after normalizing values relative to the 1994 value. An essential advantage of normalizing the values is that I can account for the time-invariant difference between Florida and other states (See Kang and Fleming (2020)). As expected, we can see that the job flow rates decreased following the reform, and the effect lasted some years after. I carried out placebo tests asking whether the results could be driven entirely by some randomness. In other words, How often would we obtain results of this magnitude if we had chosen a state randomly for the study instead of Florida? Hence, placebo tests repeat the analysis using States alternately in the control group and ask whether the conjectured effect on the job flow rates is present or not and whether the magnitude is as large as the one found with Florida.

Figure A2 in appendix A.1 shows the distribution of estimated job flows rate gaps for states in the control group that comes from the iterative procedure. The result shows that the estimated gap for Florida during the 1996-2000 period is unusually large relative to the distribution of the gaps for the states in the control group.

1.3 Model

In this section, I develop a theoretical framework to account for the aforementioned facts. The model helps to understand the possible mechanism underlining the declining labor market dynamism generated by using NCAs contracts. It also offers a framework to analyze the implication of NCAs regarding unemployment rate, productivity, and welfare.

1.3.1 Environment

I employ a modified version of the search and matching model in the spirit of Mortensen and Pissarides (1994). Time is discrete, and the horizon is infinite. There is a continuum of ex-ante identical workers of measure one, infinitely lived and risk-neutral. They derive utility from consumption and maximize the present discounted value of their utility. On the other side of the market, there is a larger continuum of risk-neutral firms with the same discount rate β as workers. The labor market is frictional. There exists a constant return to scale matching technology $M = m(u, v)$, with the unemployment rate u and the vacancy rate v as inputs. The labor market tightness $\theta = v/u$ is a sufficient statistic for the job finding and vacancy filing rates. A vacancy is matched to a worker during a period with probability $q(\theta) = m(\frac{1}{\theta}, 1)$, whereas a worker gets contact to a vacancy with probability $f = \theta q(\theta)$. Once matched, a pair firm-worker (a job) operates under an NCAs contract with probability ϕ. Non-compete agreements contract status $b = 0, 1$ determine the set of feasible contracts. Working with an NCAs contract sets $b = 1$ and restricts the worker's post-employment mobility. In this environment, firms offer training to the employed worker, enhancing the match productivity at $C(i)$ cost. Training is match-specific, and the match productivity is $p + i$ where $p > 0$ denotes the common productivity, assumed exogenous. Furthermore, an employed worker is subject to an i.i.d idiosyncratic preference shock ε that alters her decision to continue the match leading to endogenous job separation. In addition, the match could be dissolved at an exogenous rate δ. There is no on-the-job search, and the job-to-job transition is through an unemployment spell.

1.3.2 Employment and unemployment values

Workers are either employed or unemployed and searching for a job. The ex-ante homogeneous job seeker population becomes heterogeneous with respect to NCAs constraints after transitioning from employment to unemployment. Thus, due to match separation, workers are of four types: employed bound by NCAs, employed unbound by NCAs, unemployed bound by NCAs, and unemployed unconstrained by NCAs. The timing of events and decisions is as follows: First, a firm with a vacant job matches with a worker and then randomly decides to assign or not an NCAs contract to the worker. Once the contract is assigned, the firm decides how much to invest in workers' firm-specific skills, conditional on the type of contact. The firm and worker then bargain the wage. Subsequently, production takes place, and profit is shared. Second, the employed worker observes the preference level ε and decides whether to quit or continue the match, which implies an endogenous separation rate. If she quits but was under NCAs contract before job separation, she becomes unemployed, and the NCAs are binding one period ahead with probability χ. If the match continues, the worker is subject to the same NCAs status, and there is no contract renegotiation. The problem of employed workers is defined by a continuation decision :

$$W^c(b,i,\varepsilon) = \max\Big\{\underbrace{W(b,i)+\varepsilon}_{\text{stay}}, \underbrace{U(b)}_{\text{quit}}\Big\} \tag{1.2}$$

Where $U(b)$ is the value of quit, equivalently the value of being unemployed with NCAs status b (with the associated optimal quit policy $x(b,i,\varepsilon) \in \{0,1\}$)
The value of being employed is, then, given by :

$$W(b,i) = w(b,i) + \beta\Big\{\delta U(b) + (1-\delta)\mathbb{E}_\varepsilon W^c(b,i,\varepsilon)\Big\} \tag{1.3}$$

As shown later, a threshold exists for preference shock $\bar{\varepsilon}(b,i)$ under which the employee decides to quit. The expectation in equation (1.3) is only taken over preference shock because, as long as the match continues, an employed worker in state (b,i) remains in this state.

An unemployed worker receives unemployment benefit z while searching for a job. Let us assume that in expectation, the worker bound by NCAs starts with $\bar{i}_1$ and the unbound one with $\bar{i}_0$. The value of the unemployed worker unconstrained by NCAs is given by :

$$U(0) = z + \beta\Big\{f(\theta)[\phi\, W(1,\bar{i}_1) + (1-\phi)\, W(0,\bar{i}_0)] + [1-f(\theta)]U(0)\Big\} \tag{1.4}$$

Conditional on finding a job, the unbound unemployed worker is employed with NCAs with probability ϕ and is free of NCAs with counter probability. The path of unemployed worker constrained by NCAs is, however, slightly different and separates into two cases depending on whether the non-compete clause is enforceable. Unemployed value of worker bound by NCAs $U(1)$ satisfies:

$$U(1) = z+\beta(1-\chi)\Big\{f(\theta)[\phi\, W(1,\bar{i}_1)+(1-\phi)\, W(0,\bar{i}_0)]+[1-f(\theta)]U(0)\Big\}+\beta\chi\mathbb{E}[U(b')] \quad (1.5)$$

Where b' stands for the next period NCAs status. Since the NCAs constraint lasts a finite period, there is a law of motion for the status of NCAs in the post-employment period (unemployed spell). I assume that the unemployed worker bound by NCAs becomes unconstrained next period with probability μ. Hence, NCAs unemployment status b' remains 1 with probability $1-\mu$ and becomes 0 with counter probability. This probability is assumed exogenous and will be recovered later from the average duration of NCAs. χ stands for the NCAs enforcement probability and accounts for the tightness of NCAs constraint. The higher is χ, the more stringent are the NCAs. We could allow the enforcement probability χ to be endogenously linked to the probability of relaxing NCAs constraint μ. The reason is that the probability parameter μ is related to the duration of NCAs restriction, and the lower the duration, the easier it is to enforce NCAs clauses. However, I choose to exogenous χ and link μ to the average NCAs duration across States. Hence, I can account for factors related to NCAs enforcement other than their duration. Note that the training level of a typical firm has no impact on the worker's fallback position $U(0)$ or $U(1)$, which depends on the equilibrium level of training. In other words, the training level corresponds to the best response to the symmetric equilibrium profile of strategies where all firms choose either $\bar{i}_0$ and $\bar{i}_1$. The equilibrium is indeed defined by $i(b) = \bar{i}_b$, but $\bar{i}_b$ thereby $U(b)$ are taken as given when the firm chooses its optimal training level.

1.3.3 Job creation

Let V denote the value of expected profit from a vacant job. In the present framework, firms are assumed to post vacancies that might be filled by NCAs job with probability ϕ and by No NCAs job with probability $1-\phi$. Moreover, each type of implicit vacancy involves training the employee by the amount i at cost $C(i)$.

The value of expected profit of a vacant job V in the economy is given by:

$$V = -\kappa + \beta \max\nolimits_{i(0),i(1)} \Bigg\{ q(\theta) \Bigg[\tilde{\eta} \Big\{ \phi[J(1,i(1)) - C(i(1))] + (1-\phi)[J(0,i(0)) - C(i(0))] + (1-\tilde{\eta})V \Big\} \Bigg] + [1-q(\theta)]V \Bigg\} \quad (1.6)$$

Where

$$\tilde{\eta} = \eta + (1-\chi)(1-\eta)$$

stands for the probability that the match is allowed, in the sense that once randomly met, the NCAs constraint does not distort the match to be successful. η represents the endogenous probability of meeting unemployed workers unconstrained by NCAs. $J(b,i)$ is the value of filled job with NCAs status $b = 0, 1$ and training i. The explanation of the vacant job bellman equation 1.6 is standard. The vacancy posting requires a cost of recruiting κ, and with probability, $q(\theta)$, the vacancy encounters an unemployed worker either bound by NCAs or free of NCAs. Once the match is successful, which happens with probability $\tilde{\eta}$, the vacancy is filled with NCAs contract at rate ϕ and without NCAs at counter rate $(1-\tilde{\eta})$ or remains vacant otherwise.

The free entry condition of supplying a vacant job is $V = 0$ and implies job creation condition:

$$\frac{\kappa}{\beta\, q(\theta)} = \max_{i(0),i(1)} \tilde{\eta}\Big\{\phi[J(1,i(1)) - C(i(1))] + (1-\phi)[J(0,i(0)) - C(i(0))]\Big\} \tag{1.7}$$

This optimization problem from the job creation condition directly implies that the optimal training investment is described by:

$$i(b) = \text{argmax}\Big\{J(b,i) - C(i)\Big\}$$

Let $w(b,i)$ be the wage from an occupied job with a worker of NCAs status b and training intensity i. The value of filled job with NCAs status $b = 0, 1$ and training i, $J(b,i)$ satisfies:

$$J(b,i) = p + i - w(b,i) + \beta\Big\{\delta V + (1-\delta)[(1 - G(\bar{\varepsilon}(b,i)))J(b,i) + G(\bar{\varepsilon}(b,i))V]\Big\} \tag{1.8}$$

Firm's instantaneous payoff consists of production after training minus wage paid. A match is exogenously severed with probability δ and with counter probability endogenously blown up with quit probability $G(\bar{\varepsilon}(b,i))$. In that case, the job becomes vacant next period, and firm receives V. From now and later on, denote $\tilde{G}(\bar{\varepsilon}(b,i)) = (1-\delta)\, G(\bar{\varepsilon}(b,i)) + \delta$, the job separation rate.

NCAs and firm's investment choice. As training is firm-sponsoring and incurs a cost $C(i)$, a firm will choose a training level that maximizes the net value of filled job $J(b,i) - C(i)$, given the unemployment rate, labor market tightness, and unemployment value. Hence, training is set so that the marginal benefit of filling a vacancy with a pair (b, i) equals the marginal cost of training. That is :

$$\frac{\partial J(b,i)}{\partial i} = C'(i) \tag{1.9}$$

Using equation 1.8, optimal investment condition can be rewritten as

$$C'(i) = \underbrace{\frac{1}{1-\beta(1-\tilde{G}(\bar{\varepsilon}(b,i))}}_{\text{Average match duration}} \left[\underbrace{1 - \frac{\partial w(b,i)}{\partial i}}_{\text{Direct marginal profit}} \overbrace{-\beta \frac{\partial \tilde{G}(\bar{\varepsilon}(b,i))}{\partial i} J(b,i)}^{\text{Expected marginal benefit from } \Delta \text{ in quit proba.}} \right] \tag{1.10}$$

An increase of one unit of training intensity incurs a marginal cost of $C'(i)$ and generates a marginal benefit which corresponds to the RHS of Eq.(1.10). The return to training can be decomposed in two terms: (i) training raises productivity and wages through rent sharing, which gives rise to a direct return to training ; (ii) training also makes the employment relationships more stable. The more productive the match, the less easily it is destroyed; thus, the second effect corresponds to a return to job stability.
Notice that the separation rate $\tilde{G}(\bar{\varepsilon}(b,i))$ only depends on training intensity i through wage $w(b,i)$. Hence, if wages were independent of training, then the marginal benefit of training would only depend on the average match duration. Thus, higher training intensity will be associated with job type with high match duration. As shown later, this result holds after wage adjustment, which makes the role played by the wage meaningful in determining optimal training level.

1.3.4 Wage bargaining

I follow the search and matching literature and assume that wages are determined by Nash Bargaining. Consider a firm-worker match currently associated with the pair (b, i) such that it generates a positive surplus. Nash Bargaining implies that the wage, $w(b, i)$, solves :

$$(1-\rho)\,(W(b,i) - U(b)) = \rho\,(J(b,i) - V) \tag{1.11}$$

where $\rho \in [0, 1]$ denotes the worker's exogenous bargaining power. Bargaining outcomes then yields a share ρ of the total surplus of the job $S(b, i)$ to the worker and a share $1 - \rho$ to firm. The surplus sharing rule reads :

$$W(b,i) - U(b) = \rho S(b,i) = -\bar{\varepsilon}(b,i) \quad ; \quad J(b,i) - V = (1-\rho)S(b,i) \tag{1.12}$$

Using employed worker value function, filled job value together with optimal condition (1.11), it is straightforward to show that wage curve is given by :

$$w(b,i) = \rho(p+i) + (1-\rho)\left[(1-\beta)U(b) - \beta\,(1-\delta)\underbrace{\int_{-\rho S(b,i)} \varepsilon dG(\varepsilon)}_{\gamma(b,i)}\right] \tag{1.13}$$

As standard, the wage is a weighted average of the match productivity and reservation wage. However, here, the standard reservation wage $(1-\beta)U(b)$ as in Mortensen and Pissarides (1994) is distorted by the nuisance quantity $\gamma(b,i)$. This quantity is the average value of preference shock received by the worker. On average, a positive preference shock implies an increase in the utility of working and a decrease in its opportunity cost. Therefore, the reservation wage decreases. Given training level i and assuming that worker bound or unbound by NCAs has the same outside option value U, a worker with a high probability of retention or stay will receive a higher wage. In short, each worker's bargained wage depends on the training level received, the associated separation rate, and how much NCAs impact the worker's outside option.

Using the value functions and surplus sharing rule, it is straightforward to show (See appendix A.2) that the total surplus of job (b,i) satisfies:

$$S(b,i) = p+i+\beta\,[1-\tilde{G}(-\rho S(b,i))]S(b,i) - (1-\beta)U(b) + \beta(1-\delta)\int_{-\rho S(b,i)} \varepsilon dG(\varepsilon) \tag{1.14}$$

where:

$$(1-\beta)U(0) = z + \beta\, f\left[\phi\rho S(1,i(1)) + (1-\phi)\rho S(0,i(0)) + \phi\Delta U\right] \tag{1.15}$$

$$(1-\beta)U(1) = z + \beta\left[f\rho(1-\chi)\mathbb{E}_\phi[S(b,i(b))] + [f(1-\chi)\phi - (1-\mu)(1-\chi) - \mu]\Delta U\right] \tag{1.16}$$

$$(1-\beta)\Delta U = \beta\left[-f\chi\rho\mathbb{E}_\phi[S(b,i(b))] - [f\phi\chi + (1-\chi)(1-\mu) + \mu]\Delta U\right] \tag{1.17}$$

and where $\Delta U = U(1) - U(0)$. I set $\bar{i}_b = i(b)$ as a unique symmetric equilibrium, since all firms solve the same investment problem (See also Acemoglu and Pischke (1999)). From equation (1.17), employed workers constrained by NCAs have lower outside options than their peers unbound by NCAs. This result is stressed in lemma 1.

Lemma 1. *Assuming that both types of jobs exist in equilibrium (positive match surpluses), then employed workers constrained by NCAs have lower outside options than their peers unbound by NCAs, that is* $U(1) < U(0)$*.*

Proof: See Appendix A.3

The result in lemma 1 is quite intuitive. Since NCAs limit the opportunities of NCAs workers outside her match, the probability of finding a job upon separation is lower than for workers unbound by NCAs.

Equilibrium. A stationary equilibrium consists of policy functions $i(b)$, $\bar{\varepsilon}(b, i(b))$, value functions $W(b, i(b))$, $U(b)$, $J(b, i(b))$, $S(b, i(b))$ and wage function $w(b, i(b))$, labor market tightness θ and unemployment rate such that :

(i) The value functions solve (1.3) to (1.8)

(ii) Wage is given by (1.13)

(iii) Training policy function satisfies (1.10)

(iv) Free entry (1.7) pins down labor tightness

(v) Quit decision policy function satisfies $\bar{\varepsilon}(b, i(b)) = -\rho S(b, i(b))$ and

(vi) Unemployment rate u is derived from law of motion of each type of unemployment $u(0)$ and $u(1)$ which read :

$$\Big[\mu + (1-\chi) f(\theta)\Big] u(1) = \phi\,(1-u)\tilde{G}(\bar{\varepsilon}(1, i(1))) \tag{1.18}$$

$$u(0)\, f(\theta) = \mu\, u(1) + (1-\phi)\,(1-u)\tilde{G}(\bar{\varepsilon}(0, i(0))) \tag{1.19}$$

Since $u = u(0) + u(1)$, we get:

$$u = \frac{\lambda\Big[\mu + (1-\chi) f\Big] + f\phi\chi\tilde{G}(\bar{\varepsilon}(1, i(1)))}{f\phi\chi\tilde{G}(\bar{\varepsilon}(1, i(1))) + \Big[\mu + (1-\chi) f\Big](f+\lambda)} \tag{1.20}$$

where $\lambda = (1-\phi)\,\tilde{G}(\bar{\varepsilon}(0, i(0))) + \phi\,\tilde{G}(\bar{\varepsilon}(1, i(1)))$; $f = f(\theta)$

From this expression, we see that the unemployment rate is increasing in the job destruction rates for the various types of jobs contract and a decreasing function of the exit rate from unemployment $f(\theta)$. Finally, when $\phi = 0$ (economy without NCAs), we get the familiar expression $u = \dfrac{\lambda}{\lambda + f}$.

The endogenous fraction of unemployed workers constrained by NCAs $(1-\eta)$ is given by:

$$1 - \eta = \frac{u(1)}{u} = \frac{\phi \tilde{G}(\bar{\varepsilon}(1, i(1)))}{\mu + (1-\chi)f} \frac{1-u}{u} \tag{1.21}$$

which closes the model.

1.4 Qualitative insights

Before turning to quantitative analysis, I provide qualitative insights into the model. I abstract from unemployment to focus on how NCAs interact with training, separation rate, and labor tightness.

Proposition 1. *Conditional on training i, NCAs match surplus is higher than No NCAs match surplus. That is :*

$$S(i, 1) - S(i, 0)\,|_i > 0$$

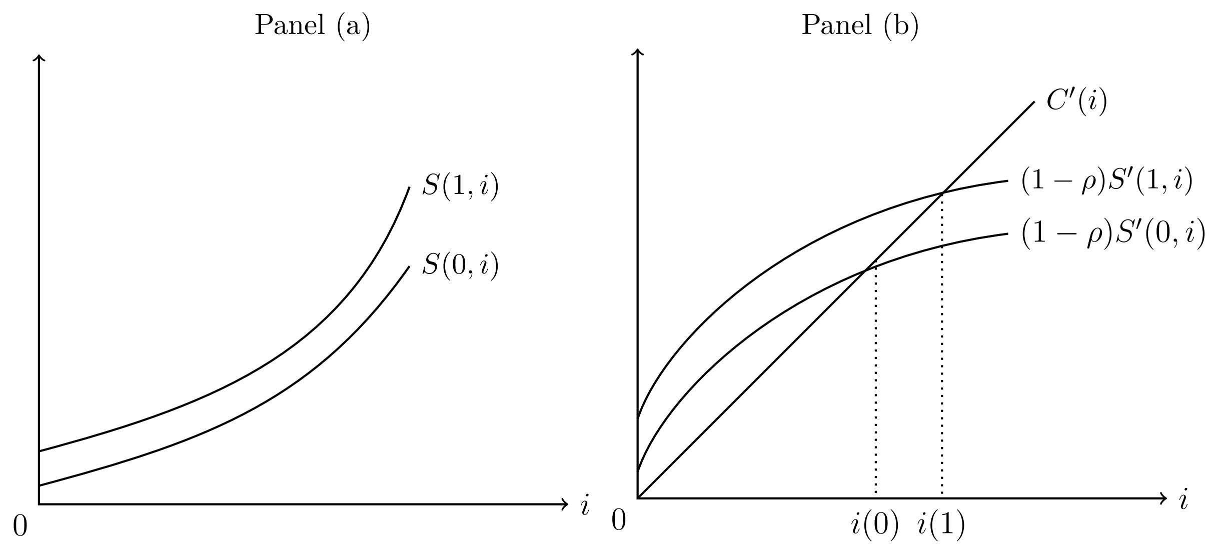
The proof is in appendix A.4. Proposition 1 states that if both types of workers (NCAs and No NCAs) received the same level of training, the match surplus would be higher in NCAs' jobs than in No NCAs' jobs for any level of training. The reason is that holding training constant across job types, the only difference between their surpluses comes from the outside options values. Hence, as surplus decreases in the outside value, from lemma 1, NCAs surplus is higher. Panel (a) in figure 1.6 illustrates this result. Consequently, NCAs worker receives higher training and experiences a lower separation rate, a result highlighted in proposition 2.

Proposition 2. *NCAs worker receives higher training and experiences a lower separation rate*

The proof of proposition 2 is straightforward (See appendix A.5), and the result is intuitive. The analysis of proposition 1 suggests that conditional on training, NCAs worker experiences lower separation than No NCAs worker. Hence, conditional on training level i, NCAs match duration is higher. Therefore the marginal benefit of investment is higher for NCAs job [10]. This result is illustrated in panel (b) of figure 1.6. The result implies, among

[10] I show that the marginal benefit is increasing in the match surplus and only depends on the latter (sufficient statistic in the model) (See appendix A.2).

Figure 1.6



others, that the optimal training policy is decreasing in the outside value of workers. This is consistent with Acemoglu and Pischke (1998) finding that a lower probability that the worker meets a new employer increases the value of human capital to the incumbent firm [11].

NCAs and equilibrium labor tightness. Let us analyze the effect, given a level of the probability of entering NCAs contract ϕ, of an increase in the policy instrument χ, which is the NCAs enforcement probability, on job creation decision. Since the effects of ϕ and χ are complementary, the results presented here are isomorphic to an increase in ϕ, given a certain level of χ. From the free entry condition (equation 1.7), we can see that the impact of tightening in NCAs enforcement on job creation depends on its net effect on the expected profit of filling a vacancy. Since a firm's investment is higher with NCAs, the incidence of higher NCAs enforcement increases the expected profit of filling a vacancy. Therefore firms will be keener to open more vacancies, increasing labor tightness.

$$\begin{aligned}\frac{\kappa}{q(\theta)} &= \beta \left\langle \underbrace{\tilde{\eta}\Big\{\phi[J(1,i(1)) - C(i(1))] + (1-\phi)[J(0,i(0) - C(i(0))]\Big\}}_{\text{Expected Marginal Benefit of filling vacancy (MB)}} \right\rangle \\ &= \beta\,\tilde{\eta}\,\overline{MB}\end{aligned}$$

[11]Although there is no on-the-job search in this model, the new employer contact rate stands here for the probability to find a job.

$$
\begin{aligned}
\frac{d\ln(MB)}{d\chi} &= \frac{d\ln(\tilde{\eta})}{d\chi} + \frac{d\ln(\overline{MB})}{d\chi} \\
&= \underbrace{\frac{1}{\tilde{\eta}}\left[-\eta + (2-\chi)\frac{\partial \eta}{\partial \chi}\right]}_{\text{Composition of job seekers w.r to NCAs constraint effect (-)}} + \underbrace{\frac{1}{\overline{MB}}\frac{\partial \overline{MB}}{\partial i}\frac{\partial i}{\partial \chi}}_{\text{Training effect (+)}}
\end{aligned}
$$

However, the incidence of higher enforcement NCAs negatively influences the marginal benefit of filling a vacancy in two ways: (i) directly through $\tilde{\eta}$ and (ii) indirectly (a general equilibrium effect) through η, the probability to meet unemployed worker unconstrained by NCAs. These adverse effects, which I call "*the composition of job seekers*" with respect to NCAs constraint effect, counteract the positive training motive effect, lowering labor tightness and may dominate. Intuitively, a tightening in NCAs enforcement will spread highly enforceable NCAs among unemployed workers. Hence, it becomes difficult for firms to fill a vacancy, lessening the expected profit.

1.5 Quantitative analysis

In this section, I calibrate the model and analyze the equilibrium effect of Non-compete agreements in a steady state. The parameters are set to match a set of moments describing the dynamics of the US labor market prior to the 2009 recession.

1.5.1 Calibration

Parameters set externally

The model period is a month. Thus, I set the discount rate $\beta = 0.9967$ so that the model implies a steady-state annualized real interest rate of about 4%. The matching function is assumed to be Cobb-Douglas: $m(u, v) = A\, u^{\alpha} v^{1-\alpha}$. As standard in search literature, I choose a conservative value for the elasticity $\alpha = 0.5$. The bargaining power ρ is equal to α to ensure that the Hosios condition is fulfilled in the benchmark economy (with NCAs). In the benchmark economy, the exogenous probability for a worker to be bound by NCAs is set to $\phi = 0.20$ in line with evidence from 2014's Non-compete survey in the US (Starr et al. (2019)). Also, like in Shi (2022), I use an average duration of NCAs restriction of 1.6 years, consistent with the data. Hence, I calibrate the probability of being unconstrained by NCAs after separation to $\mu = 0.052$. The instantaneous return of unemployment, z, is equal to 40% of the productivity p, which value is normalized to one, consistently with Shimer (2005). The benchmark calibrated value of enforcement probability χ is set to

0.7. This value corresponds to the mean of the NCAs enforceability index developed by Bishara (2011) and improved by Prescott et al. (2016). The index is normalized with values between 0 and 1. The calibrated value is also consistent with Shi (2022), who finds an enforcement probability of 0.4 in a low-enforcement regime like California. With a value of a full-enforcement regime like Florida equals 1, the calibrated value appears to be the average-enforcement regime's value. Finally, I assume a normal distribution for the preference shock with mean m and standard deviation σ. I normalize the mean to zero and internally estimate the standard deviation σ. The resulting calibrated parameters are presented in panel A of the table 1.3.

Internal calibrated parameters

I assume $C(i) = c\,i^2$ as the functional form for the training cost function that is increasing and convex in training intensity i. I jointly estimate the parameters κ, c, σ, A, δ, respectively, the per-unit cost of vacancy, the training cost parameter, the preference shock distribution standard deviation, the match efficiency parameter, and the exogenous separation rate.

I target a monthly job-finding rate of 0.34 as in Carlsson and Westermark (2022) and Fujita and Ramey (2012). Using Federal Reserve Bank data, I find an average value of labor market tightness, θ of 0.52 over the period targeted. This value of θ yields an estimated efficiency parameter A equals 0.66 together with the targeted monthly job-finding rate. The vacancy cost κ is recovered from the free entry condition given the targeted labor tightness value of 0.52. Furthermore, the standard deviation for the preference shock distribution is estimated to match the average job separation rate. The value targeted is 0.02 as in Carlsson and Westermark (2022) and consistent with Bils et al. (2011) who estimated the job separation rate from the Survey and Income Participation Program (SIPP) data over the targeted period. The 2 percent of the average job separation rate and the estimated job finding rate imply a steady-state value of the unemployment rate of 5.81 percent, which closely maps to the value in data over the period.

Finally, the exogenous separation rate δ, and the training cost parameter c are estimated by targeting respectively the ratio of the average job tenure in NCAs jobs versus No NCAs jobs and the corresponding hourly wage ratio. Using data from the 1997's National Longitudinal Youth Survey (NLSY97), I compute that, on average, NCAs worker has 73.42 weeks of job tenure with an employer, while No NCAs worker spend 62.42 weeks in employment relation. It implies a ratio of 1.17 for job tenure. Furthermore, Rothstein and Starr (2022), using NLSY97, estimated that worker bound by NCAs earns

Table 1.3: Baseline Calibration of the Model

Panel A: calibrated parameters		
β	Discount rate	0.9967
ρ	Bargaining power	0.5
ϕ	fraction of bound worker	0.2
μ	Proba. of being unconstrained	0.052
χ	NCAs enforcement Probability	0.7
z	Unemployment benefit	0.40
p	Common productivity	1
m	Preference shock mean	0
Panel B: Moment-matched parameters		
A	Matching efficiency	0.660
κ	vacancy cost	0.725
c	Training cost parameter	258.00
δ	Exogenous job separation rate	0.0196
σ	Preference shock std.	0.513

5 percent more, everything else equal. This estimate implies a targeted wage ratio of 1.05 for the baseline calibration.

Panel B of Table 1.3 summarizes the resulting internally estimated parameters. Table A2 in appendix A.1 reports the targeted moments and shows that the calibrated model fits the data moments well.

1.5.2 Accounting for the stylized facts

I now assess the model's ability to account for facts 1 and 2 outlined in Section 1.2. To do so, I simulate the model to generate artificial data comparable with the data used in the empirical analysis of Section 1.2.

Fact 1. I examine whether the model can account for the negative cross-sectional association between the incidence of NCAs and the job separation rate on average. Specifically, I replicate the cross-section relationships between both variables across States and Industries according to figure 1.3. To do so, I vary the parameter ϕ to get the same sequence of NCAs incidence across States and Industries as observed in the data [12]. Figure 1.7 shows that this exercise makes the model predict a statistically significant negative correlation

[12] Job separation rate data presented in figure 1.3 are quarterly, whereas the model is estimated monthly. Hence I estimated the monthly counterpart of the data before comparison. Since one quarter is equivalent to three months, we can infer the quarterly job separation rate s_q from the monthly rate s_m by using the relation $s_q = s_m + s_m(1-s_m) + s_m(1-s_m)^2 = 1-(1-s_m)^3$

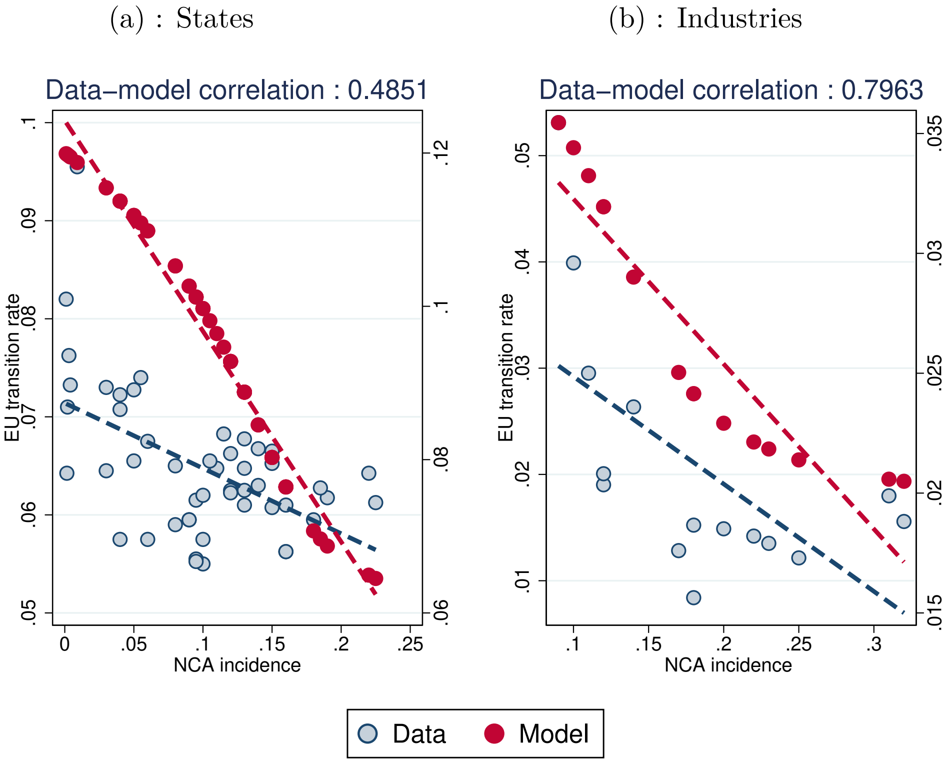


Figure 1.7: NCAs incidence and job separation rate: Data vs. Model

between the incidence of NCAs and job separation rates. As we can see, the model's ability to account for the overall magnitude of the cross-sectional correlation is quite remarkable, especially across industries with a data-model correlation of about 0.80.

Fact 2. Second, I argue that the model is also consistent with the negative cross-sectional association between the incidence of NCAs and the job-finding rate observed in the data. To examine this fact through the lens of our model, I proceed in a way analogous to the way I proceed for fact 1. Figure 1.8 shows a scatter plot in which each dot represents a state, with the x-axis and y-axis, respectively, measuring the proportion of workers constrained by NCAs and the probability of transitioning to employment from non-employment. The figure shows that State displaying significant increases in the NCAs incidence also displays a large drop in the job-finding rate, consistent with fact 2. Of course, job-finding rates in the data are also driven by factors other than the prevalence or the use of NCAs studied in the paper. Hence, the correlation observed in the data in Figure 1.4 is not as tight as the model counterpart in Figure 1.8.

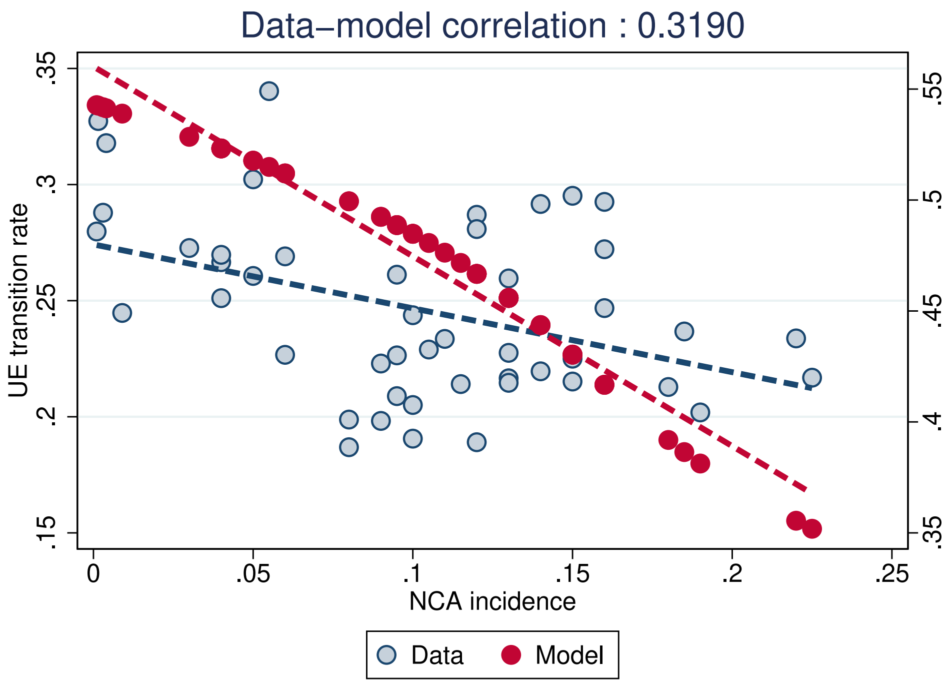


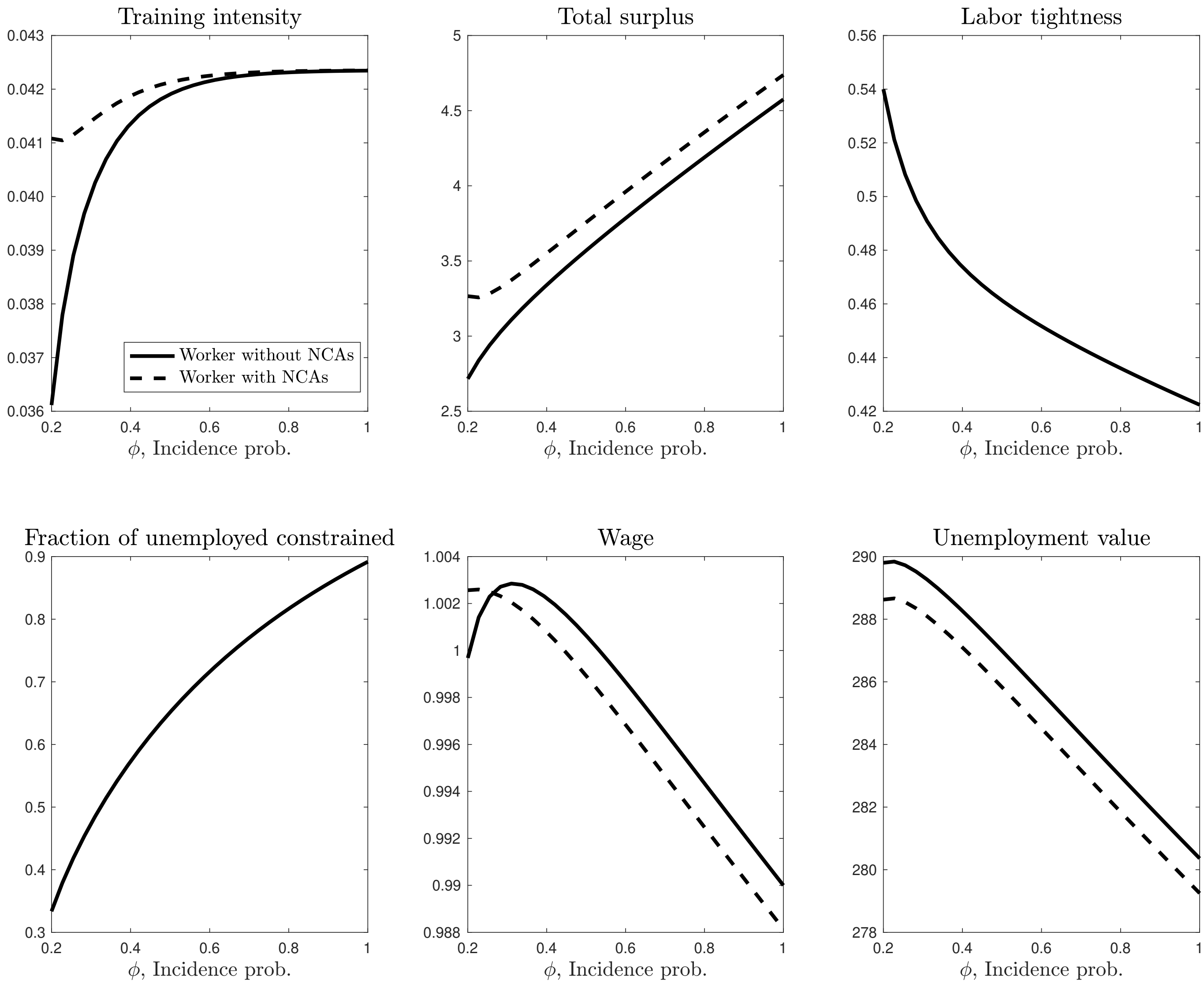
Figure 1.8: NCAs incidence and job finding rate: Data vs. Model

1.5.3 The Effects of Non-Compete Agreements incidence

With the estimated model, I start by describing the decentralized equilibrium in figure 1.9. Hence, I simulate the model with various levels of the NCAs incidence ϕ.
The results indicate that NCAs worker receives higher training intensity and experiences a lower job separation rate in line with Proposition 2. The low separation rate for a worker with NCAs results from a combination of two effects going in the same direction: the drop in the separation initiated by the worker (a quit) and the one initiated by the employer (nil here because not explicitly modeled). Intuitively, as workers' outside options decline due to the NCAs signed, the latter is less willing to quit. The decline in the quit rate encourages the employer to invest in the worker's human capital. As a result, the employer is less likely to lay off the worker. Thus, the employer could extract the maximum possible of its investment.

Results also suggest that not only does the outside option value of NCAs workers decline as the NCAs incidence increases, but the outside option value of the unconstrained worker also drops, a result somewhat surprising. Nevertheless, this finding suggests that NCAs incidence exerts a negative externality on the unconstrained worker. The rationale behind this effect can be analyzed through two channels simultaneously at play. The first channel comes from the potential decline of labor market tightness, decreasing the probability of

Figure 1.9: Comparative Statics with respect to NCAs incidence proportion - ϕ



Note. All parameters except ϕ are fixed at their baseline values. The simulation starts from the baseline value of ϕ

finding a job. The second channel derives from the fact that there is a positive probability that the NCAs unbound worker will become constrained in the future. This situation contributes to lessening the present value of the unconstrained unemployed worker. This pattern is consistent with the empirical finding in Starr et al. (2019) who examine the mobility constraint externalities of NCAs. Starr et al. (2019) find that in the US States with a higher incidence of enforceable NCAs, workers, including those unbound by NCAs, receive fewer job offers.

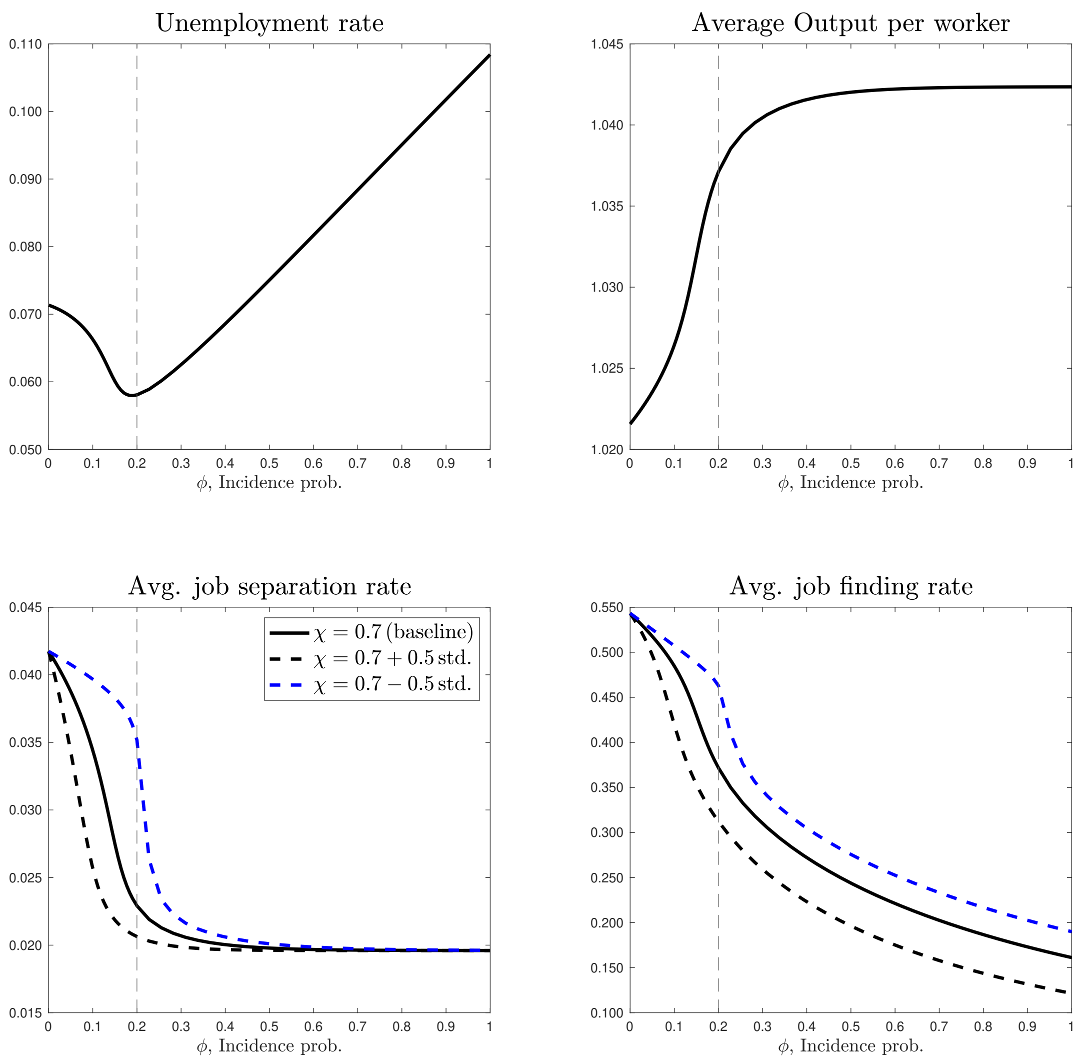
Speaking of earnings, NCAs worker receives lower wage than a worker without NCAs when the NCAs incidence is high. In our setting, training intensity and unemployment value are the key determinants of the wage profile through Nash bargaining. Since the outside option value decreases when NCAs incidence is high, the pass-through wage effect is negative. The positive training effect of higher NCAs on wages helps reduce the negative effect of the outside options. However, the adjustment is not enough to increase the wage for the NCAs worker when NCAs incidence is sufficiently high. Indeed, as the results make apparent, when the probability of signing NCAs is high, there is no significant difference between NCAs workers and No NCAs workers regarding human capital investment.

Finally, training motive and the composition of job seekers relative to NCAs constraint are two opposing forces determining the NCAs' effect on job creation. Results show a decreasing pattern of labor tightness. The declining pattern observed for labor market tightness results from the general equilibrium effect of job seekers' composition relative to NCAs constraint that appears to be dominant here. Indeed, the proportion of job seekers constrained by NCAs increases as NCAs incidence rises, and thus it becomes hard for firms to fill a vacancy. As a result, firms post fewer vacancies pushing downward the tightness of the labor market.

On average, the model implies a declining job finding rate and separation rate with NCAs incidence as shown in Figure 1.10. It suggests that the incidence of NCAs lowers labor turnover. Additionally, and in line with empirical evidence, an increase in the enforceability of NCAs decreases job flow rates, given a level of incidence of NCAs. As a result, it is not the NCAs incidence or their enforceability degree per se that harms labor market dynamics, but the combination of both. Subsequently, the effect of a higher incidence of enforceable NCAs on the unemployment rate is ambiguous. The unemployment rate rises if job flows into unemployment fall proportionally less than job flows out of unemployment. The model predicts a U-shaped curve for the unemployment rate, which suggests that higher NCAs incidence (with a threshold of about 20%) increases the unemployment rate (See figure 1.10).

Furthermore, figure 1.10 shows a positive effect of the NCAs incidence on productivity through the associated higher firm investment. Hence the use of the NCAs generates a trade-off between the enhancement of aggregate productivity and an efficient level for the unemployment rate, making it theoretically ambiguous to predict the efficiency of NCAs. I now turn to the welfare effects induced by NCAs.

Figure 1.10: Effects of NCAs incidence on productivity, unemployment, and job flows rates



Note. In each plot, the solid black curve shows the effect of the increase in the NCAs incidence when the enforcement probability is equal to its baseline value, $\chi = 0.7$. The black and blue dashed curves show the same effect when enforcement probability increases by $+/-$ a half of a standard deviation value as in data (≈ 0.23). All other parameters are set as in Table 1.3. Dashed vertical lines indicate the calibrated value of ϕ.

1.6 Welfare analysis

In this section, I quantitatively investigate the welfare effects of NCAs. In line with Charlot and Malherbet (2013), I consider that the planner chooses the job separation threshold, the labor market tightness θ, and training intensity with respect to each type of employment contract. Formally, the planner maximizes social welfare, defined as the sum of the discounted stream of aggregate output net of search and training costs,

$$\max_{\theta,\,\varepsilon(b),i(0),i(1)} \int_0^{\infty} e^{-rt}\left\{Y + uz - \theta u\kappa - \tilde{\eta}\theta q(\theta)u\Big[\phi C(i(1)) + (1-\phi)C(i(0)\Big]\right\}dt$$

Aggregate output Y is the sum of outputs for each type of job (With and without NCAs), i.e., $Y = Y^0 + Y^1$ which, at any moment in time t evolve according to:

$$\dot{Y}^1 = \tilde{\eta}\theta q(\theta)u\phi[p + i(1)] - \tilde{G}(\varepsilon(1, i(1))Y^1 \tag{1.22}$$

$$\dot{Y}^0 = \tilde{\eta}\theta q(\theta)u(1-\phi)[p + i(0)] - \tilde{G}(\varepsilon(1, i(0))Y^0 \tag{1.23}$$

At any moment in time, the unemployed, conditional to encounter an allowed match with probability $\tilde{\eta}$ can be hired on either NCAs contract at rate $\phi\theta q(\theta)$ or a job without NCAs contract with probability $(1-\phi)\theta q(\theta)$ and produce respectively $p + i(1)$ and $p + i(0)$. In the same time, a proportion $\tilde{G}(\varepsilon(b, i(b))\,, b = 0, 1$ of job of type b is destroyed.

The welfare properties of the decentralized economy are studied in two steps. As a first step, I study the welfare properties of a laissez-faire economy, i.e., an economy where a probability ϕ of signing NCAs is one ($\phi = 1$) and the NCAs duration is sufficiently large (μ=0), but there is a probability $\chi \in (0, 1)$ that NCAs are enforced. Such an economy is isomorphic to one with a strong bargaining power of employers. I show that an economy of this type is inefficient even if the hold-up problem is meaningless (higher firm investment). In the second step, I show that a cap on the NCAs duration is welfare-improving. The focus here on the capping non-compete duration as policy evaluation is for comparison with the literature (See. Shi (2022)).

1.6.1 The inefficiency of the laissez-faire economy

I first study the welfare properties of the laissez-faire equilibrium where $(\phi, \mu) = (1, 0)$. The result presented here also holds in a general case where $(\phi, \mu) \in (0, 1) \times (0, 1)$. Thus, the case $(\phi, \mu) = (1, 0)$ is reported for ease of presentation. Furthermore, I restrict myself to the case where $\beta \longrightarrow 1$. Hence, the objective of the planner becomes static and writes:

$$\max_{\theta,\,\varepsilon(1),i(1)} \tilde{\eta}\theta q(\theta)u\left\{\frac{p+i(1)}{\tilde{G}(\varepsilon(1,i(1))} - C(i(1))\right\} + uz - \theta u\kappa \tag{1.24}$$

the maximization problem is subject to the same constraint on labor market flows as the decentralized economy (1.20 and 1.21). Let ε^s, θ^s, and i^s denote the values of the endogenous variables chosen by the social planner.

Proposition 3 (*Efficient job creation.*)**.** *Given ε^s, i^s the optimal value of θ^s and solves:*

$$\frac{\kappa}{q(\theta^s)} + \frac{\tilde{\eta}\,\kappa\,\psi\,\theta^s}{\tilde{G}(\varepsilon^s)} + \tilde{\eta}(1-\psi)C(i^s) = \tilde{\eta}(1-\psi)\frac{p+i^s-z}{\tilde{G}(\varepsilon^s)} \tag{1.25}$$

where $\psi = -\theta^s \dfrac{q'(\theta^s)}{q(\theta^s}$ denotes the opposite of the elasticity of the matching function with respect to unemployment. These values can be directly compared to those obtained in the laissez-faire equilibrium.
Let ε^*, θ^* and i^* denote the equilibrium values of the key endogenous variables.

Proposition 4 (*Job creation in the laissez-faire economy.*)**.** *Given ε^* and i^*, the equilibrium value of θ^* and solves:*

$$\frac{\kappa}{q(\theta^*)} + \frac{\tilde{\eta}\,\kappa\,\rho\,\theta^*}{\tilde{G}(\varepsilon^*)}\frac{1}{1-\chi(1-\theta^* q(\theta^*))} + B\tilde{\eta}\,C(i^*) = \tilde{\eta}(1-\rho)\frac{p+i^*-z}{\tilde{G}(\varepsilon^*)} \tag{1.26}$$

where, $B = 1-\rho+\dfrac{\rho\,(1-\chi)\theta^* q(\theta^*)}{\{1-\chi[1-\theta^* q(\theta^*)]\}\tilde{G}(\varepsilon^*)}$

The comparison of job creation condition in the equilibrium and centralized outcomes yields a necessary condition. For a given training intensity and job destruction rate, a necessary condition for the equilibrium to be constrained efficient is that the well-known Hosios-Diamond-Pissarides (HDP) condition $\rho = \psi$ holds. However, this condition is not sufficient here. It is easy to verify that $\theta^* < \theta^s$ under HDP and given a training intensity and a job destruction rate. To achieve efficiency, a second-order condition is that the worker's bargaining power ρ must be set to zero ($\rho = 0$). This result is similar to the one obtained by Acemoglu and Shimer (1999), who studied the efficiency of the search and matching model under the presence of match-specific investments. While the result appears in their paper for the hold-up problem, here it holds in the presence of incidence of NCAs, which help lessen the holp-up problem, but too few jobs are created.
Note that the inefficient job creation cannot be solved by giving all the bargaining power

to the employer ($\rho = 0$); otherwise, workers do not get any return to the training that increases productivity. Hence, doing so depresses wages and creates an excessive entry of firms.

This being said, I turn to the welfare effects of capping NCAs' duration. The exercise is to understand to which degree this policy helps improve welfare.

1.6.2 Policy evaluation: Capping NCAs duration

Given that there can be little job creation, there may be room for improving welfare by capping the NCAs' duration. One advantage of this policy is its simplicity and transparency (i.e., it is easily verifiable without cost for workers and firms). We are interested here in quantifying the effects of this policy.

Using the calibrated model, I compute the welfare gains pertaining to the equilibrium allocation. Figure 1.11 depicts the result in panel (a). As we can see, a low level of NCAs incidence is desirable as it would help the economy benefit from higher productivity and low job destruction without being too harmful to job creation. The desirable level of NCAs incidence is lower than the equilibrium benchmark value of 20%. The model predicts a desirable level of 11.79%.

Next, I investigate how the optimum changes when there is a cap on NCAs duration, i.e., when the probability of loosening the NCAs constraint in the future μ rises. Results in panel (b) of figure 1.11 show that a cap on NCAs duration improves the welfare. when considering the optimum decentralized equilibrium, the welfare gains range from about 0.7 percent to 7.5 percent when the NCAs duration is capped at a range between 6 months and 12 months. Nevertheless, NCAs duration capped at six months helps to increase welfare by 6.8% from the baseline equilibrium level of NCAs incidence set to 20% with an average enforcement regime ($\chi = 0.7$). These results are consistent with Shi (2022). The paper found that in a full-enforcement regime $\chi = 1$, the optimal cap estimated at 0.6 years, – about six months – results in welfare gains of 4.8%, relative to the laissez-faire equilibrium outcome. In a low-enforcement regime $\chi = 0.4$ that resembles California, the optimal cap results in welfare gains of 0.5%. The key difference is that, while her paper studies the effects of NCAs in the managerial labor market (high-skill labor), my results have broader relevance here.

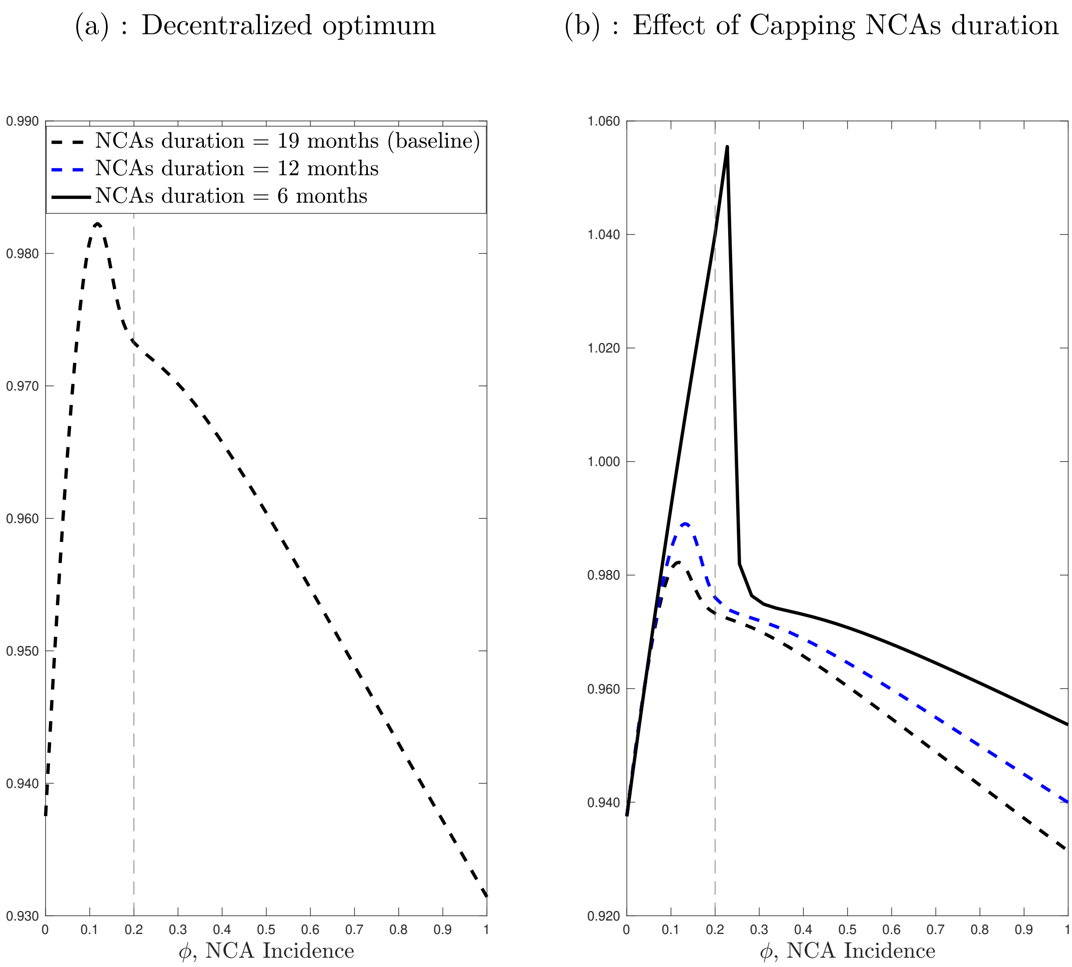


Figure 1.11: Welfare effects of NCAs

Note. Dashed vertical lines indicate the calibrated value of ϕ.

1.7 Discussion

Multi-sector analysis. A potential limitation of the analysis presented throughout the paper concerns the one-sector model used in the paper. Since NCAs constrain a firm-to-firm labor reallocation within an industry, a multi-sector model would be appropriate. It would help reduce the negative effect of NCAs on the job-finding rate since unemployed workers bound by NCAs could direct their job search to an industry other than the previous one where they were working. Marx (2011) documents this potential involuntary career detour for the duration of the contract, in the case of technical professionals. Hence, the adverse effect of the NCAs on the job-finding rate depends on the number of sectors, the distribution of firms, and the incidence of NCAs across sectors. Therefore, the negative effect of NCAs on the job-finding rate could vanish as the number of sectors becomes sufficiently large. In my framework, a sensitivity test relying on the NCAs enforcement probability χ can capture, to a certain extent, the magnitude of this issue. However, notice that the more a worker receives or has invested in industry or occupation-specific human capital, the more costly it is for him to switch occupation or industry. Therefore the higher is his incentive to wait in unemployment. In other words, A displaced worker might rationally prefer to wait through a long spell of unemployment instead of seeking employment at a lower wage in a job he is not trained for. Herz (2019) documents this theory and found that between 9% and 17% of total unemployment in the United States can be attributed to wait unemployment. This idea rationalizes the use of one sector framework since NCAs displaced workers received a higher intensity of industry-specific human capital. Furthermore, a multi-sector model would lead to an unnecessarily complicated model, along with the need to have data on worker transition rates across sectors conditional on NCAs contract status to estimate the model. Future work could extend the framework to a multi-sector model once comprehensive data on NCAs becomes available.

1.8 Conclusion

Non-compete contracts influence labor market outcomes by increasing job search frictions. This paper studies the equilibrium employment effects of the incidence of NCAs contracts. It documents that an increased incidence of enforceable NCAs is associated with a decline in labor market dynamism. Both job creation and destruction rates fall, generating an ambiguous effect on the unemployment rate in equilibrium. The model calibrated to US data predicts a higher unemployment rate, suggesting that the negative job creation effect dominates. The result can also be interpreted as unemployment mismatch implications of NCAs, in that workers with a sector-specific human capital endowment but constrained by NCAs are waiting for unemployment during their non-compete restriction period. This situation may generate a dispersion in the probability of finding a job across sectors leading to inefficiency.

Finally, I show that a restriction on the non-compete duration is welfare improving. This restriction helps the economy benefit from higher productivity and low job destruction without being too harmful to job creation.

Chapter 2

Life-cycle Worker Flows in a Dual Labor Market*

2.1 Introduction

Employment protection legislation (EPL) reforms have arguably been the primary policy response to the persistently high unemployment rate in European countries in the post-oil-shock era (see, e.g., Boeri (2011)). A significant literature has provided evidence that these reforms, in most cases focused on easing the regulation of temporary contracts, generated the formation of dual labor markets, segmented between permanent jobs with strict firing restrictions and temporary jobs (e.g., Blanchard and Landier (2002), Cahuc and Postel-Vinay (2002), Alonso-Borrego et al. (2005), Boeri and Garibaldi (2007), Bentolila et al. (2012), Cahuc et al. (2016)). A key question, with important implications for the life-cycle dynamics of employment and earnings and the formation of human capital, is whether the temporary jobs are "dead ends" leading to higher unemployment risk and unstable employment prospects for individuals, or stepping stone towards stable, protected permanent contracts (e.g., Booth et al. (2002), Faccini (2014), and García-Pérez et al. (2019)). However, most of the existing macro-search literature has been relying on models with representative agents, and, as a result, relatively little is known about the implications of labor-market duality and search frictions for the formation of life-cycle labor-market outcomes. This paper intends to fill this gap.

Our study consists of two main parts. First, using French employment survey data, we provide new estimates of the life-cycle profile of worker flows in a dual labor market with a distinction between permanent and temporary employment—for both low and

*I thank Jonathan Créchet for his contribution to this chapter high-education groups of individuals, featuring very different age employment profiles. Based on these estimates, we propose a stock-flow decomposition to gauge the contribution of life-cycle heterogeneity in flows in and out of permanent and temporary employment to the life-cycle variation in (i) the employment rate and (ii) the incidence of temporary employment. Second, we build a life-cycle equilibrium search-and-matching model with information frictions about workers' ability and heterogeneity in job separation risk as the two main ingredients, which intends to account for the empirical age profiles of worker flows. We use this model to assess the contribution of these two ingredients to the life-cycle variation of worker flows.

Our empirical analysis shows that worker flows are highly heterogeneous across age and education groups. We show that the transition probabilities from unemployment to temporary (UT) and permanent (UP) employment have a declining profile over the life cycle for high-education workers but a flat profile for low-education workers. The same holds for the transition probability from temporary to permanent employment (TP). Our stock-flow decomposition, based on Choi et al. (2015), indicates that the age profile of the probability of exiting permanent employment (into nonemployment, PN), is the first-order factor shaping the life-cycle employment rate; further, the age profile of the temporary employment exit probability (TN) is an important contributor of the employment life-cycle dynamics for highly educated individuals. Specifically, setting the TN probability at its average life-cycle level results in an approximately 6% rise in the employment rate at the age of 25 for this education group.

We complement this analysis by developing a quantitative general equilibrium model that provides a theoretical framework to rationalize these empirical life-cycle patterns. This model features heterogeneous workers and jobs, information frictions, and match-specific unemployment (i.e., employment exit) risk. In this framework, workers accumulate human capital on the job but have heterogeneous skill-accumulation abilities. This ability is unobserved to all agents in the economy, and the human capital accumulation process is subject to idiosyncratic shocks: the agents cannot tell if skill formation is the result of the true ability level or the idiosyncratic shocks. Instead, the agents use the publicly observed realized skill levels as a signal for true abilities and update their beliefs accordingly. In addition, jobs feature heterogeneity in unemployment risk drawn at the beginning of potential matches, independently of skills. In this framework, where we assume that permanent contracts have relatively high firing costs, temporary contracts can be preferred for two distinct motives: (i) learning about individuals' ability (and accumulating skills), a "screening" motive; (ii) avoiding high expected firing costs associated with high unemployment risk, a "churning" motives.

We calibrate the model to estimates of life-cycle transition probabilities from our empirical analysis for the low and high-education groups taken separately. Our model fits the age profile closely for low-educated individuals and reasonably well for those with high education. The model is consistent with the qualitative patterns observed in our worker-flow estimates. We then use the calibrated model to assess the importance of the "screening" and "churning" motives in explaining the life-cycle variation in worker flows. Specifically, we show that the discrepancy between the profile of UP transition across education groups can be explain by a learning view. We find that learning plays a crucial role in explaining the declining profile of the UP transition for high education. Conversely, the unemployment risk channel (churning view) appears to be an important factor in generating a flat profile for low-educated individuals.

The underlying intuition is as follows: low-educated individuals possess a comparative advantage in generic jobs, where their observable skills are sufficient for employment. On the other hand, high-educated individuals have a comparative advantage in complex jobs. These complex jobs involve tasks that necessitate abilities that are not directly observable. Consequently, high-education individuals sort into jobs where their true ability needs to be screened, giving rise to a learning process that unfolds over the life cycle. As a result, the fraction of high-education workers who face a higher probability of immediate ability revelation increases with age. Hence, for older workers with higher education, the probability of finding a job is lower, as they may be perceived as having lower abilities based on their observed characteristics while they are unemployed.

Since, learning and churning have different implications for employment (Faccini (2014), Blanchard and Landier (2002)), the cost or gain from EPL reforms will be different across age and skill groups. Indeed, because temporary contracts can act as stepping stone towards stable job (learning channel), the duality generated by EPL reforms through firing restrictions on permanent contracts will ultimately lead to lower unemployment rate over the life-cycle. Conversely, encouraging inefficient turnover (churning channel), temporary contracts can increase job destruction and raise unemployment rate over the life-cycle. We show that the churning effect of temporary contracts is largely at play for low educated workers and dominates. Conversely, learning and churning effects appear to offset each other for high educated workers. On average, EPL reforms contribute to increase the age-profile of unemployment rate, with young and low educated workers bearing the cost. Hence, Temporary contract jobs are more likely to be *dead-ends* jobs for low educated workers compared with their high education counterparts. This is so because the low educated market segment is characterized by a lack of downward wage flexibility with a potential binding minimum wage and a high degree of substituability between workers stemming from non-specific skills requirement. In case of dismissal, PC jobs become much more expensive and wage rigidity prevents an offsetting transfer from workers to firms in exchange for being insured against job losses (Lazear (1990)). Consequently, firms prefer to use TC in sequence rather than converting them into PC leading to excessive worker turnover.

Related literature. This paper connects the literature analyzing life-cycle outcomes in frictional labor markets (e.g., Chéron et al. (2013), Bagger et al. (2014), Menzio et al. (2016), Lalé and Tarasonis (2018), Jung and Kuhn (2019), Kuhn and Ploj (2020), and Cajner et al. (2020)) and the body of work that studies the effect of dual employment protection legislation in labor search models (Blanchard and Landier (2002), Cahuc and Postel-Vinay (2002), Berton and Garibaldi (2012), Bentolila et al. (2012), Faccini (2014), Cahuc et al. (2016), Cahuc et al. (2020), and Créchet (2019)). To the best of our knowledge, our paper is the first to study worker flows over the life cycle in a dual labor market. We contribute to the literature by showing that such worker flows feature substantial heterogeneity across age (and education) groups and that this heterogeneity matters for the life-cycle employment dynamics. We also propose a novel search-and-matching model with a life-cycle component to study labor-market duality.

Structure of the paper. The rest of the paper is organized as follows. Section 2 documents the empirical patterns of worker flows over the life cycle. Section 3 presents the model. Section 4 provides a quantitative analysis, inspecting the model mechanism to replicate the life cycle patterns. Section 5 concludes.

2.2 Empirical analysis

2.2.1 Data

We use the French Labor Force Survey (*Enquête emploi en continu*, EEC), for the period 2003-2018. The EEC is a nationally representative survey of the French population, conducted by the French national institute (INSEE). The EEC provides detailed socio-demographic and labor market information for individuals in a sample of households. In particular, the data has information on educational attainment and individuals' labor-force status (employed, unemployed, out of the labor force) and on the type of employment contract (permanent or temporary). Since 2003, the survey is said "continuous" in the sense that respondents' information is collected for each calendar week of the year. The EEC follows a rotating panel design—a household is part of the survey for up to six consecutive quarters with one-sixth of the sampled dwellings replaced every quarter—allowing to potentially follow individuals in the sampled households over several consecutive quarters. Since 2009, around 73,000 dwellings have been surveyed in each quarter.

We rely on restricted-use research files from the Data Archive of Issues of Public Statistics (Archives de Données Issues de la Statistique Publique, ADISP). One advantage of the restricted-use files is the availability of household and individual identifiers, allowing us to track individuals over consecutive quarters. Using the longitudinal dimension of the data, we estimate quarterly transition probabilities by identifying events of change in workers' labor market status.

We restrict the sample to individuals between the ages of 20 and 50 who are non-military and non-institutionalized, residing in metropolitan France. Considering this age range, we reduce the influence of schooling and retirement decisions on transition profiles, which is outside the scope of our analysis. Since we are interested in worker flows, we have also restricted our sample to individuals who have participated in at least two consecutive interviews, with labor market information available from the previous quarter. Our resulting sample consists of 1,821,333 observations for 342,116 individuals covering 2003-2018.

2.2.2 Age profiles of transition probabilities

The estimation of our age profiles of transition probabilities proceeds as follows. First, we exploit the continuous and rotating design of the EEC to estimate quarterly worker flows between permanent and temporary employment, and non-employment by age. Second, we run a simple OLS regression on a full set of age and time dummies. Third, we present the OLS predicted values averaged by age. We also display point estimates and confidence intervals for a local polynomial smoother with Epanechnikov kernel function. Let $s^j_{i,t} = 1$ if individual i has labor force status indexed by $j \in \{I, U, P, T, O\}$ at date t, and zero otherwise, where I is for out of the labor force, U is for unemployment, P and T are for permanent and temporary employment, and O is for another status (detailed below). The definition of unemployment and non-participation is standard. In our baseline definition, we classify open-ended and apprenticeship contracts into permanent employment (P).[1] Temporary-agency contracts (*contrat d'intérim*), fixed-term contracts (*contrats à durée déterminée*), are into the temporary-employment (T) category. The remaining status

[1]In the robustness analysis, we propose an alternative classification where the apprentices are counted in T instead of P.

(self-employed and entrepreneurs) are classified into the O category (along with those with no information about the contract type, 0.02% of the sample).[2]

Using our EEC sample for 2003-2018, we first compute the following quarterly transition probabilities

$$\pi_{t,a}^{jk} = \frac{\sum_{i \in \iota(t,a)} \omega_i \mathcal{I}(s_{i,t-3}^{j} = 1 \text{ and } s_{i,t}^{k} = 1)}{\sum_{i \in \iota(t,a)} \omega_i \mathcal{I}(s_{i,t-3}^{j} = 1)}, \tag{2.1}$$

for each monthly date t in our sample period and each age $a = 20, ..., 50$, where $\iota(t,a)$ is the set of indexes for individuals of age a appearing in the sample at t. The variable $\omega_{i,t}$ represents the survey weight of individual i at time t, and $\mathcal{I}(.)$ is the indicator function taking the value of one if the expression is true (zero otherwise). Hence, $\pi_{t,a}^{jk}$ simply estimates the fraction of individuals in state j at time t among those who were in state k in the previous quarter and aged a at time t.

Next, we run a weighted OLS regression on a full set of dummies for age and time fixed-effects

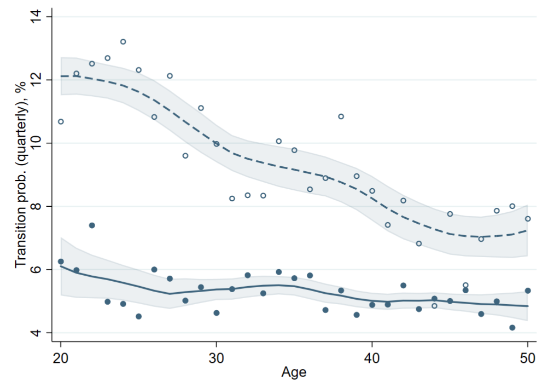
$$\pi_{t,a}^{jk} = \gamma_t^{jk} + \beta_a^{jk} + \varepsilon_{t,a}^{jk} \tag{2.2}$$

for given j, k, where the observation weight for cell t, a is the individual weighted count for that cell. Then, we compute the mean of the predicted values for each age as our estimates of the age-specific quarterly transition probabilities. Finally, we compute smoothed age profiles and 95% confidence intervals using local polynomials with an Epanechnikov kernel function. Our results for transitions between unemployment and permanent and temporary employment are reported in figure 2.1. We depict the life-cycle transition profiles by education groups. We consider the primary and secondary-education individuals (referred to as the low-education group) from one side and the tertiary-education individuals (referred to as the high-education group) from the other. In the appendix, we show transitions in and out of participation.

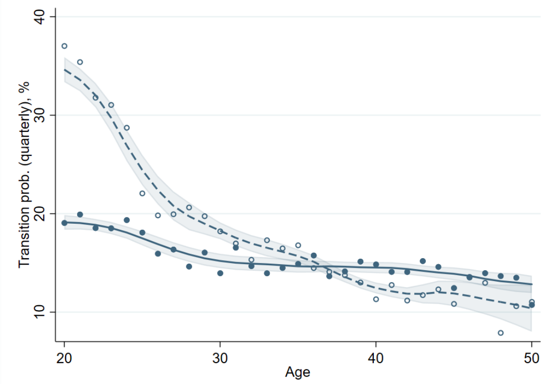
Empirical findings. Transition probabilities display significant variation over the working life of individuals and a marked differentiation among education groups. First, job-finding rates, measured by UP and UT transitions rates, exhibit a decreasing profile for highly educated workers, but a flat profile for low-educated individuals. Unsurprisingly, highly educated unemployed workers are more likely to secure permanent contracts compared to

[2]Finally, for those individuals counted as interns or in subsidized contracts (*contrats aidés*) but for whom the relevant contract information is missing are imputed as being a temporary job, which is the dominant category (more than 80% of individuals with an internship or subsidized contract). These observations for which the information is imputed represent less than 0.1% of the total number of observations.

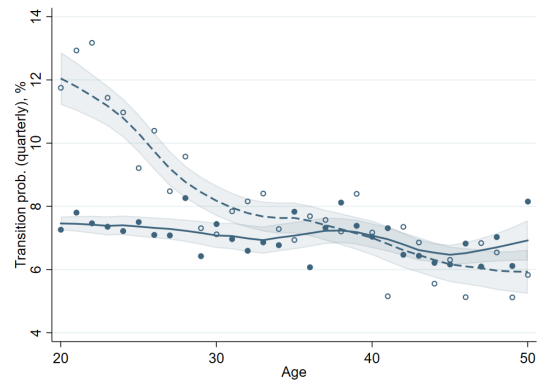
Figure 2.1: Age profiles of quarterly transition probabilities, by education group



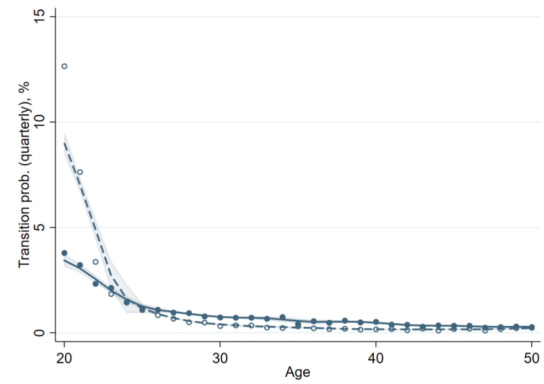
(a) UP



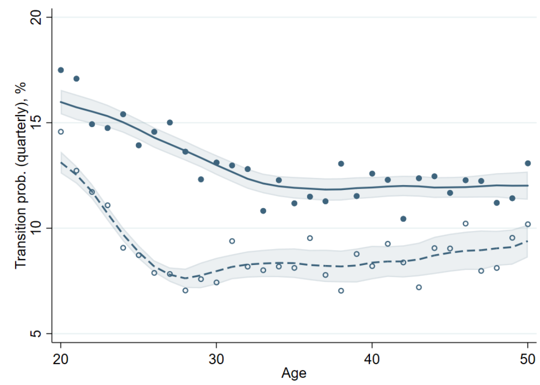
(b) UT



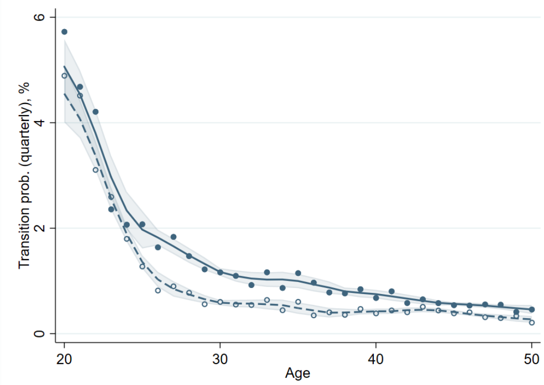
(c) TP



(d) PT



(e) TU



(f) PU

Notes: quarterly transition probabilities by age between unemployment (U), non-employment (N), employment (E) and temporary (T), and permanent employment (P), computed using *Enquête emploi continu* (EEC) data for 2004-2018. The dots indicate estimated mean transition probabilities by age, and lines represent a point estimate of a local polynomial model with Epanechnikov kernel with 95% confidence interval. The plain lines and dots are for dropout and secondary-education individuals. The dashed lines and empty dots are for the tertiary-education individuals. See text for more details.

their low-educated counterparts. This pattern holds for jobs with temporary contracts before the late 30s and reverses thereafter. A reason behind this is that highly educated individuals who are over 38 years old and working in temporary jobs may have lower abilities. As a result, they are more likely to compete for temporary jobs that require less education, where low-educated individuals have a comparative advantage.

Second, separation rates, measured by TU and PU, decrease for both education groups. However, TU decreases much more rapidly for highly educated workers. The job separation rate from temporary employment becomes steady, starting at around 28 for high education, whereas it is around 35 for low-educated workers. This suggests a difference in skill accumulation across education groups. Highly educated workers typically have a lower risk of job loss, which enhances skill accumulation and further reduces job separation over the life cycle.

Finally, turning to job-to-job moves, we observe that the transition from temporary to permanent employment (TP) decreases over the worker life-cycle for highly educated workers but is steadily constant for low-educated workers. The pattern is similar to the UT transition rate. We also notice a substantial transition from permanent contract employment to temporary employment among the youths, particularly for highly educated workers. This could occur through a job-to-job move that enhances match quality.

2.2.3 Markov Chain Analysis

In this section, we follow a method developed in Choi et al. (2015) by proposing a way to account for the contribution of each transition to the determination of age profiles of the employment rate and the employment share of temporary contracts. With our estimates for transition probabilities computed above, we construct, by education group e, an age-specific Markov transition matrix $\Gamma_{a,e}$. Starting from initial conditions on the distribution of workers among labor force statuses at a starting age a_0, we compute the implied labor market status as

$$S_{a,e} = \left(\prod_{a'=1}^{a-1} (\Gamma_{a',e})^4 \right) S_{a_0,e}, \tag{2.3}$$

where $S_{a,e}$ represents the vector for the distribution of individual of age a (expressed in years) in education group e into labor status N,T,P; with N, a non-employment status. $\Gamma_{a,e}$ represents the quarterly transition probability matrix for age a and education e. a_0, e represents the initial age for the different education groups and equals 20 in our sample.

Notice that the age-specific transition matrix is taken at power four since our transition probabilities are quarterly. Using (2.3), we can obtain life cycle profiles of employment and employment share of temporary jobs that are implied by the estimated transition probability matrix. We compare the computed lifetime sequences of employment and employment share of temporary jobs to the actual lifetime profiles obtained from the data. The results are depicted in figure 2.2. In each subfigure, we display the value of R−squared of the linear regression between the actual profile and the implied one. The estimated transition by the Markov chain does very well in replicating the actual profiles. Indeed, the R-squared of the regression of the dotted line against the solid line is always above 95 percent.

Results in figure 2.2 show a predominant proportion of temporary contracts held by young workers, regardless of their education group. This proportion gradually diminishes with worker age, albeit at a faster rate for highly educated individuals. Nonetheless, the relatively slower decline in the temporary employment share, for low-educated individuals, suggests an additional factor at play, which may manifest as idiosyncratic separation shocks in accordance with the churning viewpoint.

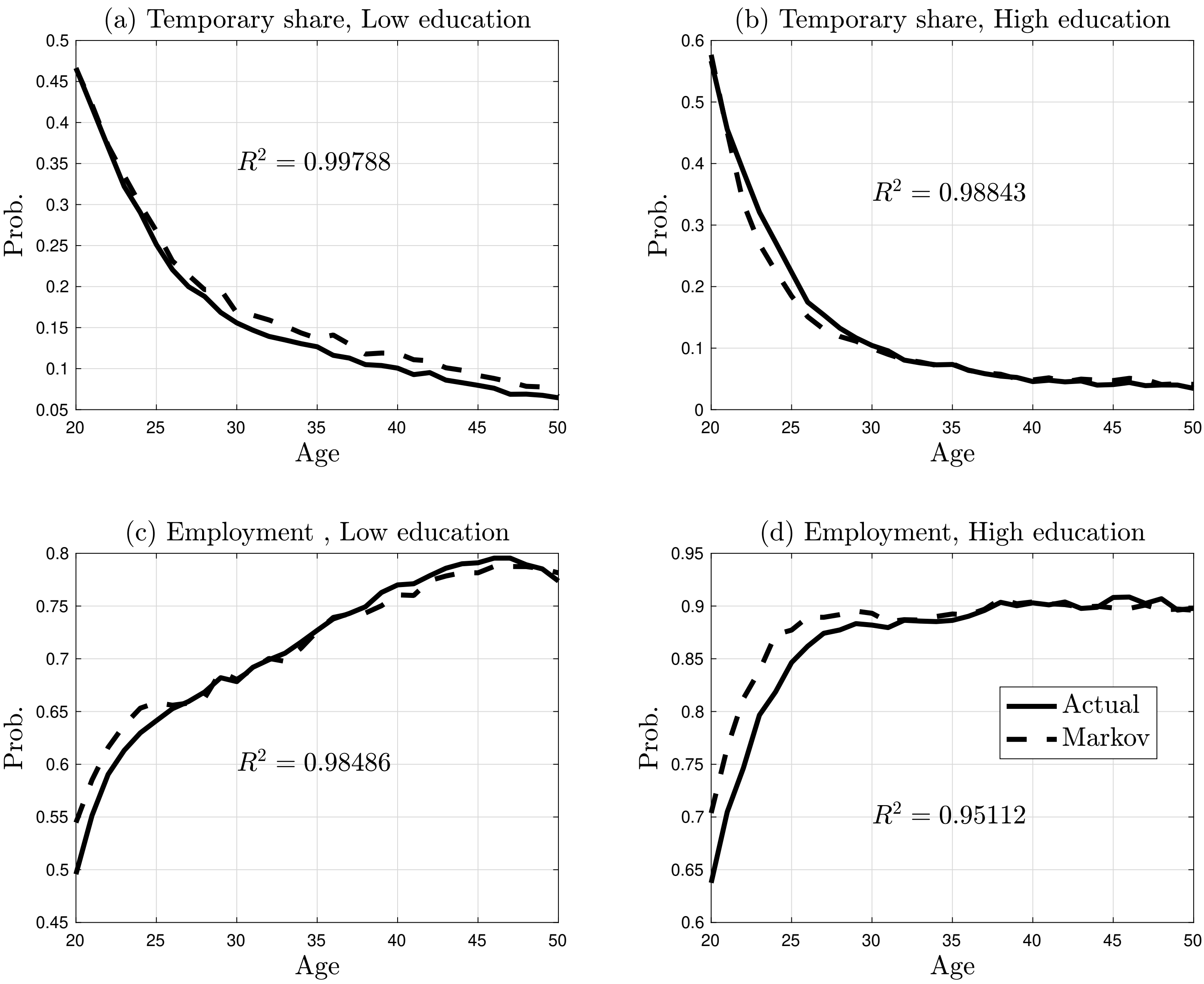
Looking at the low-education sample, the rate of employment increases throughout the lifespan until approximately mid to late 40s, at which point it begins to decline. Conversely, for individuals with higher level of education, employment increases rapidly and stabilizes at around 30 years of age. These findings suggest that there may be a differential rate of skill acquisition across education groups, as discussed in the previous sections.

2.2.4 Decomposition

With the constructed transition matrices, we perform a set of decomposition exercises. Two sets of labor market status are considered: one that distinguishes between the unemployment state (U) and inactivity (I), along with the employment states (T and P); and another that combines U and I into a non-employment (N) state. For ease of presentation, we present the analysis for three states (N, T, P). The findings with four states are presented in Appendix B. They are qualitatively similar to the three states' results.

We use the "*all but one change*" (AB1C) method for the decomposition. This involves the following steps:(i) fixing the value of the transition rate for which the contribution is to be assessed to its average sample value across ages; (ii) creating a counterfactual transition matrix with this alternative transition probability, by adjusting the element on the associated diagonal to keep the transition matrix well-defined; (iii) and computing the

Figure 2.2: Markov chain implied employment and temporary job share



counterfactual implied age profiles distributions. Figures 2.3 and 2.4 show the alternative employment profiles for both high and low-education group workers. Figures B3 and B4 in appendix B present the results for the temporary employment share. To understand the graphs, notice that the first subfigure in Figure 2.3, depicts a hypothetical life-cycle employment rate if the job-finding rate into a temporary contract (NT) was fixed at the life-cycle average for all ages, instead of being age specific. Here, whenever there is a significant difference between the two lines (that is, the $1 - R^2$ is high), the particular transition probability contributes to the shape of the life-cycle profile in either employment rate or temporary employment share. The same logic applies to the other subfigures.

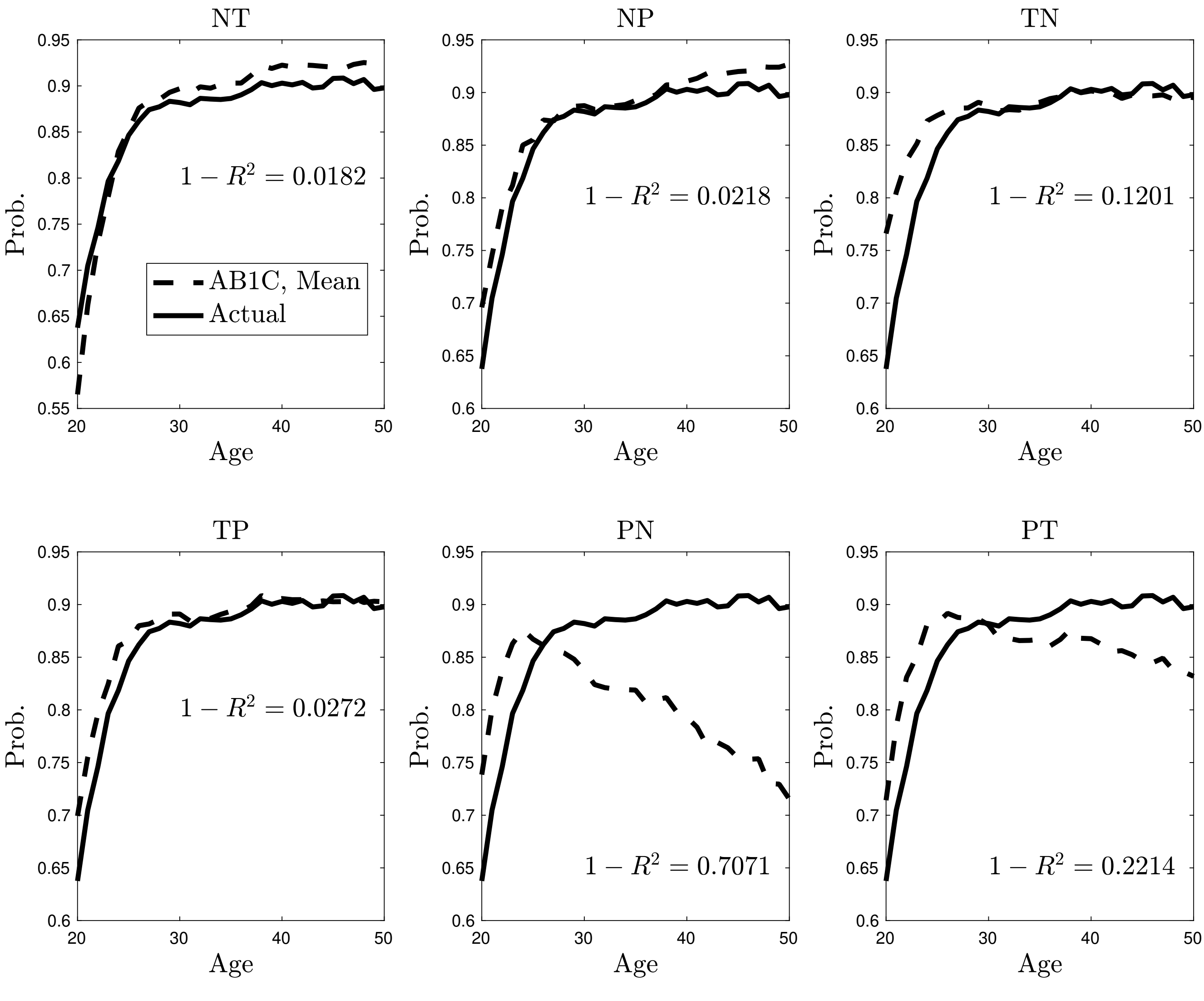
Results from Figures 2.3 and 2.4 indicate that employment exit probability from permanent job, PN, is the most important contributor in explaining the employment rate over the course of a lifetime for individuals with lower levels of education. However, for those with higher education, in addition to PN, job separation from temporary contract TN and job-to-job move from permanent to temporary employment, PT, also matter significantly. In particular, the PN transition emerges as the primary factor accounting for high employment rates among workers aged 30 and above, irrespective of their educational background. Moreover, the probability of transitioning from a temporary job to non-employment, TN, plays a significant role in explaining the low employment rates among highly educated young workers, specifically those under the age of 30. Fixing this probability at its average value across the life-cycle results in an overall increase in the employment rate over the life-cycle. In particular, for individuals with a high level of education, fixing the TN probability at its average level raises the employment rate by approximately 6% at the age of 25.

In summary, these findings indicate that labor market duality has different implications for age-specific employment dynamics across skill groups, as well as for the formation of youth employment.

For the dynamics of temporary employment share over the life-cycle, no specific contributor stands out when considering three states. This suggests that the distinction between unemployment and inactivity (being out of the labor force) plays a significant role in explaining the dynamics of temporary job shares across different ages. When we differentiate between unemployment and inactivity within the non-employment state, job separation from permanent contract to unemployment (PU) emerges as the most influential factor driving these dynamics (see figures B8 and B9 in Appendix B).

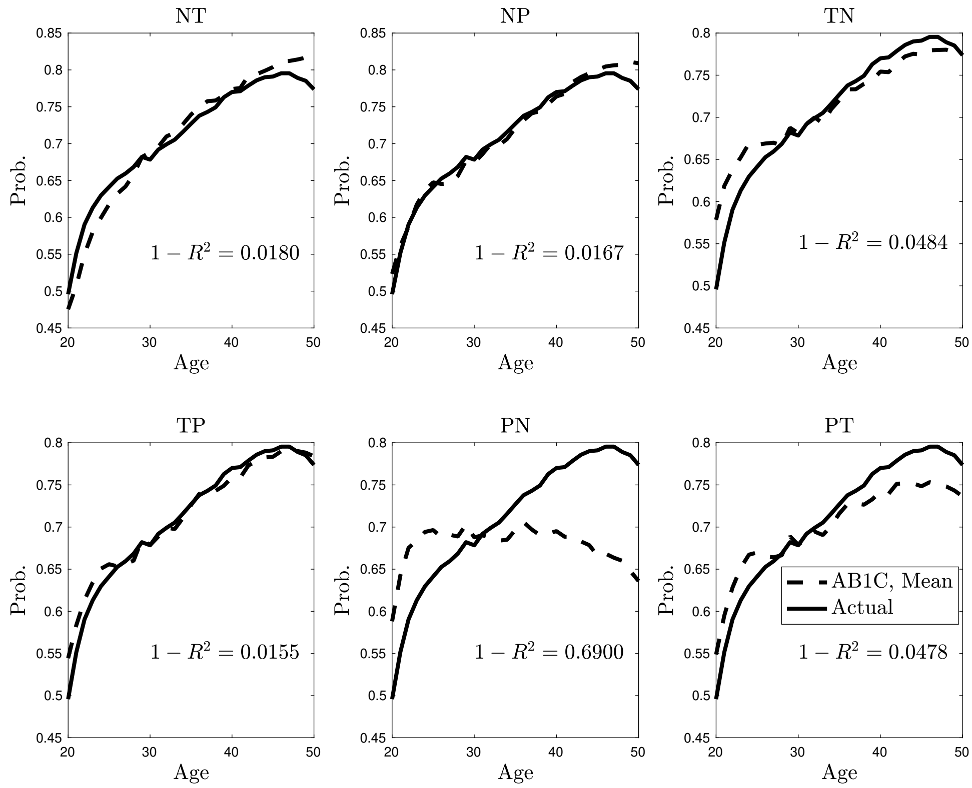
Our decomposition exercise provides valuable insights for the implementation of policies aimed at influencing the overall employment rate or employment rates within specific age and skill groups. However, the nature of policy recommendations will largely

Figure 2.3: AB1C flow decomposition of employment by age: high-education



depend on the theoretical model used to explain the observed transitions of workers over the life cycle in a dual labor market. In the next section, we fill this gap by proposing a model that accurately matches the observed life cycle profile of labor market transitions. Furthermore, the decomposition process helps identify the specific flows that need to be carefully modeled in order to replicate the observed evolution of employment over the life cycle.

Figure 2.4: AB1C flow decomposition of employment by age: low-education



2.3 Model

2.3.1 Environment

We present a search-and-matching model with heterogeneous workers and jobs. This model features uncertainty and Bayesian learning about worker ability and match-specific unemployment risk. Time is discrete, goes to infinity, and is indexed by $t = 0, 1, ...$ The economy is populated by a large number of risk-neutral workers and firms. The population of workers is constant and normalized to $L = 1$, and the population of firms, denoted by $M > 0$ is determined in equilibrium. In each period, a worker has a probability ξ of exiting the population (dying) and being replaced by a newborn worker.

Skills. Workers have skill level denoted by $x_t \in \mathbb{R}_+$. A newborn worker has skill normalized to one. A worker employed at time t accumulates skills following the process

$$\ln x_{t+1} = A + \alpha \ln x_t + \varepsilon_{t+1} \tag{2.4}$$

where $A \in \{\underline{A}, \overline{A}\}$, $0 \leq \underline{A} \leq \overline{A}$ denotes the skill-acquisition ability of the worker. ε_t is i.i.d., normally distributed with mean zero and variance σ_ε^2, and $\alpha \in (0,1)$. We assume that the process for skill dynamics differs between employment and unemployment: an unemployed worker faces the following skills process

$$\ln x_{t+1} = A_0 + \alpha \ln x_t + \varepsilon_{t+1}, \tag{2.5}$$

where $A_0 \leq 0$, meaning that on average, skill depreciates when the worker is unemployed. The skill acquisition probability A is drawn at the worker's birth. A fraction π of workers are born with skill $A = \overline{A}$, and the remaining fraction has $A = \underline{A}$. The ability A of worker is *not* observed by any agents in the economy, nor the realization of the disturbance term in (2.4). However, the skill level x_t is observable and can be relied upon as a signal informative about the true ability level A. Hence, there is uncertainty regarding the precise role of ability in driving the skill dynamics versus the role of the disturbance terms in (2.4). As such, the agents use the realized skill levels implied by (2.4) and (2.5) as signals for forming and updating Bayesian beliefs regarding the distribution of the true, unobserved worker's ability. At a time t, these beliefs are represented by a probability $\tilde{\pi}_t$ that the worker has high ability $\overline{A}$.

Conditional on prior beliefs at time t described by $\tilde{\pi}_t$ and on the current (log) skill level x_t, the next period $(t+1)$ posterior beliefs are updated based on the realized skill level following:

$$\tilde{\pi}_{t+1} = \frac{\tilde{\pi}_t f\Big(\ln x_{t+1} - \alpha \ln x_t - \overline{A}\Big)}{\tilde{\pi}_t f\Big(\ln x_{t+1} - \alpha \ln x_t - \overline{A}\Big) + (1-\tilde{\pi}_t) f\Big(\ln x_{t+1} - \alpha \ln x_t - \underline{A}\Big)}, \tag{2.6}$$

where f is the probability density function of a normal distribution with mean 0 and variance σ_ε^2. Moreover, the initial beliefs for a worker born at time t_0 are described by distribution parameters equal to their population counterparts:

$$\tilde{\pi}_{t_0} = \pi \tag{2.7}$$

for all $t_0 \geq 0$.

Jobs. Workers with varying skill levels choose jobs based on the specific skill they possess, and these jobs are further distinguished by the extent to which they utilize this skill ("task complexity"). Hence, jobs are heterogeneous and have type indexed by $j \in \{0, 1\}$. There are *generic* ($j = 0$) and *complex* ($j = 1$) jobs. The output produced at time t by a match in a complex job depends on the worker's skill level x_t, whereas the output produced by a generic job is independent of skills. The output of a worker-firm match in a complex job is given by

$$y_t = \zeta x_t^{\rho}, \tag{2.8}$$

where $\zeta > 0$ and $\rho \in (0, 1)$. The output produced by a match in a generic job is equal to $\overline{y}$. We assume that $\overline{y} > 0 = \ln(x_{t_0})$ for any birth date t_0. Low-skill workers have a comparative advantage in generic jobs, whereas the highly skilled have a comparative advantage in complex jobs.

Moreover, a match has a probability of separation δ. This probability is assumed heterogeneous across matches. Job type j and the probability δ are stochastically drawn at the beginning of potential matches between workers and firms upon meeting in the labor market, as explained in more detail below.

Search frictions. Workers are either unemployed or employed, and firms have jobs that are either vacant or occupied. An unemployed worker receives period utility $b > 0$. The per-period cost of posting a vacancy is $c > 0$. There is a search on the job; thus, unemployed and employed workers search for jobs. The labor market tightness is denoted $\theta_t = v_t/(u_t + s\, n_t)$, where $v_t > 0$ is the mass of vacant jobs, u_t is the mass of unemployed workers, and n_t the mass of employed workers; $s > 0$ is the search intensity of employed workers relative to the unemployed. We denote by $n_{s,t} = u_t + sn_t$ the effective mass of job seekers.

There is a standard Cobb-Douglas matching function $m(n_s, v) = \chi n_s^{\eta} v^{1-\eta}$, with $\chi > 0$ the efficiency of matching and $\eta \in (0, 1)$ the elasticity of matching with respect to the effective mass of job seekers. Matching is random. The contact rate of an unemployed worker is $sp(\theta) = \chi\theta^{1-\eta}$, whereas for a vacancy it is $q(\theta) = \chi\theta^{-\eta}$. Each worker-firm pair brought together via the matching technology draws a job type $j = 0, 1$ and a separation risk $\delta \in [0, 1]$. The probability of drawing a job of type $j = 0, 1$ is γ_j. We assume a probability $\overline{\gamma}$ of drawing a complex job, $\gamma_1 = \overline{\gamma}$.

The exogenous probability of separation is drawn from a distribution with c.d.f.

$G_\delta(.|j)$, dependent on the job type. Based on these elements and the worker's current unemployment or employment status and job type, the agents evaluate if it is mutually beneficial to form a match, and matching takes place accordingly.

Bargaining. As in Postel-Vinay and Robin (2002), we assume full bargaining power to the firm combined with sequential auctions and Bertrand competition between employers or firms. Hence, in the absence of an outside offer received by workers, firms extract the entire surplus of their match, but workers can use outside offers to trigger wage renegotiation and increase their share of the surplus. Wages are renegotiated following Lise and Postel-Vinay (2020). Worker's surplus share is endogenous and is a result of competition between firms.

This assumption allows us to introduce on-the-job search at a modest computational cost. Hence, the model features a job ladder with heterogeneous risk of unemployment. We show that this job ladder feature and Bayesian learning about the ability of worker are the keys to explaining the empirical facts we highlight regarding transition rates. Essentially and as it will become clear later, assuming full bargaining power to the firm implies that competition between firms only affects the distribution of the surplus between agents. As a result, the surplus functions are independent of the search on the job outcomes. This simplifies the computation of surplus functions dramatically, even in the presence of rich state space (see Lise and Postel-Vinay (2020)).

Labor market institutions. Firms can either offer a temporary or a permanent contract. We denote by TC, a temporary contract and PC a permanent contract. A permanent contract incurs firing costs of F, whereas a temporary contract has no firing costs. Temporary contracts are governed by regulations, and restrictions on these contracts are captured by a tax τ on the output of a match in a temporary job. Both F and τ represent deadweight losses that capture the effects of employment protection legislation (EPL). Alternatively, τ can be interpreted as a reduced-form approach for capturing contractual frictions that are inherent to temporary jobs, which helps accounting for the coexistence of permanent and temporary jobs as observed in the data. Rationalizing this coexistence is beyond the scope of this paper [3]. Additionally, temporary contracts have a stochastic maximum duration. With probability ϕ, the contract will come to an end and must be converted into a permanent contract. Existing legislation only permits the conversion of a temporary contract into a permanent one.

[3]See Cahuc et al. (2016), Créchet (2019), for papers that rationalize coexistence of permanent and temporary contracts.

Timing. The timing of events for each worker type is as follows:

Unemployed worker:

(i) He/she exits the labor market with probability ξ or stays with the complement probability;

(ii) If stays, observes the new skill level x_t implied by process (2.5).

(iii) Searches and receives an offer with probability $sp(\theta)$;

(iv) If receives an offer, draws a job type $j = 0, 1$ and an exogenous separation probability δ;

(v) Based on skill, belief, the job type, and the probability of separation, the agents evaluate the surplus in a PC and a TC jobs and decide whether they form a match or not and the type of contract;

(vi) If there is no offer or the surplus is not high enough to make matching mutually profitable, the agent stays unemployed.

Permanent worker:

(i) He/she exits the labor market with probability ξ, stays otherwise;

(ii) Updates skill and belief according to (2.4) and (2.6);

(iii) Receives exogenous separation shock with probability δ or stay otherwise;

(iv) If stays, he receives an outside offer with probability $sp(\theta)$, and draws a job type j' and a probability of separation δ' for the new potential match ;

(v) In the case of an offer, compares the current surplus with the outside surplus; leaves the current match for the outside match if this is profitable, and chooses the best contract type;

(vi) If there is no transition to an outside match, the worker stays employed if the surplus in the current match associated with the current skill and belief from stage (ii) is positive; otherwise, the worker returns to unemployment.

Temporary worker:

(i) He/she exits the labor market with probability ξ, and stays otherwise;

(ii) Updates skill and belief;

(iii) Receives exogenous separation shock with probability δ or stay otherwise;

(iv) With probability $1-\phi$, the agents are free to choose between a TC and PC contracts and choose the contract type yielding the more surplus; with the complement probability, the agents are required to convert the T into a P

(v) Receives a potential outside offer and evaluates the current and outside surplus; continues the match or separates for a new match or unemployment.

2.3.2 Value functions

We consider a steady-state recursive equilibrium of the labor market and drop time subscript. For extra clarity, let the dying probability $\xi = 0$ for the ease of the model's presentation. We denote by a and a' the current and next-period value of a variable a.

Let $\omega = (p, x) \in \Omega \equiv [0, 1] \times \mathbb{R}_+$ be a vector describing the worker's state: the belief for the distribution of the skill-acquisition ability and the current skill level. Moreover, denote by $S_P : \Omega \times \{0, 1\} \times [0, 1] \to \mathbb{R}_+$ and $S_T : \Omega \times \{0, 1\} \times [0, 1] \to \mathbb{R}_+$ the total worker-firm surplus functions in a permanent and a temporary contract, respectively. Let U be the worker's lifetime discounted utility value of unemployment.

As typically assumed in the literature (see Cahuc and Postel-Vinay (2002), Faccini (2014)), firing costs impact the firm's outside option during an ongoing match (i.e., in periods after the match's initial date) but not at the hiring stage. As such, this introduces a distinction between an ongoing and a hiring stage in a permanent contract. We use S_P to denote the surplus function in the continuation stage. Hence, the surplus at the hiring stage is $S_P - F$. Thus, the surplus from a new match being formed at the hiring stage is lower than that from a continuing or ongoing match because the employer only incurs firing costs once the worker has been dismissed. At the time of the first encounter between the worker and the employer, a disagreement cannot cause firing costs since no contract is yet signed. By the same logic, in the stage where the agents consider converting the temporary contract into a permanent contract (called the *conversion* stage), the surplus function is $S_P - F$.

From the assumptions that the firm has complete bargaining power and that non-work income b is independent of skills, it follows that the worker's discounted utility value of unemployment over their lifetime is simply:

$$U(p) = \frac{b}{1-\beta}, \tag{2.9}$$

for all $p \in [0, 1]$.

In addition, define

$$S_0(\omega, j, \delta) \equiv \max\Big(S_P(\omega, j, \delta) - F, S_T(\omega, j, \delta), 0\Big) \tag{2.10}$$

for all $\omega \in \Omega$, $j \in \{0, 1\}$, $\delta \in [0, 1]$, which is the maximized surplus of a potential match upon contact between a firm with a vacancy and an unemployed worker in state ω, conditional on drawing job characteristics (j, δ).

As previously mentioned, wage renegotiation takes place as in Postel-Vinay and Robin (2002) or Lise and Postel-Vinay (2020), but with adjustments made to account for the presence of both permanent and temporary contracts. Importantly, we assume that in the case of renegotiation, the worker can use the threat represented by firing costs to negotiate wages up to the point where the firm is indifferent between paying firing costs and keeping the worker. Hence, the employer's willingness to pay in a permanent job is the wage such that the profit of the active job equals the value of a vacant position net of firing costs.[4]

We denote by $\nu \in [0, 1]$ the surplus share of a worker in a given match. Due to assumption of firms having full bargaining power, workers hired from unemployment have $\nu = 0$. In subsequent periods, they can use outside offers to trigger competition between employers and improve their surplus, implying that $\nu \geq 0$ in general. Let begin by assuming a worker in a permanent contract and in state (ω, j, δ). Conditional on receiving an outside offer from a vacancy with job characteristics (j', δ'), the worker moves to the new job if $S_0(\omega, j', \delta') > S_P(\omega, j, \delta)$, and otherwise stays with the same employer (assuming $S_P(\omega, j, \delta) \geq 0$). Conditional on staying, the worker receives an updated surplus share given by[5]

$$\nu' = \mathcal{I}\Big(\nu S_P(\omega, j, \delta) > S_0(\omega, j', \delta')\Big)\nu + \mathcal{I}\Big(\nu S_P(\omega, j, \delta) \leq S_0(\omega, j', \delta')\Big)\frac{S_0(\omega, j', \delta')}{S_P(\omega, j, \delta)} \tag{2.11}$$

In the case of job-to-job move, the worker surplus share in the new match is:

$$\nu' = \frac{S_P(\omega, j, \delta)}{S_0(\omega, j', \delta')} \tag{2.12}$$

As a result, the worker expected surplus, conditional on receiving an outside offer (with

[4]We abstract from transfers between workers and firms upon separations (i.e., severance payments). See Postel-Vinay and Turon (2014) for a case where such transfers are allowed.

[5]See appendix B for sequences that give the result

probability $sp(\theta)$), reads:

$$
\begin{aligned}
&\Delta_{W,P}(\omega, j, \delta, \nu) = \\
&\sum \gamma_j \int \min \left\{ \max \Big(\nu S_P(\omega, j, \delta), S_0(\omega, j', \delta'), 0 \Big), \max \Big(S_P(\omega, j, \delta), 0 \Big) \right\} dG_\delta(\delta'|j')
\end{aligned}
\tag{2.13}
$$

for all ω, j, δ; the expected surplus of the firm conditional on an outside offer is

$$
\begin{aligned}
&\Delta_{J,P}(\omega, j, \delta, \nu) = \\
&\sum \gamma_j \int \max \left\{ \min \Big(S_P(\omega, j, \delta) - S_0(\omega, j', \delta'), (1-\nu) S_P(\omega, j', \delta') \Big), 0 \right\} dG_\delta(\delta'|j')
\end{aligned}
\tag{2.14}
$$

It is easy to see that $\Delta_{W,P}(\omega, j, \delta, \nu) + \Delta_{J,P}(\omega, j, \delta, \nu) = \max(S_P(\omega, j, \delta), 0)$ for all $\nu \in [0, 1]$. Hence, there is no gain in match surplus resulting from searching on the job. However, from the worker's perspective, there is a gain. The worker receives the total surplus of the current match. This follows from the assumption of zero bargaining power to the worker, implying that the worker's gains and the firm's losses offset each other. Hence, the total surplus of a permanent job can be expressed as:

$$
S_P(\omega, j, \delta) = y_j - b + (1-\beta) F + \beta(1-\delta) \int \max \Big\{ S_P(\omega', j, \delta), 0 \Big\} dH_x(x'|\omega), \tag{2.15}
$$

such that the next-period worker's state vector $\omega' = (p', x')$ has belief p' updated following:

$$
p' = \frac{pf\Big(\ln x' - \alpha \ln x - \overline{A}\Big)}{pf\Big(\ln x' - \alpha \ln x - \overline{A}\Big) + (1-p) f\Big(\ln x' - \alpha \ln x - \underline{A}\Big)} \tag{2.16}
$$

for all $p \in [0, 1]$ and all $x \geq 0$. The next-period skill x' follows the normal mixture distribution with density:

$$
\begin{aligned}
&h(x'|x, p) = \\
&\frac{1}{x'\sigma\sqrt{2\pi}} \left\{ p \exp\left[-\frac{1}{2} \frac{(\ln x' - \alpha \ln x - \overline{A})^2}{\sigma^2} \right] + (1-p) \exp\left[-\frac{1}{2} \frac{(\ln x' - \alpha \ln x - \underline{A})^2}{\sigma^2} \right] \right\},
\end{aligned}
\tag{2.17}
$$

and associated c.d.f. $H(.|x, p)$.

Hence, the surplus function (2.15) has a current-period value given by the match current output net of the annuity value of unemployment and firing costs. An exogenous separation occurs with probability δ. The next-period expectation for the discounted total lifetime value is taken over the distribution of next-period skills x' implied by the current skill level x and by the current beliefs regarding the distribution of the skill-acquisition ability, p. This distribution is described by (2.17). Moreover, the agents internalize that their next-period beliefs p' will be updated based on the realization of x' and given the current state, following (2.16).

Worker's gains and employer's losses from on-the-job search do not show up in the equation for the total surplus since, as discussed above, they offset each other. With full bargaining power to the employer, on-the-job search outcomes only affect the distribution of the surplus over time, leaving the total surplus unchanged. Here, we can interpret the job-to-job move as if the worker stays in the same match but extracts the entire surplus.

Similarly, the worker-firm match surplus in a temporary job is

$$\begin{aligned}S_T(\omega, j, \delta) = {} & (1-\tau)y_j - b \\ & + \beta(1-\delta)(1-\phi)\int \max\Big\{S_T(\omega', y, \delta), S_P(\omega', y, \delta) - F, 0\Big\} dH_x(x'|\omega) \\ & + \beta(1-\delta)\phi \int \max\Big\{S_P(\omega', y, \delta) - F, 0\Big\} dH_x(x'|\omega),\end{aligned} \tag{2.18}$$

such that (2.16) to (2.17) are satisfied. With probability ϕ, the agents must convert the temporary contract into a permanent one or terminate the match. With the complement probability $1-\phi$, the agents are allowed to continue into a temporary job, convert the contract into permanent or endogenously dissolve the match.

Since unemployment income is independent of skill, the surplus in a generic job is independent of skill following the assumption of zero bargaining power to the worker. As such, the surplus of a generic ($j = 0$) permanent job satisfies

$$\begin{aligned}S_P(\omega, 0, \delta) &= S_P(0, \delta) \\ &= \overline{y} - b - (1-\beta)F + \beta(1-\delta)\max\Big(S_P(0, \delta), 0\Big),\end{aligned} \tag{2.19}$$

for all $\delta \in [0, 1]$. In a temporary job, we have

$$\begin{aligned}S_T(\omega, 0, \delta) &= S_T(0, \delta) \\ &= \overline{y} - b + \beta(1-\delta)\Big[(1-\phi)\max\Big(S_T(0, \delta), S_P(0, \delta) - F, 0\Big) \\ &\qquad + \phi \max\Big(S_P(0, \delta) - F, 0\Big)\Big]\end{aligned} \tag{2.20}$$

In steady-state, the equilibrium surplus in a permanent job is,

$$S_P(0,\delta) = \frac{\overline{y} - b + (1-\beta)F}{1-\beta(1-\delta)}, \tag{2.21}$$

for all $\delta \in (0,1)$, independently of the worker's state ω. Moreover, in equilibrium, a temporary job that has been formed upon meeting between the worker and the firm in the match must have a higher surplus than in a P job. Otherwise, the T match would not have been formed in the first place. Hence, the surplus in a T solves

$$S_T(0,\delta) = \frac{\overline{y} - b + \beta\phi(1-\delta)\max\Big(S_P(0,\delta) - F, 0\Big)}{1-\beta(1-\delta)(1-\phi)}, \tag{2.22}$$

for all $\delta \in (0,1)$.

2.3.3 Wages

To derive the equilibrium wage functions, it is useful to denote by $W_{P,i}(\omega, y, \delta; \nu)$ the value function of a worker in a permanent contract receiving surplus share $\nu \in [0,1]$, resulting from past renegotiation triggered by previous outside offers. The index i indicates whether the state is taken to be in the hiring/conversion stage ($i = 0$) or in the continuation stage ($i = 1$). Notice that

$$W_{P,i}(\omega, j, \delta; \nu) - U = \nu\Big(S_P(\omega, y, \delta; \nu) + \mathcal{I}(i = 1)F\Big). \tag{2.23}$$

Further, the worker's surplus, after making use of (2.13), can be written as

$$\begin{aligned} W_{P,i}(\omega, j, \delta; \nu) - U &= w_{P,i}(\omega, j, \delta; \nu) - b + \beta(1-\delta) \\ &\times \int \Big[(1 - sp(\theta))\nu \max(S_P(\omega', j, \delta), 0) + sp(\theta)\Delta_{W,P}(\omega', j, \delta; \nu)\Big] dH_x(x'|\omega) \end{aligned} \tag{2.24}$$

for all $i, \omega, y, \delta, \nu$, where $w_{P,i}(\omega, y, \delta; \nu)$ denotes the wage. From the perspective of the worker, the surplus gains in the eventuality of a contact with an outside firm, $\Delta_{W,P}$, show up in expectations regarding the next-period surplus. With probability $1 - sp(\theta)$, there is no outside offer, and the surplus share of the worker remains unchanged.

We have, for a worker in a temporary contract

$$
\begin{aligned}
&W_T(\omega, j, \delta, \nu) - U = w_{P,i}(\omega, j, \delta; \nu) - b + \beta(1-\delta) \\
&\times \int \Big\{ (1-\phi)\Big[(1 - sp(\theta))\nu \max(S_T(\omega', j, \delta, \nu), S_P(\omega', j, \delta, \nu) - F, 0) + sp(\theta)\Delta_{W,T}(\omega', j, \delta, \nu) \Big] \\
&\qquad + \phi \Big[(1 - sp(\theta))\nu \max(S_P(\omega', j, \delta; \nu) - F, 0) + sp(\theta)\Delta_{W,P,0}(\omega', j, \delta, \nu) \Big] \Big\} dH_x(x'|\omega),
\end{aligned}
\tag{2.25}
$$

where

$$
\begin{aligned}
&\Delta_{W,T}(\omega, j, \delta; \nu) = \\
&\qquad \int\int \min\Big\{ \max\Big(\nu S_T(\omega, j, \delta), S_0(\omega, j', \delta'), 0\Big), \max(S_T(\omega, j, \delta), S_P(\omega, j, \delta) - F, 0) \Big\} \\
&\qquad\qquad \times dG_\delta(\delta'|j') dG_j(j')
\end{aligned}
$$

$$
\begin{aligned}
&\Delta_{W,P,0}(\omega, j, \delta; \nu) = \\
&\qquad \int\int \min\Big\{ \max\Big(\nu (S_P(\omega, j, \delta) - F), S_0(\omega, j', \delta'), 0\Big), \max(S_P(\omega, j, \delta) - F, 0) \Big\} \\
&\qquad\qquad \times dG_\delta(\delta'|j') dG_j(j')
\end{aligned}
$$

represent the expected surplus of the worker, conditional on the state and on a contact with an outside firm, in a TC and in PC (at the conversion stage) respectively.

Using (2.15) and (2.24) the wage in a PC can be written as

$$
\begin{aligned}
w_{P,i}(\omega, j, \delta, \nu) &= \nu y_j + (1-\nu)b + \nu(\mathcal{I}(i=1) - \beta)F \\
&\quad - sp(\theta) \int \Big(\Delta_{W,P}(\omega', j, \delta; \nu) - \nu \max(S_P(\omega', j, \delta; \nu), 0) \Big) dH_x(x'|p)
\end{aligned}
\tag{2.26}
$$

for $i = 0, 1$, and the wage in a temporary contract is written as, using (2.18) and (2.25)

$$
\begin{aligned}
&w_T(\omega, j, \delta; \nu) = \nu y_j + (1-\nu)b \\
&- sp(\theta)(1-\phi) \int \Big(\Delta_{W,T}(\omega', j, \delta; \nu) - \nu \max(S_T(\omega', j, \delta; \nu), S_P(\omega', j, \delta; \nu) - F, 0) \Big) dH_x(x'|\omega) \\
&- sp(\theta)\phi \int \Big(\Delta_{W,P,0}(\omega', j, \delta; \nu) - \nu \max(S_P(\omega', j, \delta; \nu) - F, 0) \Big) dH_x(x'|\omega)
\end{aligned}
\tag{2.27}
$$

for all ω, j, δ, and ν. Worker collects a fraction ν of the match output net of the expected gains from renegotiation due to on-the-job search, and a fraction $1-\nu$ of the annuity value of unemployment. In the case of a permanent contract, the worker also collects a fraction ν of the annuity value of firing costs at the continuation stage ($i = 1$), and the same fraction of the discounted firing costs.

2.3.4 Equilibrium

We assume free entry of firms, which in equilibrium implies zero expected profits from vacancy posting. Let $u(a)$ and $n(a)$ denote the measures at age a of unemployed and employed workers respectively. Free entry yields the following equation

$$\frac{c}{\beta\, q(\theta)} = \sum_a \Bigg\{ \underbrace{\frac{u(a)}{u+s\,n} E\Big[\max(S_0(\omega, j, \delta, \nu=0), 0)\Big]}_{\text{Vacancy meets unemployed}} + \underbrace{s\frac{n(a)}{u+s\,n} E\Big[\mathcal{I}_{(S_0(\omega,j',\delta',\nu')>S_0(\omega,j,\delta,\nu))}(1-\nu')\max(S_0(\omega, j', \delta', \nu'), 0)\Big]}_{\text{Vacancy meets employed}} \Bigg\} \tag{2.28}$$

The expectations are taken with respect to the distribution of worker states and job characteristics in the pool of employed and unemployed job searchers of age a.

Definition. *The stationary market equilibrium is a list of functions $\{S_0, S_T, S_P, \nu, w\}$, labor market stocks $\{u(a), n(a)\}$ for all age a, and labor market tightness θ such that: (i) S_T, S_P and S_0 satisfy respectively 2.18, 2.15, 2.10; ν satisfies 2.11 and 2.12; w solves 2.23 and 2.25 given the labor market tightness θ; (ii) the labor market tightness θ solves 2.28 given S_0, S_T, S_P, ν, the labor market stocks and the cross-sectional distribution of workers' skill, beliefs and job characteristics; (iii) the labor market stocks and distributions of workers' skill, beliefs and job characteristics are constant over time.*

2.4 Calibration

This section describes the calibration strategy. We perform two calibrations: one for each education group. The calibration is at the quarterly frequency. Hence, one period in the model represents a quarter in a worker's life. Some parameters are assigned to standard values and are assumed to be the same across education groups. The parameters governing the distribution of unemployment risk, skill and beliefs, the composition of job type, and some institutional factors are separately calibrated to match salient features of workers' life cycle in high and low-education groups.

2.4.1 Assigned parameters

The assigned parameters are reported in table 2.1. The time unit is set to a quarter, and the working-life duration equals 38 years. Taken together, these imply an exogenous dying probability of $\xi = 0.0065$. We set $\beta = 0.9902$ (a 4% annual discount rate). The elasticity of matching is set to $\eta = 0.5$, a conventional value. The matching efficiency χ is part of the internal calibration procedure described below. Hence, a value for the firms' search costs c will be backed out to satisfy the free-entry condition, using the calibrated value for χ and the normalization of labor tightness value $\theta = 1$. On average, when a worker is not employed, his log-skill x depreciates and drifts down toward a low level of ability A_0, which we normalize to 0, in line with Kehoe et al. (2019). In addition, we normalize to one, $\zeta = 1$, the scale parameter for the complex job production function.

Among institutional parameters, only the tax τ on the output of a match in a temporary job and the probability to convert a temporary contract to a permanent one, ϕ, are preset. We set $\tau = 0$, and let y in the benchmark model be interpreted as after-tax output. We calibrate the parameter for the duration restriction ϕ to 0.1175. This value matches two years of an expected duration of a temporary contract before conversion to a permanent contract. This is consistent with legislation in many countries for the maximum duration of these contracts.

The process of skill dynamics is governed by the persistence parameter α. We set α to 0.9702 in line with Santos and Rauh (2022), which approximates mean earnings profile from a standard Mincer regression of log wages, controlling for education. We assume that initial belief about ability is uniform across ability level. Hence, we set the probability of having high ability belief initially to $p_0 = 0.5$.

2.4.2 Internally calibrated parameters

The following remaining parameters are separately calibrated to match salient features of workers' life cycle in high- and low-education groups using a simulation-based method. Those are the matching efficiency χ, the non-work income b, the firing cost F, the employed worker search intensity on the job s, the proportion of complex job $\bar{\gamma}$, the high and low level of potential ability (A_h, A_l), the variance of disturbance embed in skill learning σ_ε, the shape parameters for job separation distribution with respect to job type, and the elasticity ρ of output with respect to skill x in the complex job. We assume the job separation δ is drawn from a beta distribution with shapes (λ_1, λ_2)

Table 2.1: Benchmark values of preset parameters

Parameter	Description	Value
β	Discount rate	0.9902
ξ	Exogenous dying probability	0.0066
$\overline{y}$	Output for generic job	1.4286
τ	Tax on temporary contract	0
η	Elasticity of matching function	0.5
ζ	Scale for complex job production function	1
ϕ	Expected max duration of TC	0.1175
α	AR1 skill dynamics persistence, employment	0.9702
p_0	Proportion having high ability beliefs A_h	0.5
A_0	Ability in skill process from unemployment	0

The calibration of the parameters mentioned above minimizes the sum of the relative differences (in absolute values) of a set of simulated moments and their empirical counterparts. We target the following transition rates, computed from 2003-2018 EEC data: the age profiles of the UP, UT, PT, PU, TP, and TU. We also target the unemployment age profile and the age profile of the share of employment in a temporary contract. Additional details, including a discussion of how the parameters are informed by these moments, are provided in the appendix.

2.4.3 Model fit

The estimated parameters are reported in table 2.2, and the model fit to the data is displayed in figures 2.5, 2.6, and 2.7. Figure 2.5 plots the unemployment rate and the share of temporary employment in the model along with its empirical counterpart. Panel (a) presents results for low education group and panel (b) reports results for the high-education group.

We observe that the model fits the data very well, capturing the decline in the unemployment rate and a share of temporary contract jobs as workers age. This is a result of the combination of the behavior of transition rates over the life-cycle. Figure 2.6 plots the transition rates for the low-education group. As we can see, the model matches very well the transition profiles. It generates the flat profile observed in the data for UP, UT, and TP transition rates throughout the life cycle. In addition, the model delivers the declining profile for job separation rate as measured by PU and TU as workers age, although, in the model, the separation rate from temporary jobs to unemployment slightly decreases at the end of the careers. This could be due to an absence of participation

Table 2.2: Benchmark values of estimated parameters

Parameter	Description	Value	
		Low-educ.	High-educ.
b	Non work utility	0.9629	0.9517
F	Firing cost	1.9727	1.8942
χ	Matching efficiency	0.3216	0.3450
s	Employed search intensity	0.5	0.5
ρ	Complex job output function parameter	0.0249	0.3442
$\lambda_{1,g}$	Shape 1 for generic job sepa. distribution	0.3267	1.8047
$\lambda_{2,g}$	Shape 2 for generic job sepa. distribution	1.1875	1.5121
$\lambda_{1,c}$	Shape 1 for complex job sepa. distribution	2	0.1745
$\lambda_{2,c}$	Shape 2 for complex job sepa. distribution	7.1283	2.7585
$\bar{\gamma}$	Proportion of complex job	0.6745	0.4305
σ_{ε}	Standard deviation for skill disturbance	0.0181	0.1852
A_l	Low level of ability belief	0.0076	0.0011
A_h	High level of ability belief	0.0387	0.0251

margin in the model. In the data, transitions from employment to inactivity are relatively high for the oldest workers (e.g., Choi et al. (2015)), a pattern that could be reproduced in the presence of a distinction between unemployment and non-participation. Nonetheless, we are confident about our model's ability to explain employment dynamics over the life cycle, since it remarkably replicates the profile of PU transition. Indeed, PU emerges as the most important factor explaining the employment dynamics for low-education individuals over the life cycle according to our decomposition exercise in the previous section.

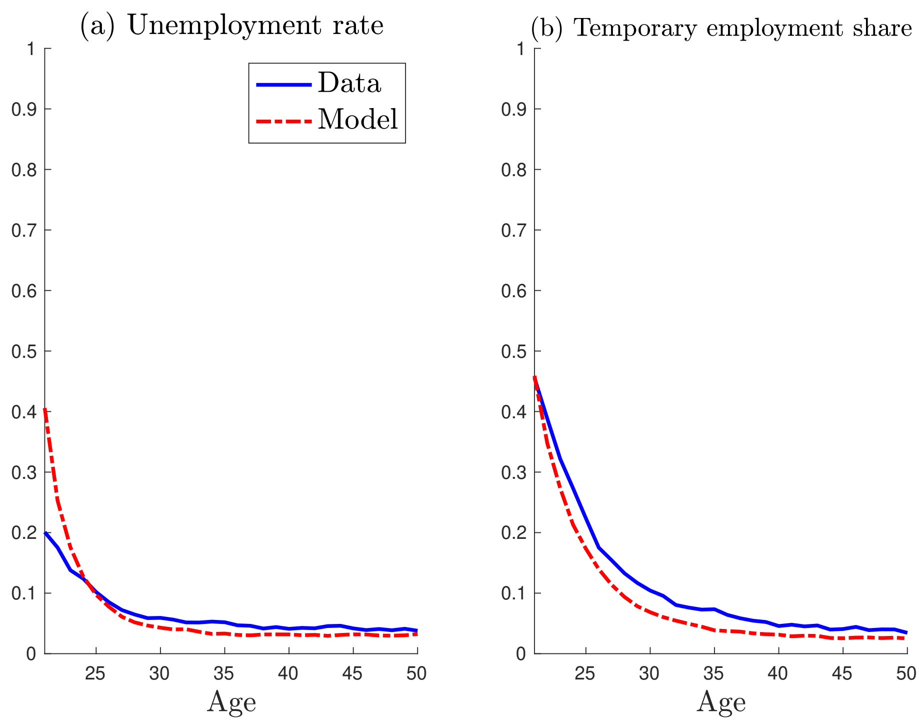
Figure 2.7 plots the transition rates for high education group. The model fairly fits the data counterpart and captures the declining shape of the transition rates. The transition UP, PU, PT, and TU are well matched but the model has difficulties with fitting the level of UT and TP in data. Overall, the model is capable of generating the salient features of transition profiles observed in the data. Again, a very interesting feature is that the model remarkably fits the age profile of PU and PT transition rates for high-education individuals. These transitions are the most important contributors in explaining total employment rate dynamics over the life cycle for high-education groups (see decomposition exercise).

In the next, we explore the role of learning versus idiosyncratic unemployment risk in fitting the observed transition rates.

Figure 2.5: Target unemployment and temporary employment share profiles - Model vs. Data

(a) Low education

(b) High education



Notes: The solid blue lines denote the data and the dashed red lines denote the model.

2.4.4 Model Mechanisms

How does the model achieve desirable life-cycle properties for the worker flows across skill groups? It is instructive to zoom into two channels captured by the model: learning about worker ability, and idiosyncratic unemployment risk.

We argue that the model generates a declining profile for employment exit transitions (PU, TU) and job-to-job transition (PT), regardless of the education group, due to skill accumulation. As workers age, they accumulate skills on the job, possibly through learning by doing, and become less likely to separate from their current employment. Conversely, the relatively flat life-cycle profile of job-finding rates (UP, UT) for the low-skill group primarily results from idiosyncratic unemployment risk. In contrast, the declining profile observed among high-skill workers is driven by learning about worker ability. Hence, Bayesian learning plays a more significant role for high-education workers, whereas heterogeneity in unemployment risk is the primary factor contributing to the life-cycle variation in worker flows for the low-educated group.
To test our theory, we investigate the contribution of the learning channel to the model fit of the job-finding rate (UP) for low-education versus high-education workers. We compare the life-cycle profiles of the benchmark model with those of a counterfactual model where we alternatively switch off the learning and the idiosyncratic unemployment risk δ. More precisely, to eliminate the learning in the model, we significantly reduce the standard deviation of the disturbance σ_ε, ($\sigma_\varepsilon \longrightarrow 0$). This reduction effectively diminishes the noise in the worker's ability signal, which reflects the firm's choice of recruitment and screening practices. With lower noise, the ability of the worker is revealed upon contact, eliminating the need for a screening process and, consequently, the learning mechanism. To eliminate the idiosyncratic unemployment risk, we substantially increase the second shape parameter of the beta distribution for job separation draws, ensuring that $\delta = 0$ becomes nearly zero with high probability. By doing so, we remove the individual variation in unemployment risk experienced by workers. To isolate the effects of removing each channel separately, we keep the remaining model parameters unchanged from the baseline case, except for the vacancy cost c. We recalibrate the model to match the labor market tightness $\theta = 1$, consistent with the benchmark case. The results of these counterfactual scenarios are presented in Figure 2.8.

Panel (a) of Figure 2.8 depicts a scatter plot comparing the UP transition between the benchmark model and the model with only the learning mechanism, for high-education individuals. The same logic applies to the other subfigures. As we can see, the learning model yields higher R−squared compared to the model focusing solely on the unemployment risk channel. This suggests that learning plays a crucial role in explaining the declining profile of the UP transition for high education. Conversely, the unemployment risk channel appears to be an important factor in generating a flat profile for low-educated individuals.

The underlying intuition is as follows: Low-educated individuals possess a comparative advantage in generic jobs, where their observable skills are sufficient for employment. On the other hand, high-educated individuals have a comparative advantage in complex jobs. These complex jobs involve tasks that necessitate abilities that are not directly observable. Consequently, high-education individuals sort into jobs where their true ability needs to be screened, giving rise to a learning process that unfolds over the life cycle. As a result, the fraction of high-education workers who face a higher probability of immediate ability revelation increases with age. Hence, for older workers with higher education, the probability of finding a job is lower, as they may be perceived as having lower abilities based on their observed characteristics while they are unemployed.

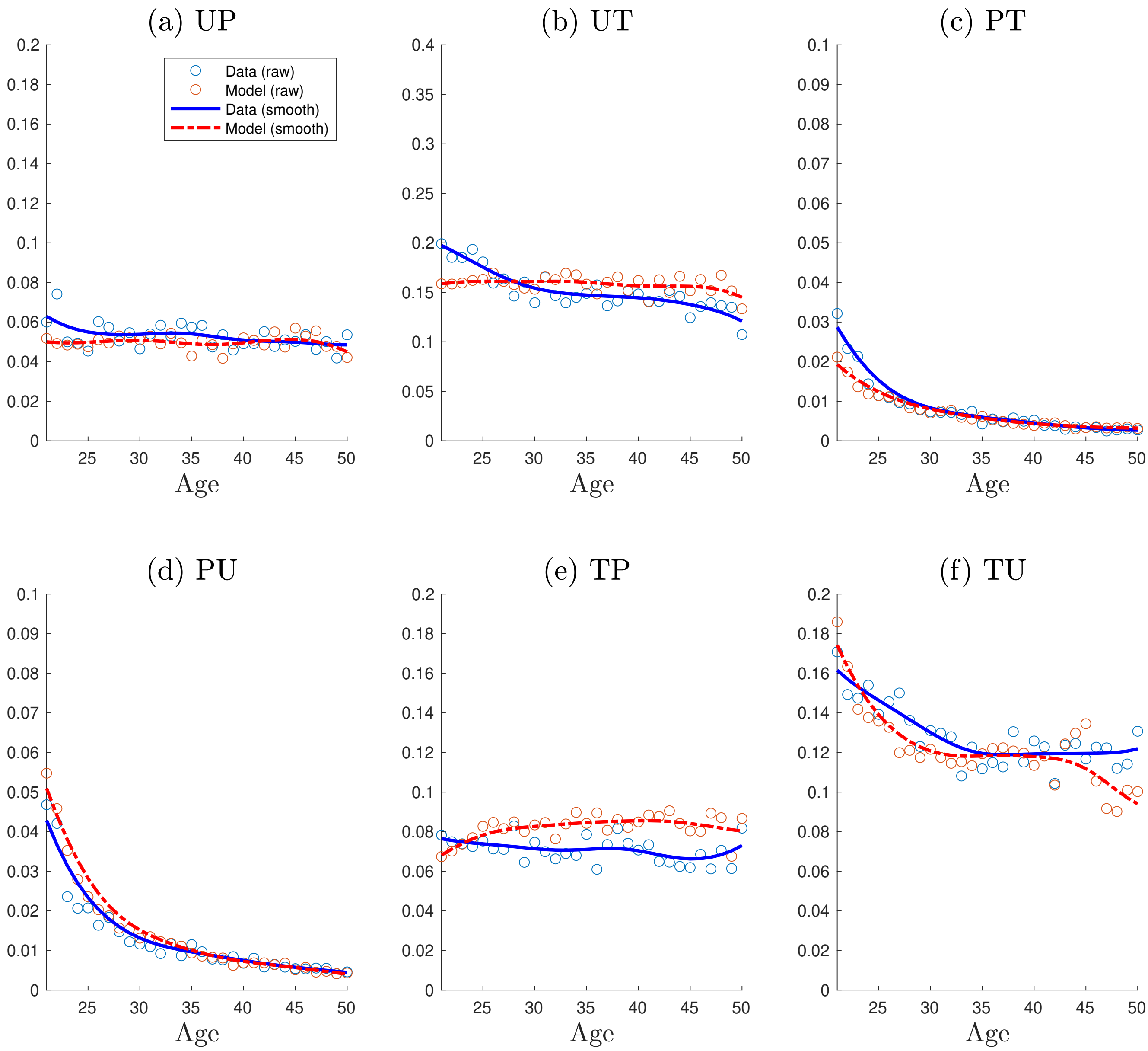
Since, learning and churning have different implications for employment (Faccini (2014), Blanchard and Landier (2002)), the cost or gain from EPL reforms will be different across age and skill groups. In the next section, we explore the distributional effect of these reforms.

2.4.5 Distributional effect of EPL reforms

What are the implications for the distribution of the cost of the Employment Protection Legislation reforms across skill and age groups? The answer holds significance in shaping targeted policy aimed at lessening the adverse impacts of EPL reforms, calling for a reform of EPL reforms.

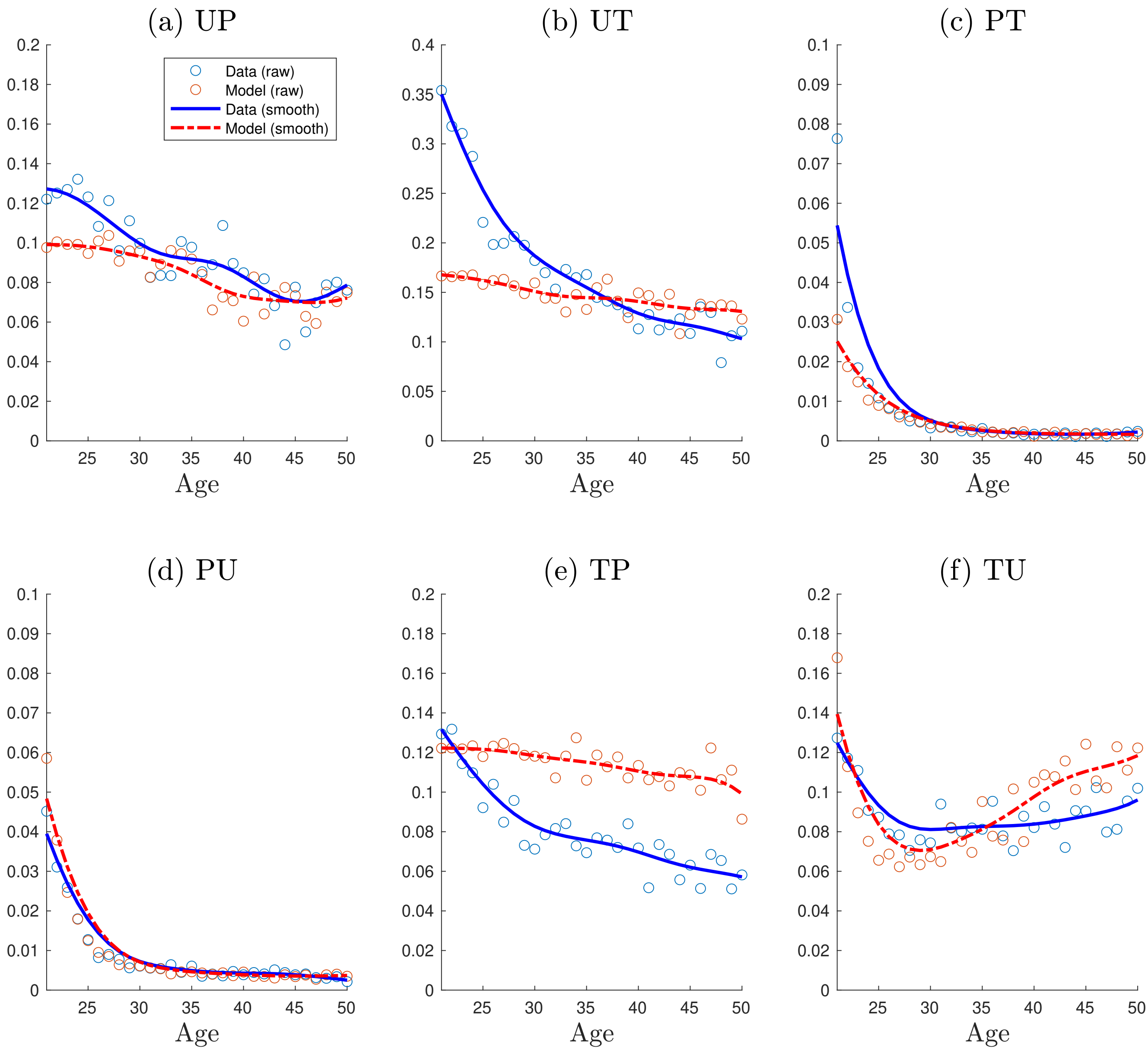
Our decomposition analysis shows that the employment exit probability matters more in explaining the life-cycle patterns of employment. Hence, since temporary contracts can act as stepping stone towards stable job (learning channel), the duality generated by EPL reforms through firing restrictions on permanent contracts will ultimately lead to lower unemployment rate over the life-cycle. Conversely, encouraging inefficient turnover (churning channel), temporary contracts can increase job destruction and raise unemployment rate over the life-cycle. Since, churning is more at play with low educated workers, the latter would disproportionately bear the cost of EPL reforms. To test our intuition, we conduct an experiment in which we compare the benchmark with a

Figure 2.6: Target transition profiles - low education



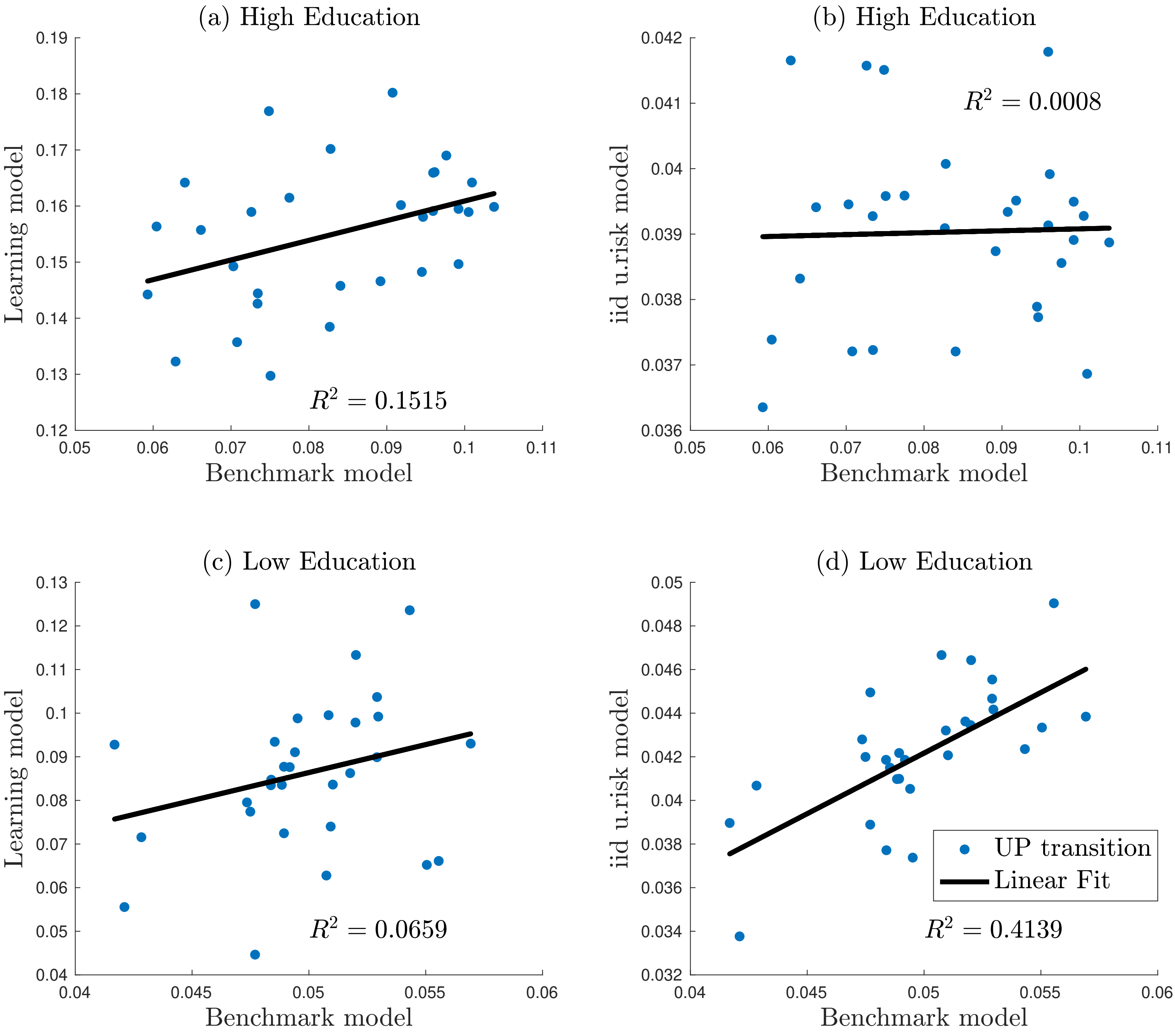
Notes: The plots show quarterly transition probabilities. The solid blue lines denote the data and the dashed red lines denote the model.

Figure 2.7: Target transition profiles - high education



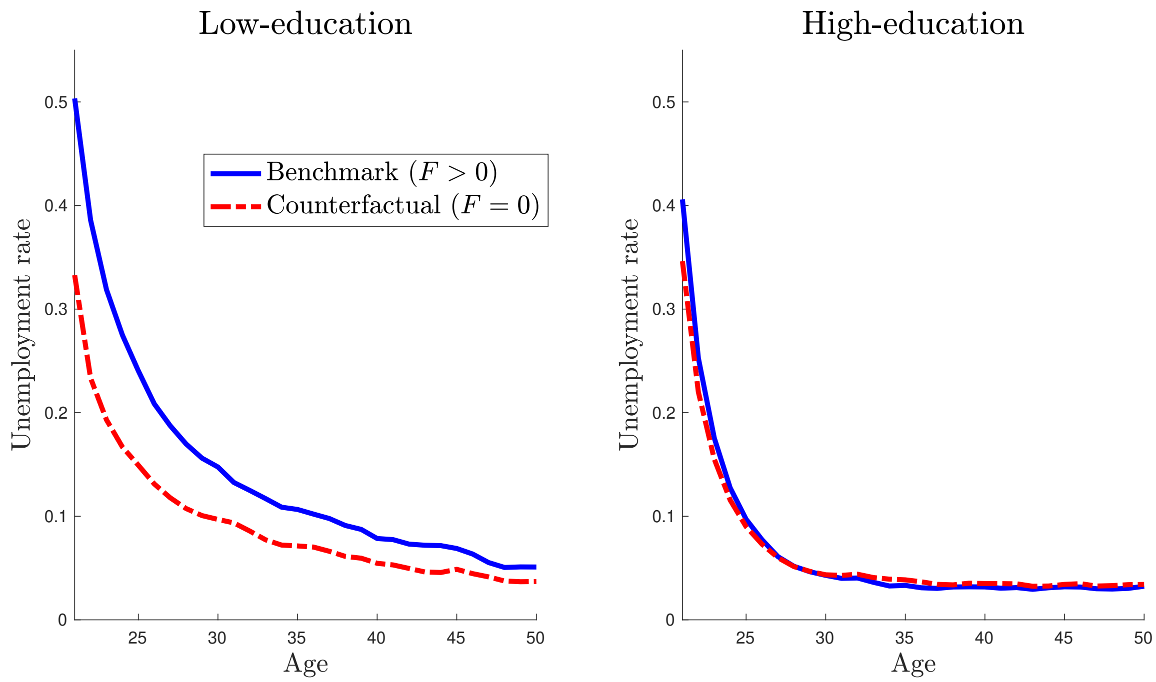
Notes: The plots show quarterly transition probabilities. The solid blue lines denote the data and the dashed red lines denote the model.

Figure 2.8: Role of learning versus idiosyncratic unemployment risk



counterfactual economy without firing cost ($F = 0$). We keep the labor market tightness constant in order to focus on partial equilibrium factors (information frictions, churning) instead of general equilibrium channel. The results are depicted in figure 2.9.

Figure 2.9: Distributional effect of EPL reform on unemployment rate by age



The EPL reforms, indeed, generates higher unemployment rate over the life-cycle for low educated individuals. This suggest that the churning effect of temporary contracts is largely at play for low educated workers and dominates. Conversely, learning and churning effects appear to offset each other for high educated workers. On average, EPL reforms contribute to increase the age-profile of unemployment rate, with young and low educated workers bearing the cost. Hence, TC jobs are more likely to be *dead-ends* jobs for low educated workers compared with their high education counterparts. This is so because the low educated market segment is characterized by a lack of downward wage flexibility with a potential binding minimum wage and a high degree of substituability between workers stemming from non-specific skills requirement. In case of dismissal, PC jobs become much more expensive and wage rigidity prevents an offsetting transfer from workers to firms in exchange for being insured against job losses (Lazear (1990)). Consequently, firms prefer to use TC in sequence rather than converting them into PC leading to excessive worker turnover.

2.5 Conclusion

This paper examines life-cycle patterns of worker flows in a dual labor market characterized by the presence of permanent contracts subject to high firing costs and temporary contracts. A decomposition analysis relying on estimates of worker flows based on French Labor survey data shows that this duality between temporary and permanent employment has an important age component and different implications for age-specific employment dynamics across education groups, as well as for the formation of youth employment.

We propose a model that matches the observed life cycle profile of labor-market transitions. The model generates a declining profile for employment exit transitions (PU, TU) and job-to-job transitions (PT), regardless of the education group, due to skill accumulation. We use this model to investigate the primitive sources of these patterns. On the other hand, the relatively flat life-cycle profile of job-finding rates (UP, UT) for the low-skill group primarily results from idiosyncratic unemployment risk. In contrast, the declining profile observed among high-skill workers is driven by learning about worker ability. Hence, Bayesian learning plays a more significant role for high-education workers, whereas heterogeneity in unemployment risk is the primary factor contributing to the life-cycle variation in worker flows for the low-educated group. Furthermore, the model provides a tool for assessing the effect of temporary contracts and firing costs on employment, aggregate productivity, and the life-cycle dynamics of earnings.

Chapter 3

Climate Policy, Financial Frictions and Aggregate Productivity

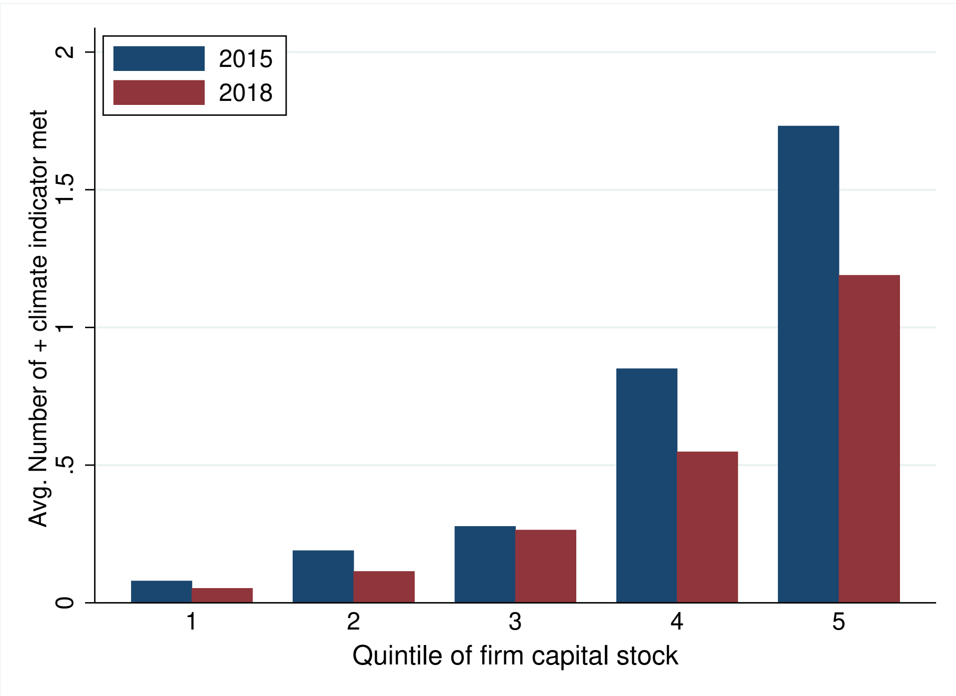
3.1 Introduction

There is a growing concern about the threat pertain to climate change. The risks to the economy broadly range from physical risk (water scarcity , rising sea levels, flood) to financial risk, through stranded asset, that potentially affect the financial stability of the overall economy. Consequently, regulators have taken up the task of designing environmental policies aimed at enhancing resilience to climate change consequences and facilitating a smooth transition towards a carbon-neutral economy. Among the various climate policies, emissions taxes and output-based intensity standards have emerged as recurring approaches. While there is a consensus among many studies regarding their efficacy in reducing emissions, a debate exists regarding their efficiency in terms of the allocation of factors across production units (see Nordhaus (2007), Muller and Mendelsohn (2009), Holland (2012), Li and Shi (2017)). This study contributes to this literature by analyzing the macroeconomic effects resulting from the implementation of an emission tax, in conjunction with a green financing policy. The green financing policy aims to redirect capital towards environmentally friendly firms.

More interestingly, this paper investigates the impact of these policies in an environment where heterogeneous firms face credit constraints when seeking to leverage capital for production purposes. The motivation behind this analysis stems from the observed positive relationship between the stock of capital held by a firm and its climate performance, as depicted in Figure 3.1. Firms with higher capital stocks tend to exhibit greater environmental practices. This relationship holds true across sectors (see to Appendix C). This observation suggests that certain firms may encounter difficulties in adopting environmentally friendly practices not due to lower productivity, but rather due to insufficient resources available for investment in emission abatement technologies.

To examine the implications of climate policy, I construct a general equilibrium model of heterogeneous firms. The model builds upon the framework established by Buera and Moll (2015), incorporating features related to environmental policies. In the model, firms differ in their productivity and capital holdings. Additionally, they have access to abatement technologies. The heterogeneity in capital holdings leads to variations in firm-level emission abatement efforts, ultimately resulting in differences in emission intensity. Through the lens of the model, I argue that in this environment, misallocation of capital

Figure 3.1: Climate performance and firm capital stock



Note. Data on climate indicators come from MSCI. Firm capital stock is computed using the Compustat database. The dataset consists of publicly listed firms operating within the United States. See appendix C for details

may occur when imposing proportional emission tax: Some firms with high productivity but low asset might exit the market due to the carbon tax burden, and some others with moderate productivity level but wealthy may be able to sustain their operations. This is essentially arises when the reduction in emissions exhibits less sensitivity to investment in abatement technology. However, it is important to note that this misallocation occurs because of the availability of abatement technology. In the absence of such technology, the proportional emission tax would essentially function as a tax on output, distorting the optimal allocation of inputs across firms in a way that is uncorrelated with neither productivity nor firm's size. As a result, the marginal product of inputs would remain unaffected across firms.

Related Literature This paper contributes to a growing literature in environmental economics that stresses the role of firm-level heterogeneity in assessing specific environment policy. For example, Tombe and Winter (2015) use a heterogeneous firms model estimated to the United States to evaluate the productivity losses from output-based intensity standards. Li and Sun (2015), Li and Shi (2017) examine the welfare effects of emission taxes and output-based standard. I differ from these studies by my focus on the effects of emission taxes together with a green financing in an environment where firms are financially constrained and engaged in pollution abatement. Relatedly, Fang et al. (2023) examines how financial frictions and policy uncertainty jointly influence firms' investments in pollution abatement. My paper finds consistently with these authors that financially constrained firms are less likely to invest in pollution abatement. I differ from them with my further analysis that this heterogeneity in pollution abatement leads to a distortions of capital allocation across firms.
In this vein, my paper is closely related to studies on the aggregate consequences of misallocation across firms (Hsieh and Klenow (2009), Restuccia and Rogerson (2008), Restuccia and Rogerson (2013)). In this line of research, firm-level distortions lead to large loss of aggregate output and measured productivity, especially when they are correlated with firm size or productivity. A distortion analyzed here is emission tax that is not correlated to firm fundamentals but happen to have a potential to generate misallocation due to heterogeneity in firm emission abatement investment.

In the next section, I present the model and give some qualitative insights

3.2 Model

3.2.1 Setup

Time is discrete. There is a continuum of entrepreneurs that are indexed by $i \in [0, 1]$. Entrepreneurs are heterogeneous in their productivity z_{it}, their capital holdings, k_{it}, and their debt, d_{it}. Each period, entrepreneurs draw new productivity from a distribution $\psi(z)$. This productivity shock is independent and identically distributed across entrepreneurs and also over time. These assumptions imply a law of large numbers so the share of entrepreneurs experiencing any particular sequence of shocks is deterministic. The heterogeneity of firms in their productivity and wealth levels leads them to differ in their pollution abatement investment and, ultimately, pollution emissions. Entrepreneurs have preferences:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_{it}) \, , \, u(c) = \log(c) \tag{3.1}$$

Each entrepreneur owns a private firm that uses k_{it} units of capital and l_{it} units of labor to produce y_{it} units of output, where $\alpha \in (0, 1)$.

$$y_{it} = \left(z_{it} k_{it}\right)^{\alpha} l_{it}^{1-\alpha} \tag{3.2}$$

Pollution and Environmental Policy. A firm's production results in the emission of pollutants, which are determined by the firm's emission intensity, pollution abatement efforts, and production scale. The model incorporates heterogeneity in emission intensity by extending the existing pollution models for representative firms. Hence, firms can accumulate pollution abatement technology through past investment and as a result lower emission intensity. Following Fang et al. (2023), I assume that firm i's emissions at time t is given by:

$$e_{it} = \frac{\bar{e}}{\mu_{it}} y_{it} \tag{3.3}$$

where $\bar{e}$ represents the default level of emission intensity, and μ_{it} denotes the level of accumulated abatement technology. Firm can improve its abatement technology through investment, which follows the law of motion:

$$\mu_{it+1} = (1 - \delta_{\mu})\mu_{it} + f(\tilde{x}_{it}) \tag{3.4}$$

where $\tilde{x}_{it}$ is the amount of investment goods in R&D invested in new abatement. $f(.)$ is a technology transforming investment goods into emission abatement effort. Pollution has regulatory consequences due to environmental policies. Firm i is subject to a pollution penalty τe_{it}, where τ is a carbon tax which is proportional to the level of pollution emissions and hence common across firms.

Entrepreneurs also have access to the following linear technology to transform final goods into investment goods:

$$k_{it+1} = (1 - \delta)k_{it} + x_{it} - \tilde{x}_{it} \tag{3.5}$$

where x_{it} is total investment and δ is the depreciation rate.

Budgets. Entrepreneurs hire workers in a competitive labor market at a wage w_t. They also trade in risk-free bonds. Denote by d_{it} the stock of bonds issued by an entrepreneur; that is his debt. When $d_{it} < 0$ the entrepreneur is a net lender. The budget constraint is:

$$c_{it} + x_{it} = y_{it} - w_t\, l_{it} - \tau e_{it} - (1 + r_t)d_{it} + d_{it+1} \tag{3.6}$$

or, by making use of 3.3,

$$c_{it} + x_{it} = \Big(1 - \tau\, \frac{\bar{e}}{\mu_{it}}\Big) y_{it} - w_t\, l_{it} - (1 + r_t)d_{it} + d_{it+1} \tag{3.7}$$

Entrepreneurs face borrowing constraints that reflect a *green financing*:

$$d_{it+1} \leq \bigg(\theta_t \exp\Big\{ - \frac{\lambda}{\mu_{it+1}} \Big\}\bigg) k_{it+1} \tag{3.8}$$

Firm i can externally finance at most a fraction $1 - \bigg(\theta_t \exp\Big\{ - \frac{\lambda}{\mu_{it+1}} \Big\}\bigg)$ of its next period capital stock. This maximum fraction has two components : a common factor θ_t and firm-specific factor $\exp\Big\{ - \frac{\lambda}{\mu_{it+1}} \Big\}$ reflecting the green financing. As we can see, the firm-specific factor depends directly on its emission intensity (emission per output) or its abatement effort. This way of modeling green financing is consistent with the main purpose of the policy, which is to allocate more capital to environmentally friendly firms. Hence as Ehlers et al. (2020) point out, a rating system based on carbon intensity could provide a useful signal to investors for greening their investment and encourage firms to reduce their carbon footprint. Higher emissions (lower abatement technology) translate into lower firm leverage. $\lambda \geq 0$ represents the response of green financing to firm emissions. When $\lambda = 0$, the green financing is shut down, and $\lambda = \infty$ corresponds to the most aggressive green financing policy.

An entrepreneur's productivity next period, z_{it+1}, is revealed at the end of period t, before the entrepreneur issues his debt d_{it+1}. Hence, entrepreneurs can borrow to finance investment corresponding to their new productivity. The budget constraint of entrepreneurs can be simplified slightly. The capital income of an entrepreneur is

$$\Pi(z_{it}, k_{it}, \mu_{it}) = \max_{l_{it}} \Big(1 - \tau\, \frac{\bar{e}}{\mu_{it}}\Big) y_{it} - w_t\, l_{it} \tag{3.9}$$

Maximizing out over labor, we obtain the following simple and linear expression for profits:

$$\Pi(z_{it}, k_{it}, \mu_{it}) = z_{it}\, k_{it}\, \pi_t \Big(1 - \tau\, \frac{\bar{e}}{\mu_{it}}\Big)^{1/\alpha} \quad ; \pi_t = \alpha \Big(\frac{1 - \alpha}{w_t}\Big)^{\frac{1-\alpha}{\alpha}} \tag{3.10}$$

The budget constraint of the entrepreneur hence reduces to:

$$c_{it} + k_{it+1} + f^{-1}\Big[\mu_{it+1} - (1-\delta_\mu)\mu_{it}\Big] = z_{it}\, k_{it}\, \pi_t \Big(1 - \tau\, \frac{\bar{e}}{\mu_{it}}\Big)^{1/\alpha} + (1-\delta)k_{it} - (1+r_t)d_{it} + d_{it+1} \tag{3.11}$$

3.2.2 Recursive Problem for firms

The problem of an entrepreneur can be written recursively as:

$$V_t(z_{-1}, z, k, d, \mu) = \max_{c,k',d'\mu'} \log c + \beta E\Big[V_{t+1}(z, z', k', d', \mu')\Big] \tag{3.12}$$

$$\text{s.t. } c + k' - d' + f^{-1}\Big[\mu' - (1-\delta_\mu)\mu\Big] = z_{-1}\, k\, \pi_t \Big(1 - \tau\, \frac{\bar{e}}{\mu}\Big)^{1/\alpha} + (1-\delta)k - (1+r_t)d$$

$$d' \leq \Big(\theta_t \exp\Big\{-\frac{\lambda}{\mu'}\Big\}\Big)k' \quad , k' \geq 0,\ \mu' > 0$$

Here we denote by z_{-1} the productivity of an entrepreneur in the current period, by z his productivity in the next period, and by z' his productivity is two periods ahead. The expectation is taken over z' only, because —as previously discussed—I assume that an entrepreneur knows z at the time he chooses capital and debt holdings.

For simplicity, let's assume that the technology function f is an identity function. This problem can be simplified. To this end define an entrepreneur's "cash-on-hand," m_{it}, and "net worth," a_{it}, as

$$m_{it} = z_{it}\, k_{it}\, \pi_t \Big(1 - \tau\, \frac{\bar{e}}{\mu_{it}}\Big)^{1/\alpha} (1-\delta)k_{it} - (1+r_t)d_{it} + (1-\delta_\mu)\mu_{it} \tag{3.13}$$

$$a_{it} = k_{it} + \mu_{it} - d_{it} \tag{3.14}$$

We can show that the following dynamics is equivalent to 3.12:

$$\begin{aligned} V_t(m, z) &= \max_{a'} \log(m - a') + \beta E\Big[V_{t+1}(\tilde{m}_{t+1}(a', z), z')\Big] \\ \tilde{m}_{t+1}(a', z) &= \max_{k',\mu',d'}\ z\, k'\, \pi_{t+1}\Big(1 - \tau\, \frac{\bar{e}}{\mu'}\Big)^{1/\alpha} + (1-\delta)k' + (1-\delta_\mu)\mu' - (1+r_{t+1})d' \\ &\text{s.t.} \quad k' + \mu' - d' = a' \quad ; k' \leq \frac{1}{1 - \Big(\theta_t \exp\Big\{-\frac{\lambda}{\mu'}\Big\}\Big)}(a' - \mu') \end{aligned} \tag{3.15}$$

The interpretation of this result is that the problem of an entrepreneur can be solved as a two−stage budgeting problem. In the first stage, the entrepreneur chooses how much net worth, a', to carry over to the next period. In the second stage, conditional on a', he then solves an optimal portfolio allocation problem where he decides how to split his net worth between capital, k', abatement effort μ' and bonds, $-d'$. The borrowing constraint immediately implies that the amount of capital he holds can be at most a multiple $\tilde{\lambda}(\mu') = \Big[1 - \Big(\theta_t \exp\Big\{-\frac{\lambda}{\mu'}\Big\}\Big)\Big]^{-1}$ of this net worth after abatement investment.

Workers. There is a unit mass of workers who are hand-to-mouth consumers. Workers have preferences over consumption C_t^W and hours worked L_t. They have disutility towards pollution emission E_t and the parameter ζ captures the degree of this disutility. They took E_t as given. The total carbon tax income collected is rebated to workers as a lump-sum transfer of T.

$$\sum_{t=0}^{\infty} \beta^t \Big[u(C_t^W) + \nu(L_t) - \zeta E_t\Big] \tag{3.16}$$

Recursive Equilibrium. A recursive competitive equilibrium consists of (i) value function $V(z,k,\mu)$, (ii) policy functions $k'(z,k,\mu)$, $\mu'(z,k,\mu)$, $d'(z,k,\mu)$, $a'(z,k,\mu)$, $l(z,k,\mu)$ and (iii) bounded sequences of prices $\{r_t, w_t\}_{t=0}^{\infty}$, incumbents' measures of firms $\{\Gamma_t\}_{t=0}^{\infty}$ such that, for all $t \geq 0$:

1. $V(z,k,\mu), k'(z,k,\mu), \mu'(z,k,\mu), d'(z,k,\mu), a'(z,k,\mu), l(z,k,\mu)$ solve the incumbent's problem;
2. The labor market clears: $\int l_t(z,k,\mu) d\Gamma_t(z,k,\mu) = L_t(w_t)$ where L_t is the labor supply solving 3.16 given that $C_t^W = w_t L_t + T$
3. Total debt satisfies : $\int d'(z,k,\mu) d\Gamma(z,k,\mu) = 0$
4. Aggregates quantities satisfy resources constraint:

$$\underbrace{C_t^W + C_t^E}_{C_t} + X_t = Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \tag{3.17}$$

$$K_{t+1} = (1-\delta)K_t + X - \int \tilde{\mu}'(z,k,\mu) d\Gamma(z,k,\mu) \tag{3.18}$$

5. w_t clears the labor market and $r_t + \delta = \alpha A_t K_t^{\alpha-1} L_t^{1-\alpha}$. A_t is the endogenous TFP.
6. T satisfies $T = \tau E_t = \tau \int e_t(z,k,\mu) d\Gamma(z,k,\mu)$

3.2.3 Model's insights

I will begin by providing the model's qualitative insights. To differentiate between the effect of carbon tax policy and green financing, I will start by shutting down the green financing policy which is equivalent to set $\lambda = 0$.

Lemma 2. *Entrepreneurs save a constant fraction of cash-on-hand:*

$$a' = \beta m = \beta\left[z\, k\, \pi_t\Big(1 - \tau\,\frac{\bar{e}}{\mu}\Big)^{1/\alpha} + (1-\delta)k + (1-\delta_\mu)\mu - (1+r_t)d\right] \tag{3.19}$$

This follows from the logarithmique utility function. We can use a more general CRRA function $(u(c) = \dfrac{c^{1-\sigma}}{1-\sigma})$. The log-utility corresponds to the case $\sigma = 1$.

Lemma 3. *Capital and debt holdings are linear in net worth minus abatement investment effort.*

$$k' = \tilde{\lambda}(a' - \mu') \quad ; \quad d' = (\tilde{\lambda} - 1)(a' - \mu') \tag{3.20}$$

The linearity property follows directly from the fact that firms' technologies display constant returns to scale in capital and labor. The linearity of capital and debt delivers much of the tractability of my model.

Proposition 5. *Assume that firms only produce with capital ($\alpha = 1$), then abatement investment policy solves:*

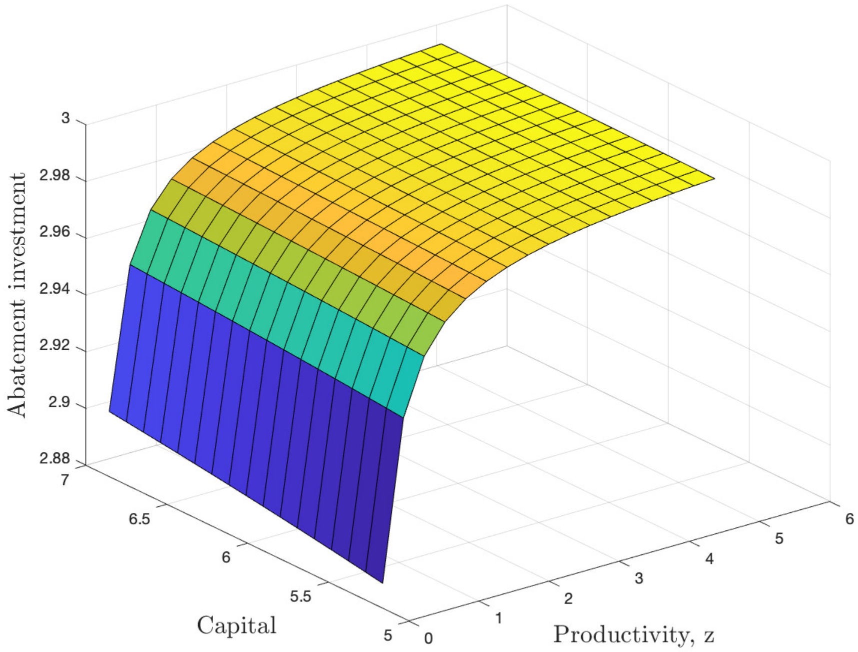
$$z\pi_{t+1}\left[(a' - \mu')\frac{\tau\,\bar{e}}{\mu'^2} - \Big(1 - \frac{\tau\,\bar{e}}{\mu'}\Big)\right] = \frac{\delta_\mu + r_{t+1}}{\tilde{\lambda}} - (\delta + r_{t+1}) \tag{3.21}$$

and, given firm's abatement technology μ, abatement investment increases with capital and productivity.

Equation 3.21 comes from the first order condition in the problem 3.15 and the result follows since the LHS of equation 3.21 is a decreasing function of abatement investment μ' and an increasing function of productivity and net worth a'. Hence, given a firm's abatement technology μ, abatement investment increases with capital and productivity. However, this result is not easy to show analytically when allowing labor input in the production function. Intuitively, adding labor input adds labor obligation margins and may distort the emission abatement investment. I provide a numerical simulation using plausible calibrated values of model parameters. Figure 3.2 shows the result and indicates that proposition 6's conclusion holds even after accounting for labor input[0].

[0] I use the following parametrization of the model: $\beta = 0.95$, $\delta = 0.05$, $\alpha = 1/3$, $\tilde{\lambda} = 3$, following Buera and Moll (2015). In addition I set $\bar{e} = 10$, $\delta_\mu = 0.2$ following Fang et al. (2023)

Figure 3.2: Abatement investment policy, given abatement technology



Proposition 6. *Given firm's abatement technology μ, there exists a productivity threshold for being active $\underline{z}'(k)$.*
1. Policy functions satisfy:

$$k' = \begin{cases} \tilde{\lambda}(a' - \mu') & \text{if } z \geq \underline{z}'(k) \\ 0 & \text{if } z \leq \underline{z}'(k) \end{cases} \quad ; \quad d' = \begin{cases} (\tilde{\lambda} - 1)(a' - \mu') & \text{if } z \geq \underline{z}'(k) \\ -a' & \text{if } z \leq \underline{z}'(k) \end{cases}$$

and, μ' solves 3.15 given policy function k' et d' if $z \geq \underline{z}'(k)$, otherwise $\mu' = 0$
2. The threshold $\underline{z}'(k)$ decreases with firm capital stock k, given abatement technology μ.

The existence of the productivity threshold is easy to derive in the case of full depreciation of abatement technology, that is $\delta_\mu = 1$. With $\delta_\mu = 1$, the productivity cut-off $\underline{z}'(k)$ solves the following equation:

$$z\tilde{\lambda}\pi_{t+1}\left(1 - \tau\,\frac{\bar{e}}{\mu'}\right)^{1/\alpha} + (1-\delta)\,\tilde{\lambda} - (1 + r_{t+1})(\tilde{\lambda} - 1) = 0 \qquad (3.22)$$

The decreasing of the threshold with capital stock k is intuitive and follows from the fact that abatement investment increases with capital stock. Indeed, firms with higher stock of capital have room for emission abatement in order to reduce the carbon tax burden and help them to stay active. This can ultimately generate a misallocation of capital and reduce aggregate productivity. I discuss the potential misallocation effect of climate policy in the next section

3.2.4 Climate policy and capital misallocation

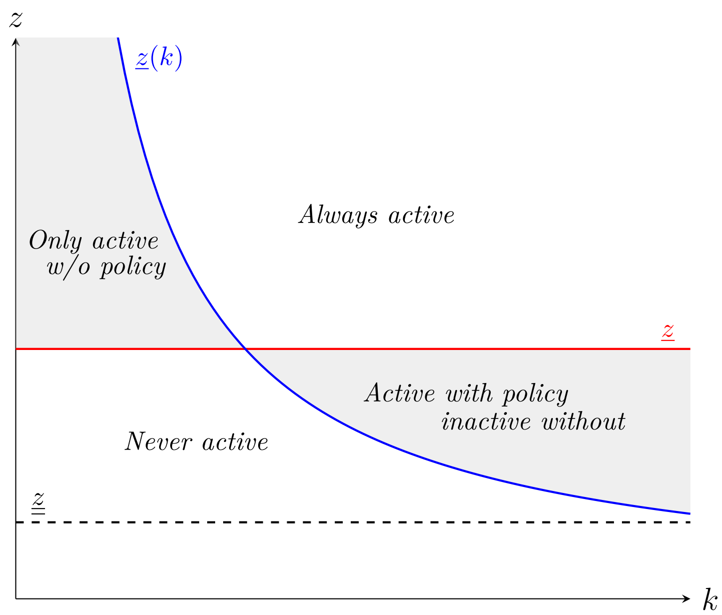
Figure 3.3 illustrates that capital misallocation can occur in the presence of climate policy leading firms to engage in emission abatement. First, let suppose there is no climate policy in place. There exists a productivity level cut-off $\underline{z}$ that determines the decision of firms to operate or exit the market because it is not anymore profitable to run the firm. This productivity threshold determines the aggregate productivity in the economy and only depends on the quality of credit markets $\tilde{\lambda}$, a common factor across firms. As the credit market improves (an increase in $\tilde{\lambda}$), the threshold increases, indicating a reallocation of capital toward more productive firms resulting in an increase in TFP. As I illustrate in the figure 3.3, firms above the cut-off $\underline{z}$ are active without any climate policy in place.

Now, suppose that firm emissions are priced with the introduction of carbon tax and that firms have access to abatement technology to reduce their carbon emission. Given a fixed level of productivity and abatement technology, firms' investment in emission abatement is positively correlated with their capital holdings. This gives rise to heterogeneity in the burden of the carbon tax across firms. Consequently, the threshold for productivity, at which firms either choose to remain active or exit the market, critically depends on their capital stock. This threshold, denoted as $\underline{z}(k)$ and illustrated in Figure 3.3, exhibits a decreasing relationship with the level of capital.

The model distinguishes five distinct types of entrepreneurs. The *first* category consists of entrepreneurs with very low productivity levels, below a certain threshold denoted as $\underline{\underline{z}}$. Regardless of their capital holdings, these entrepreneurs never engage in productive activities and instead prefer to rent out their capital. There also exist a group of entrepreneurs with moderate productivity levels, falling between $\underline{\underline{z}}$ and $\underline{z}$. This group further divides into two subsets. The first subset which is the *second* category includes entrepreneurs who possess limited capital and would be active in the market under the carbon tax policy if they had sufficient assets to mitigate their carbon tax burden. The second subset which is the *third* category comprises entrepreneurs who possess ample capital and utilize it to abate emissions, thereby remaining active in the market. The *fourth* category encompasses highly productive and wealthy entrepreneurs who are consistently active, irrespective of the presence or absence of the carbon tax policy. The final category encompasses productive and talented entrepreneurs who, due to insufficient resources for emission abatement, are compelled to exit the market. We interpret that as if the economy exchanges these entrepreneurs with wealthy but less productive entrepreneurs. This capital reallocation from highly productive to less productive firms results in a misallocation of resources. This misallocation effect could be amplified if there exist a minimum of emission abatement $\underline{\mu}$ in order to reduce emission. In summary, proportional carbon emission taxes could amplify the existing misallocation generated by credit market imperfections governed by the parameter $\tilde{\lambda}$.

However, it is important to note that this misallocation occurs importantly because of the availability of abatement technology. In the Absence of this technology, the proportional emission tax would essentially function as a tax on output, distorting the optimal allocation of inputs across firms in a way that is uncorrelated with neither productivity nor firm's size. As a result, the marginal product of inputs would remain unaffected across firms.

Figure 3.3: Capital misallocation



How does the incorporation of green financing, with the intention of further reducing pollution emissions and achieving a carbon-neutral economy, interact with the carbon tax policy? The answer to this question depends on how it will operate. If it is modeled as outlined in Equation 3.8, it can introduce a second-order effect related to the potential misallocation of capital resulting from the implementation of carbon taxes. This situation calls for coordination between the two policies.

The misallocation in the presence of green financing would be lessened if we were to naturally assume that the green financing mechanism directly depends positively on productivity. Holding all other factors constant, firms that exhibit higher productivity levels would be allocated more capital. This adjustment would shift the blue curve in Figure 3.3 to the left, reducing the degree of misallocation. Policies aimed at mitigating the potential misallocation effect of green financing could include subsidizing abatement technology or ensuring a smooth and undistorted diffusion of green technologies.

3.3 Conclusion

This paper examines the effects of climate policy in the presence of financial frictions. I construct a general equilibrium model with heterogeneous firms. In the model, firms differ in their productivity and capital holdings. They also have access to abatement technology. This heterogeneity in capital leads to heterogeneity in firms' emissions abatement and ultimately to emission intensity. In this environment, the model generates predictions that capital misallocation may occur reducing aggregate productivity. This paper offers a framework to quantitatively estimate a potential output loss pertaining to emission tax in conjunction with a green financing. In a future version of this paper, I will additionally examine an optimal design of policy to lessen the distortions.

Bibliography

Abadie, A., A. Diamond, and J. Hainmueller (2015). Comparative politics and the synthetic control method. *American Journal of Political Science 59*(2), 495–510.

Acemoglu, D. and J.-S. Pischke (1998). Why do firms train? theory and evidence. *The Quarterly journal of economics 113*(1), 79–119.

Acemoglu, D. and J.-S. Pischke (1999). The structure of wages and investment in general training. *Journal of political economy 107*(3), 539–572.

Acemoglu, D. and R. Shimer (1999). Holdups and efficiency with search frictions. *International Economic Review 40*(4), 827–849.

Albert, C. (2021). The labor market impact of immigration: Job creation versus job competition. *American Economic Journal: Macroeconomics 13*(1), 35–78.

Alonso-Borrego, C., J. Fernández-Villaverde, and J. E. Galdón-Sánchez (2005). Evaluating Labor Market Reforms: A General Equilibrium Approach. NBER Working Paper 11519, National Bureau of Economic Research.

Bagger, J., F. Fontaine, F. Postel-Vinay, and J.-M. Robin (2014). Tenure, experience, human capital, and wages: A tractable equilibrium search model of wage dynamics. *American Economic Review 104*(6), 1551–1596.

Bentolila, S., P. Cahuc, J. J. Dolado, and T. Le Barbanchon (2012). Two-Tier Labour Markets in the Great Recession: France Versus Spain. *Economic Journal 122*(562), 155–187.

Berton, F. and P. Garibaldi (2012). Workers and Firms Sorting into Temporary Jobs. *Economic Journal 122*(562), 125–154.

Bils, M., Y. Chang, and S.-B. Kim (2011). Worker heterogeneity and endogenous separations in a matching model of unemployment fluctuations. *American Economic Journal: Macroeconomics 3*(1), 128–54.

Bishara, N. D. (2011). Fifty ways to leave your employer: Relative enforcement of covenants not to compete, trends, and implications for employee mobility policy. *University of Pennsylvania Journal of Business Law 13*(3), 751.

Blanchard, O. and A. Landier (2002). The Perverse Effects of Partial Labour Market Reform: Fixed-Term Contracts in France. *Economic Journal 112*(480), 214–244.

Boeri, T. (2011). Institutional Reforms and Dualism in European Labor Markets. Volume 4 of *Handbook of Labor Economics*, pp. 1173 – 1236. Elsevier.

Boeri, T. and P. Garibaldi (2007). Two Tier Reforms of Employment Protection: A Honeymoon Effect? *Economic Journal 117*(521), 357–385.

Booth, A. L., M. Francesconi, and J. Frank (2002, 06). Temporary Jobs: Stepping Stones or Dead Ends? *The Economic Journal 112*(480), F189–F213.

Buera, F. J. and B. Moll (2015). Aggregate implications of a credit crunch: The importance of heterogeneity. *American Economic Journal: Macroeconomics 7*(3), 1–42.

Cahuc, P., O. Charlot, and F. Malherbet (2016). Explaining the Spread of Temporary Jobs and its Impact on Labor Turnover. *International Economic Review 57*(2), 533–572.

Cahuc, P., O. Charlot, F. Malherbet, H. Benghalem, and E. Limon (2020). Taxation of temporary jobs: good intentions with bad outcomes? *The Economic Journal 130*(626), 422–445.

Cahuc, P. and F. Postel-Vinay (2002). Temporary Jobs, Employment Protection and Labor Market Performance. *Labour Economics 9*(1), 63–91.

Cahuc, P., F. Postel-Vinay, and J.-M. Robin (2006). Wage bargaining with on-the-job search: Theory and evidence. *Econometrica 74*(2), 323–364.

Cajner, T., I. Güner, and T. Mukoyama (2020). Gross worker flows over the life cycle.

Callahan, M. B. (1985). Post-employment restraint agreements: A reassessment. *The University of Chicago Law Review 52*(3), 703–728.

Carlsson, M. and A. Westermark (2022). Endogenous separations, wage rigidities, and unemployment volatility. *American Economic Journal: Macroeconomics 14*(1), 332–54.

Charlot, O. and F. Malherbet (2013). Education and employment protection. *Labour Economics 20*, 3–23.

Chéron, A., J.-O. Hairault, and F. Langot (2013). Life-cycle equilibrium unemployment. *Journal of Labor Economics 31*(4), 843–882.

Choi, S., A. Janiak, and B. Villena-Roldán (2015). Unemployment, participation and worker flows over the life-cycle. *The Economic Journal 125*(589), 1705–1733.

Créchet, J. (2019). Risk sharing in a dual labor market.

Ehlers, T., B. Mojon, and F. Packer (2020). Green bonds and carbon emissions: Exploring the case for a rating system at the firm level. *BIS Quarterly Review, September*.

Faccini, R. (2014). Reassessing Labour Market Reforms: Temporary Contracts as a Screening Device. *Economic Journal 124*(575), 167–200.

Fang, M., P.-H. Hsu, and C.-Y. Tsou (2023). Pollution abatement investment under financial frictions and policy uncertainty. *Available at SSRN*.

Fujita, S. and G. Ramey (2012). Exogenous versus endogenous separation. *American Economic Journal: Macroeconomics 4*(4), 68–93.

Furman, J. and P. Orszag (2018). 1. a firm-level perspective on the role of rents in the rise in inequality. In *Toward a Just Society*, pp. 19–47. Columbia University Press.

García-Pérez, J. I., I. Marinescu, and J. Vall Castello (2019). Can fixed-term contracts put low skilled youth on a better career path? evidence from spain. *The Economic Journal 129*(620), 1693–1730.

Garmaise, M. J. (2011). Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *The Journal of Law, Economics, and Organization 27*(2), 376–425.

Haltiwanger, J. (2015). Job creation, job destruction, and productivity growth: The role of young businesses. *economics 7*(1), 341–358.

Herz, B. (2019). Specific human capital and wait unemployment. *Journal of Labor Economics 37*(2), 467–508.

Holland, S. P. (2012). Emissions taxes versus intensity standards: Second-best environmental policies with incomplete regulation. *Journal of Environmental Economics and management 63*(3), 375–387.

House, W. (2016). Non-compete agreements: Analysis of the usage. *Potential Issues, and State Responses*.

Hsieh, C.-T. and P. J. Klenow (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics 124*(4), 1403–1448.

Jung, P. and M. Kuhn (2019). Earnings losses and labor mobility over the life cycle. *Journal of the European Economic Association 17*(3), 678–724.

Kang, H. and L. Fleming (2020). Non-competes, business dynamism, and concentration: Evidence from a florida case study. *Journal of Economics & Management Strategy 29*(3), 663–685.

Kehoe, P. J., V. Midrigan, and E. Pastorino (2019). Debt constraints and employment. *Journal of political Economy 127*(4), 1926–1991.

Krueger, A. B. and O. Ashenfelter (2018). Theory and evidence on employer collusion in the franchise sector. Technical report, National Bureau of Economic Research.

Kuhn, M. and G. Ploj (2020). Job stability, earnings dynamics, and life-cycle savings.

Lalé, E. and L. Tarasonis (2018). The life-cycle profile of worker flows in europe. *Available at SSRN 3221252*.

Lazear, E. P. (1990). Job security provisions and employment. *The Quarterly Journal of Economics 105*(3), 699–726.

Li, Z. and S. Shi (2017). Emission taxes and standards in a general equilibrium with productivity dispersion and abatement. *Macroeconomic Dynamics 21*(8), 1857–1886.

Li, Z. and J. Sun (2015). Emission taxes and standards in a general equilibrium with entry and exit. *Journal of Economic Dynamics and Control 61*, 34–60.

Lise, J. and F. Postel-Vinay (2020). Multidimensional skills, sorting, and human capital accumulation. *American Economic Review 110*(8), 2328–76.

Long, B. S. (2004). Protecting employer investment in training: Noncompetes vs. repayment agreements. *Duke LJ 54*, 1295.

Marx, M. (2011). The firm strikes back: non-compete agreements and the mobility of technical professionals. *American Sociological Review 76*(5), 695–712.

Meccheri, N. (2009). A note on noncompetes, bargaining and training by firms. *Economics Letters 102*(3), 198–200.

Menzio, G., I. A. Telyukova, and L. Visschers (2016). Directed search over the life cycle. *Review of Economic Dynamics 19*, 38–62.

Moll, B. (2014). Productivity losses from financial frictions: Can self-financing undo capital misallocation? *American Economic Review 104*(10), 3186–3221.

Mortensen, D. T. and C. A. Pissarides (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies 61*(3), 397–415.

Muller, N. Z. and R. Mendelsohn (2009). Efficient pollution regulation: getting the prices right. *American Economic Review 99*(5), 1714–1739.

Nordhaus, W. D. (2007). To tax or not to tax: Alternative approaches to slowing global warming. *Review of Environmental Economics and policy*.

Nunn, R. (2016). Non-compete contracts: Economic effects and policy implications. *US Department of the Treasury, Office of Economic Policy*.

Postel-Vinay, F. and J.-M. Robin (2002). Equilibrium Wage Dispersion with Worker and Employer Heterogeneity. *Econometrica 70*(6), 2295–2350.

Postel-Vinay, F. and H. Turon (2014). The Impact of Firing Restrictions on Labour Market Equilibrium in the Presence of On-the-job Search. *Economic Journal 124*(575), 31–61.

Potter, T., B. Hobijn, and A. Kurmann (2022, January). On the Inefficiency of Non-Competes in Low-Wage Labor Markets. School of Economics Working Paper Series 2022-2, LeBow College of Business, Drexel University.

Prescott, J. J., N. D. Bishara, and E. Starr (2016). Understanding noncompetition agreements: The 2014 noncompete survey project. *Mich. St. L. Rev.*, 369.

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics 11*(4), 707–720.

Restuccia, D. and R. Rogerson (2013). Misallocation and productivity.

Rothstein, D. S. and E. Starr (2022). Mobility restrictions, bargaining, and wages: Evidence from the national longitudinal survey of youth 1997. *BLS Monthly Labor Review*.

Santos, M. R. and C. Rauh (2022). How do transfers and universal basic income impact the labor market and inequality?

Shi, L. (2022). Optimal regulation of noncompete contracts.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American economic review 95*(1), 25–49.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics 15*(2), 127–148.

Starr, E. (2019). Consider this: Training, wages, and the enforceability of covenants not to compete. *ILR Review 72*(4), 783–817.

Starr, E., N. Balasubramanian, and M. Sakakibara (2017). Screening spinouts? how noncompete enforceability affects the creation, growth, and survival of new firms. *Management Science 64*(2), 552–572.

Starr, E., J. Frake, and R. Agarwal (2019). Mobility constraint externalities. *Organization Science 30*(5), 961–980.

Starr, E. P., J. J. Prescott, and N. D. Bishara (2021). Noncompete agreements in the us labor force. *The Journal of Law and Economics 64*(1), 53–84.

Tombe, T. and J. Winter (2015). Environmental policy and misallocation: The productivity effect of intensity standards. *Journal of Environmental Economics and Management 72*, 137–163.

Appendices

A Appendix for chapter 1

A.1 Tables and Figures

Figure A1: Effect of NCAs enforcement strengthening on job creation rate in Florida - firms aged 10 years or less.

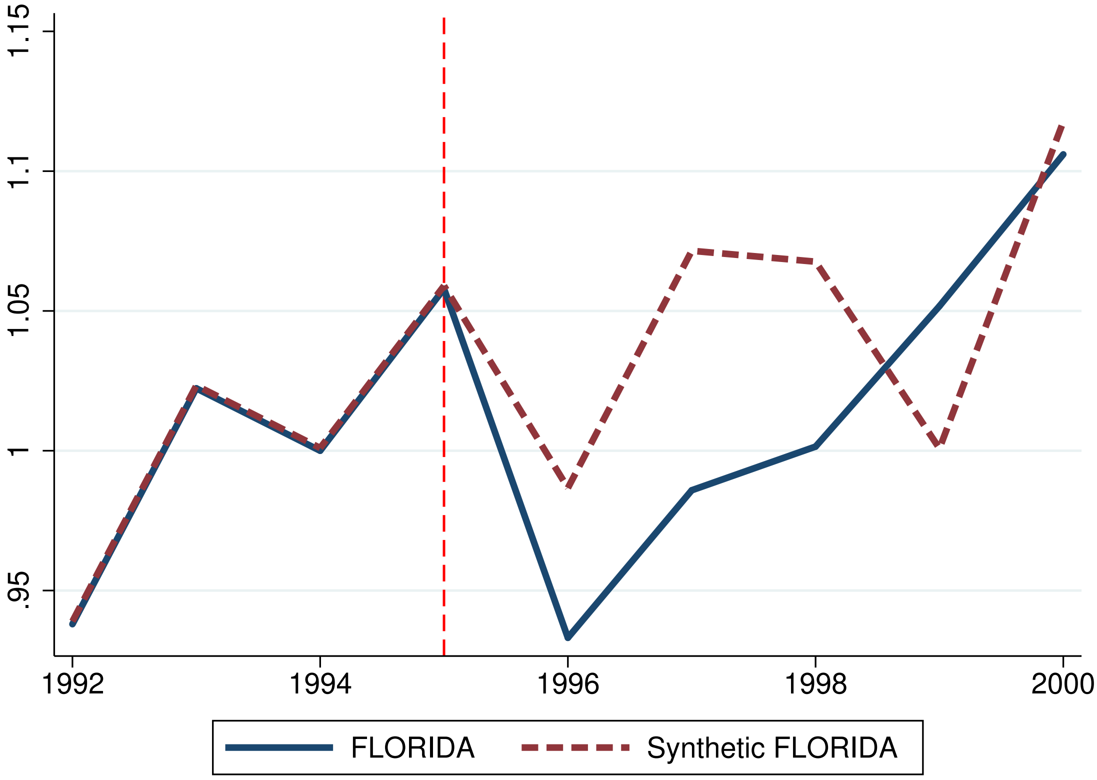


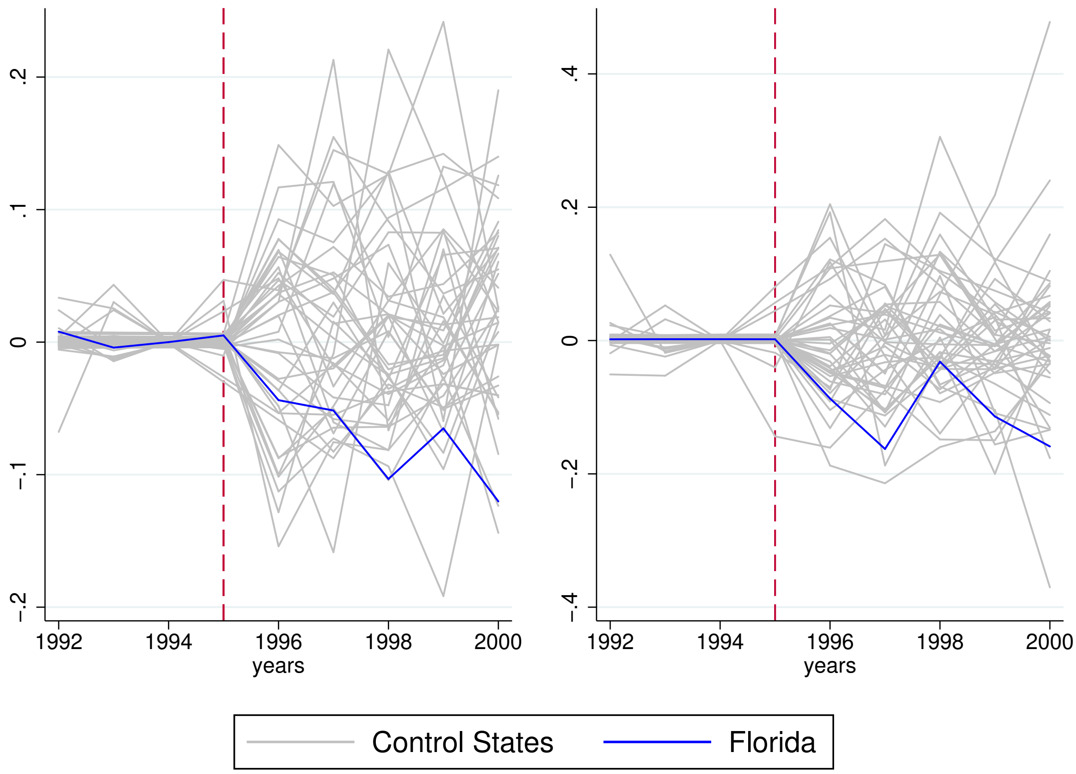
Table A1: NCAs incidence and employment transition rates

Dependent var.	Job losing (Y/N)		Job finding (Y/N)	
	(1)	(2)	(3)	(4)
NCAs inc. × Enforceability		-0.029^{***}		-0.155^{***}
		(0.0000)		(0.0005)
Controls.	Yes	Yes	Yes	Yes
Year/state FE	Yes	Yes	Yes	Yes
N. Obs	250,876	250,876	19,141	19,141

Note.- Standard errors in parenthesis, clustered at state level.$*_{p<0.1}$, $**_{p<0.05}$, $***_{p<0.01}$

Figure A2: Placebo test

(a) : Job Destruction Rate Gap (b) : Job Creation Rate Gap



-Notes: The gray lines represent the gap associated with each of the 46 runs (states included in the control group) of the placebo test. the blue line denotes the estimated gap for Florida

Table A2: Targeted moments

Moments	Data	Model
Average job finding rate	0.34	0.36
labor tightness	0.52	0.54
Average job separation rate	0.020	0.023
Wage ratio	1.05	1.003
job tenure ratio	1.17	1.16

A.2 Proofs

A.3 Proof of Lemma 1

Recall that from equations (1.4) and (1.5) we have:

$$U(0) = z + \beta\Big\{f(\theta)[\phi W(1,\bar{i}_1) + (1-\phi) W(0,\bar{i}_0)] + [1-f(\theta)]U(0)\Big\} \tag{23}$$

$$U(1) = z + \beta(1-\chi)\Big\{f(\theta)[\phi W(1,\bar{i}_1) + (1-\phi) W(0,\bar{i}_0)] + [1-f(\theta)]U(0)\Big\} + \beta\chi\mathbb{E}[U(b')]$$

Replacing $U(0)$ in $U(1)$ expression yields:

$$U(1) = z + (1-\chi)[U(0) - z] + \beta\chi[\mu U(0) + (1-\mu)U(1)] \tag{24}$$

Rearranging equation (24) to obtain:

$$(1-\beta)U(0) = z + \Big[\beta(1-\mu) - \frac{1}{\chi}\Big]\Delta U \tag{25}$$

Where $\Delta U = U(1) - U(0)$.
Now, using equation (23) we obtain:

$$(1-\beta)U(0) = z + \beta f(\theta)\Big[\phi W(1,\bar{i}_1) + (1-\phi) W(0,\bar{i}_0) - U(0)\Big] \tag{26}$$

Hence, by using Nash bargaining conditions: $W(1,\bar{i}_1) - U(1) = \rho S(1,\bar{i}_1)$ and $W(0,\bar{i}_0) - U(0) = \rho S(0,\bar{i}_o)$, we can rewrite (26) as:

$$(1-\beta)U(0) = z + \beta f(\theta)\Big\{\rho\Big[\phi S(1,\bar{i}_1) + (1-\phi)S(0,\bar{i}_0)\Big] + \phi\Delta U\Big\} \tag{27}$$

Subtracting terms at each side of equations 25 and 27 yields:

$$\Big[-1 + \chi\beta[1-\mu-\phi f(\theta)]\Big]\Delta U = \chi\beta f(\theta)\rho\Big[\phi S(1,\bar{i}_1) + (1-\phi)S(0,\bar{i}_0)\Big] \tag{28}$$

There are two cases:

- <u>Case 1</u> : $1 - \mu - \phi f(\theta) \leq 0$

In this case we have $\Big[-1 + \chi\beta[1-\mu-\phi f(\theta)]\Big] < 0$ and assuming that both types of jobs exist in equilibrium $S(1,\bar{i}_1) > 0$ and $S(0,\bar{i}_0) > 0$ meaning positive surpluses, then (28) yields $\Delta U < 0$, that is $U(1) < U(0)$

- <u>Case 2</u> : $1 - \mu - \phi f(\theta) > 0$

In this case we have $0 < 1 - \mu - \phi f(\theta) < 1$, since $\mu + \phi f(\theta) > 0$. Hence $0 < \chi\beta[1 - \mu - \phi f(\theta)] < \chi\beta < 1$. Finally $-1 < \Big[-1 + \chi\beta[1 - \mu - \phi f(\theta)] \Big] < 0$. Again, assuming that both types of jobs exist in equilibrium $S(1, \bar{i}_1) > 0$ and $S(0, \bar{i}_0) > 0$ meaning positive surpluses, then (28) yields $\Delta U < 0$, that is $U(1) < U(0)$. Notice that if NCAs contract are unenforceable ($\chi = 0$) then $U(0) = U(1)$, that is workers constrained or not by NCAs have the same outside option value.

In all cases, we have $U(1) < U(0)$, so long as $\chi > 0$.

A.4 Proof of Proposition 1

From equation (1.3), we have:

$$W(b,i) = w(b,i) + \beta\Big\{\delta U(b) + (1-\delta)\mathbb{E}_\varepsilon \max\Big\{W(b,i) + \varepsilon, U(b)\Big\}\Big\} \tag{29}$$

But,

$$\max\Big\{W(b,i) + \varepsilon, U(b)\Big\} = \begin{cases} W(b,i) + \varepsilon & \text{if } \varepsilon \geq \bar{\varepsilon}(b,i) \\ U(b) & \text{otherwise} \end{cases}$$

where $\bar{\varepsilon}(b,i) = U(b) - W(b,i)$. Hence, rewriting equation (28) reads:

$$W(b,i) = w(b,i) + \beta\Big\{\delta U(b) + (1-\delta)(1 - G(\bar{\varepsilon}(b,i)))\mathbb{E}_\varepsilon\Big[W(b,i) + \varepsilon | \varepsilon > \bar{\varepsilon}(b,i)\Big] + (1-\delta)U(b)G(\bar{\varepsilon}(b,i))\Big\}$$

That is:

$$W(b,i) = w(b,i) + \beta\Big\{U(b)\tilde{G}(\bar{\varepsilon}(b,i)) + (1-\delta)(1 - G(\bar{\varepsilon}(b,i)))W(b,i) + (1-\delta)\int_{\bar{\varepsilon}(b,i)} \varepsilon dG(\varepsilon)\Big\} \tag{30}$$

where $\tilde{G}(\bar{\varepsilon}(b,i)) = (1-\delta)\, G(\bar{\varepsilon}(b,i)) + \delta$. Now reorganizing and using $\bar{\varepsilon}(b,i) = U(b) - W(b,i)$ yields:

$$(1-\beta)W(b,i) = w(b,i) + \beta\,[(1-\delta)\, G(\bar{\varepsilon}(b,i)) + \delta]\, \bar{\varepsilon}(b,i) + \beta(1-\delta)\int_{\bar{\varepsilon}(b,i)} \varepsilon dG(\varepsilon) \tag{31}$$

Furthermore, from equation (1.8), we have:

$$J(b,i) = p + i - w(b,i) + \beta\Big\{\delta V + (1-\delta)[(1 - G(\bar{\varepsilon}(b,i)))J(b,i) + G(\bar{\varepsilon}(b,i))V]\Big\} \tag{32}$$

With free-entry condition (V=0) and rearrangement, we obtain:

$$(1-\beta)J(b,i) = p + i - w(b,i) - \beta\left[(1-\delta)\,G(\bar{\varepsilon}(b,i)) + \delta\right] J(b,i) \tag{33}$$

Total surplus: $S(b,i) = W(b,i) + J(b,i) - U(b)$ and $\bar{\varepsilon}(b,i) = U(b) - W(b,i)$. Hence, by summing up equations (31) and (33) and subtracting $(1-\beta)U(b)$ reads:

$$(1-\beta)S(b,i) = p + i + \beta\left[(1-\delta)\,G(\bar{\varepsilon}(b,i)) + \delta\right]\bar{\varepsilon}(b,i) + \beta(1-\delta)\int_{\bar{\varepsilon}(b,i)} \varepsilon dG(\varepsilon) \tag{34}$$

$$-\beta\left[(1-\delta)\,G(\bar{\varepsilon}(b,i)) + \delta\right] J(b,i) - (1-\beta)U(b) \tag{35}$$

Using Nash bargaining: $W(b,i) - U(b) = \rho S(b,i)$ and $J(b,i) = (1-\rho)S(b,i)$. Therefore :

$$(1-\beta)S(b,i) = p + i - \beta\left[(1-\delta)\,G(-\rho S(b,i)) + \delta\right] S(b,i) - (1-\beta)U(b) \tag{36}$$

$$+\beta(1-\delta)\int_{-\rho S(b,i)} \varepsilon dG(\varepsilon) \tag{37}$$

Hence Total surplus $S(b,i)$ for $b = 0,1$ satisfies equation 37 and depends on training intensity i and NCAs job status b. From equation 37, conditional on training intensity i, the only difference between the NCAs total match surplus and the one without NCAs comes form difference in the outside option value U of both types of job. Since $U(1) < U(0)$ as shown in Lemma 1, the proposition 1 holds.

A.5 Proof of Proposition 2

Given Aggregate variables, η, u and θ, Firm's optimal investment $(i^\star(0), i^\star(1))$ for NCAs job and job without NCAs respectively solve:

$$(1-\rho)S'(0, i^\star(0)) = C'(i^\star(0)) \tag{38}$$

$$(1-\rho)S'(1, i^\star(1)) = C'(i^\star(1)) \tag{39}$$

Differentiate (37) for $b = 0,1$ give:

$$(1-\beta)S'(b,i) = 1 - \beta\left[(1-\delta)\,G(-\rho S(b,i)) + \delta\right] S'(b,i) + \tag{40}$$

$$\beta\,(1-\delta)\rho(1-\rho)S'(b,i)S(b,i)\frac{\partial G}{\partial \varepsilon}(-\rho S(b,i)) \tag{41}$$

I guess and verify that $\frac{\partial G}{\partial \varepsilon}(-\rho S(b,i)) = 0$ and therefore we obtain:

$$S'(b,i) = \frac{1}{1 - \beta[1 - \tilde{G}(-\rho S(b,i))]} \tag{42}$$

where $\tilde{G}(-\rho S(b,i)) = (1-\delta)\, G(-\rho S(b,i)) + \delta$. Optimal investment condition becomes for $b = 0, 1$:

$$\underbrace{\frac{1-\rho}{1-\beta[1-\tilde{G}(-\rho S(b,i))]}}_{\text{Marginal benefit}} = \underbrace{C'(i)}_{\text{Marginal cost}} \tag{43}$$

Using proposition 1, conditional on training, the marginal benefit of investing in NCAs job is higher relative to the job without NCAs. Hence NCAs worker receives higher training. Finally, total match surplus is higher with NCAs job. Since separation rate is decreasing function of match surplus, therefore NCAs worker experiences lower separation rate.

A.6 Proof of Proposition 3

The result stems from the first order condition for θ of the problem 1.24 subject to constraints and 1.20 and 1.21.

For the specific case $\mu = 0$ and $\phi = 1$, equations 1.20 and 1.21 imply that $\eta = 0 \implies \tilde{\eta} = 1 - \chi$. Additionally, equation 1.20 becomes:

$$u = \frac{\tilde{G}(\varepsilon(1,i))}{\tilde{G}(\varepsilon(1,i)) + \tilde{\eta}\theta q(\theta)} \tag{44}$$

where I make the use of the fact that $\tilde{\eta} = 1 - \chi$. Hereafter, let denote $q = q(\theta)$, $i(1) = i_1$, $C(i(1)) = C_1$ and $\tilde{G}(\varepsilon(1,i)) = \tilde{G}_1$. Hence, the FOC with respect to θ yields:

$$0 = \tilde{\eta}\left[\frac{p+i_1}{\tilde{G}_1} - C_1\right][u(q+\theta q') + \theta q u'] + u'z - u\kappa - \theta u'\kappa$$

Divide by u, we obtain:

$$0 = \tilde{\eta}\left[\frac{p+i_1}{\tilde{G}_1} - C_1\right]\left(q + \theta q' + \frac{\theta q u'}{u}\right) + \frac{u'}{u}(z - \theta\kappa) - \kappa$$

Now using $\frac{u'}{u} = -\frac{\tilde{\eta}(q+\theta q')}{\tilde{G}_1 + \tilde{\eta}\theta q}$ from 44, we have:

$$0 = \tilde{\eta}\left[\frac{p+i_1}{\tilde{G}_1} - C_1\right]\left(q + \theta q' - \frac{\tilde{\eta}(q+\theta q')}{\tilde{G}_1 + \tilde{\eta}\theta q}\theta q\right) - \frac{\tilde{\eta}(q+\theta q')}{\tilde{G}_1 + \tilde{\eta}\theta q}(z - \theta\kappa) - \kappa$$

Now, dividing by q and making use of $\psi = -\frac{\theta q'}{q}$, we have:

$$0 = \tilde{\eta}\left[\frac{p+i_1}{\tilde{G}_1} - C_1\right]\left(1 - \psi - \frac{\tilde{\eta}\theta q(1-\psi)}{\tilde{G}_1 + \tilde{\eta}\theta q}\right) - \frac{\tilde{\eta}(1-\psi)}{\tilde{G}_1 + \tilde{\eta}\theta q}(z - \theta\kappa) - \frac{\kappa}{q}$$

Rearranging gives :

$$0 = \tilde{\eta}\left[\frac{p+i_1}{\tilde{G}_1} - C_1\right]\left((1-\psi)\frac{\tilde{G}_1}{\tilde{G}_1 + \tilde{\eta}\theta q}\right) - \frac{\tilde{\eta}(1-\psi)}{\tilde{G}_1 + \tilde{\eta}\theta q}(z - \theta\kappa) - \frac{\kappa}{q}$$

Finally, multiplying by $\frac{\tilde{G}_1 + \tilde{\eta}\theta q}{\tilde{G}_1}$, rearranging and simplifying yield the result in the main text.

A.7 Proof of Proposition 4

For the specific case $\mu = 0$ and $\phi = 1$, free-entry condition 1.7 yields:

$$\frac{\kappa}{\beta q} = \tilde{\eta}[J_1 - C_1] \tag{45}$$

using equation 1.8 to derive expression for J_1, we have:

$$\frac{\kappa}{\beta q} = \tilde{\eta}[\frac{p + i_1 - w_1}{1 - \beta(1 - \tilde{G}_1)} - C_1]$$

Inserting wage expression (equation 1.13), yields:

$$\frac{\kappa}{\beta q} = \tilde{\eta}(1-\rho)\left[\frac{p + i_1 - (1-\beta)U_1}{1 - \beta(1 - \tilde{G}_1)} - C_1\right] \tag{46}$$

Let pause here. From equation 1.16, we have with $\phi = 1$ and $\mu = 0$:

$$(1-\beta)U_1 = z + \beta(1-\chi)\Big\{f\rho S_1 - (1-f)\Delta U\Big\} \tag{47}$$

and from equation 1.17,

$$S_1 = \frac{-1 + \chi\,\beta(1-f)}{\chi\,\beta\,f\,\rho}\Delta U$$

Replacing S_1 by this expression in 47 and rearranging gives:

$$(1-\beta)U_1 = z - \frac{1-\chi}{\chi}\Delta U \tag{48}$$

Going back to equation 46, we have:

$$\frac{\kappa}{\beta q} = \tilde{\eta}(1-\rho)\left[\frac{p + i_1 - z + \dfrac{1-\chi}{\chi}\Delta U}{1-\beta(1-\tilde{G}_1)} - C_1\right] \tag{49}$$

But, recall that $\Delta U = \dfrac{\chi\,\beta\,f\,\rho}{-1+\chi\,\beta(1-f)}S_1$ and using 45 together with sharing rule 1.12 which yields $S_1 = \dfrac{1}{1-\rho}\left(\dfrac{\kappa}{\beta\,\tilde{\eta}q} + C_1\right)$,

$$\Delta U = \frac{\chi\,\beta\,f\,\rho}{-1+\chi\,\beta(1-f)}\frac{1}{1-\rho}\left(\frac{\kappa}{\beta\,\tilde{\eta}q} + C_1\right)$$

Finally, replacing ΔU in 49 and taking β to 1 give the result in the main text.

While the efficiency analysis in general case with $(\mu, \phi) \in (0,1) * (0,1)$ is difficult to prove analytically, I argue that the conclusion for the specific case still holds because of the presence of firm-sponsoring investment in worker human capital that causes a hold-up problem. Yes, The availability of NCAs contracts as instruments help to lessen the problem but does not fully solve it.

B Appendix for chapter 2

B.1 Proofs

1. **Updated value of worker surplus share (expression 2.11) & 2.12**

The result holds for any type of contract. Hence, for simplicity, we abstract for any contract subscript and unnecessary notation. Consider a type$-\omega$ worker employed at a type$-(j,\delta)$ firm and assume that the worker receives an outside offer from a firm of type type$-(j',\delta')$. Bertrand competition between the type$-(j,\delta)$ and type$-(j',\delta')$ employers implies that the worker ends up in the match that has higher total value, that is, they stay in their initial job if $S(\omega,j,\delta) \geq S_0(\omega,j',\delta')$ and moves to the type$-(j',\delta')$ job otherwise. Following, Lise and Postel-Vinay (2020), the new contract, regardless of the moving decision, worths:

$$W' = \min\Big\{S+U, \max\Big(S_0+U, W\Big)\Big\} \tag{50}$$

where, W is the worker value in the current match, and for the ease of presentation, we denote $S(\omega,j,\delta)$ by S and $S_0(\omega,j',\delta')$ by S_0. Worker surplus share in the new contract reads:

$$W' - U = \min\Big\{S, \max\Big(S_0, \nu S\Big)\Big\} \tag{51}$$

where ν is the current surplus share. Let $\tilde{S}$ be the surplus in the new contract. We have $\tilde{S} = S\mathcal{I}(S \geq S_0) + S_0\mathcal{I}(S < S_0)$. Denote by ν', the updated surplus share. Thus, we have:

$$\nu'\tilde{S} = \min\Big\{S, \max\Big(S_0, \nu S\Big)\Big\} \tag{52}$$

that is:

$$\nu' = \min\Big\{\frac{S}{\tilde{S}}, \max\Big(\frac{S_0}{\tilde{S}}, \nu\frac{S}{\tilde{S}}\Big)\Big\} \tag{53}$$

If the worker stays, that is $S \geq S_0$, then:

$$\nu' = \min\Big\{1, \max\Big(\frac{S_0}{S}, \nu\Big)\Big\} \tag{54}$$

If the worker moves, that is $S < S_0$, then:

$$\nu' = \min\Big\{\frac{S}{S_0}, \max\Big(1, \nu\frac{S}{S_0}\Big)\Big\} \tag{55}$$

which imply that:

$$\nu' = \nu\mathcal{I}(\nu S > S_0) + \frac{S_0}{S}\mathcal{I}(\nu S \le S_0), \quad \text{if stay} \tag{56}$$

$$\nu' = \frac{S}{S_0}, \quad \text{if move} \tag{57}$$

B.2 Markov chain analysis (4 states)

We perform the same exercise with four states where we depict the non-employment into inactivity and unemployment. Hence we compute the contribution of the age variation of each transition probability between states I, U, T, P in the age variation of the employment stock and the employment share of temporary jobs. Here,

$$S_{a,e} = \begin{pmatrix} I_{a,e} \\ U_{a,e} \\ T_{a,e} \\ P_{a,e} \end{pmatrix} \tag{58}$$

represents the vector for the distribution of individual of age a in education group e into status I, U, T, P. Each element of this vector represents a probability of having a given labor-market status conditional on age a and education group e. Moreover, let

$$\Gamma_{a,e} = \begin{pmatrix} II_{a,e} & IU_{a,e} & IT_{a,e} & IP_{a,e} \\ UI_{a,e} & UU_{a,e} & IT_{a,e} & IP_{a,e} \\ II_{a,e} & IU_{a,e} & TT_{a,e} & IP_{a,e} \\ II_{a,e} & IU_{a,e} & IT_{a,e} & PP_{a,e} \end{pmatrix} \tag{59}$$

represents the quarterly transition probability matrix for age a and education e. We have

$$S_{a,e} = \left(\prod_{a'=1}^{a-1} (\Gamma_{a',e})^4 \right) S_{a_0(e),e}, \tag{60}$$

where $a_0(e)$ represents the initial age in our sample for the different education groups. Notice that the age-specific transition matrix is taken at the power 4, since our transition probabilities are quarterly. Using (60), we can compute the life cycle path of E_a, T_a, and P_a that is implied by the estimated transition probability matrix, for a given initial state vector, $S_{a(0),e}$. We could also compute the contribution to U_a, but for consistency and comparative purposes, we only present the results for E_a and T_a, as we did for the 3-state analysis in the main text. Figures B5–B9 show the findings.

B.3 Tables and Figures

Figure B3: AB1C Decomposition of the importance of Flows: temporary employment share, High education (3 states)

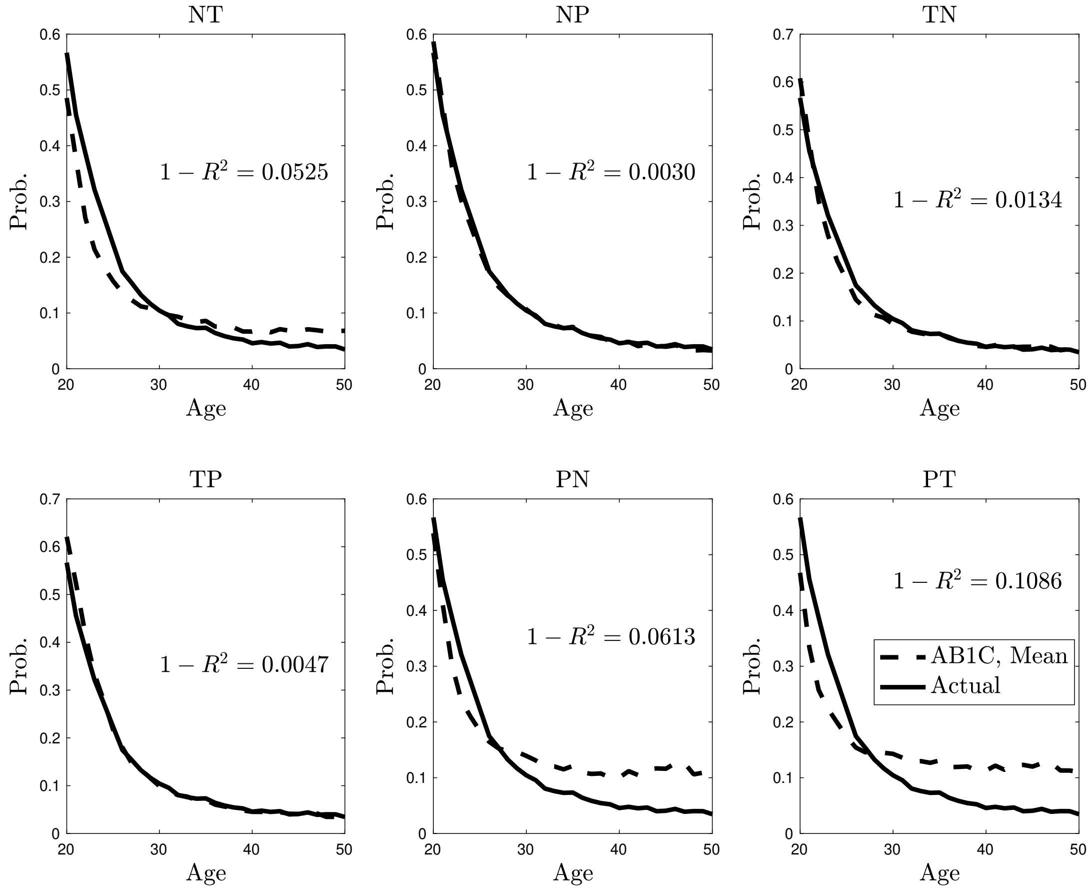


Figure B4: AB1C Decomposition of the importance of Flows: temporary employment share, Low education (3 states)

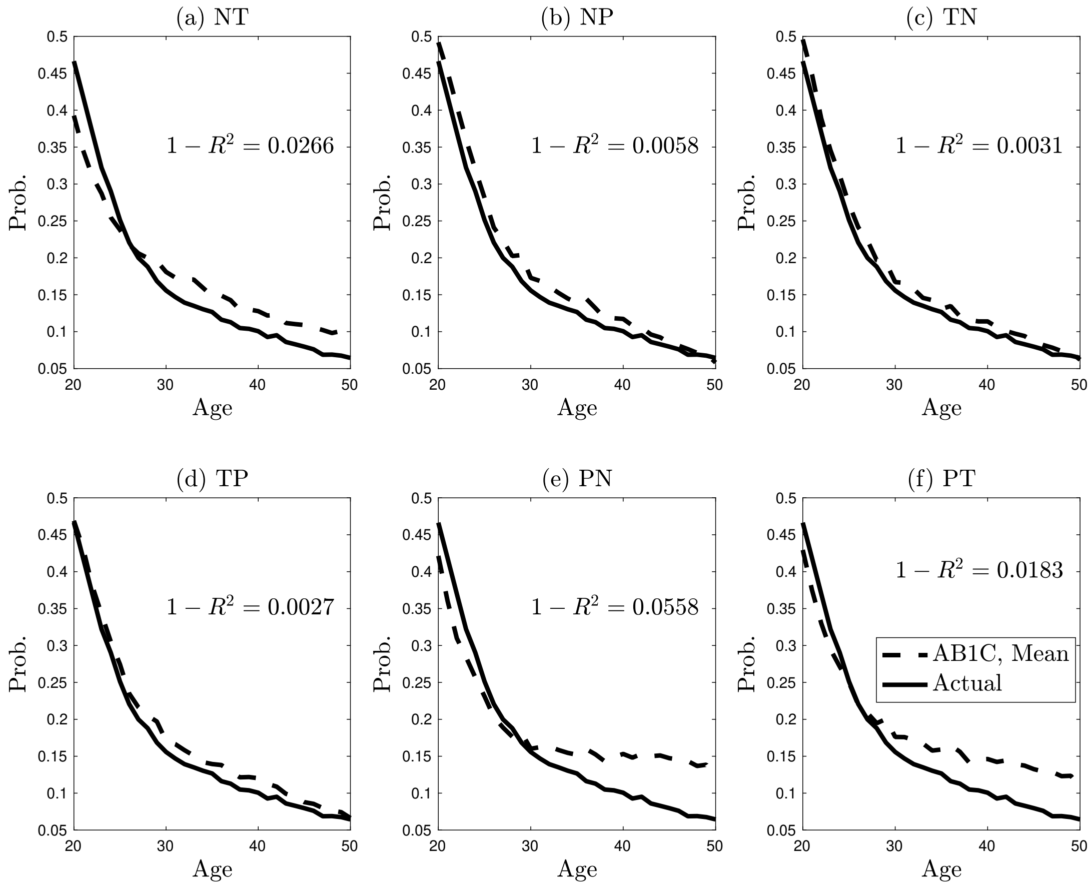


Figure B5: Markov chain simulated employment and temporary job share (4 states)

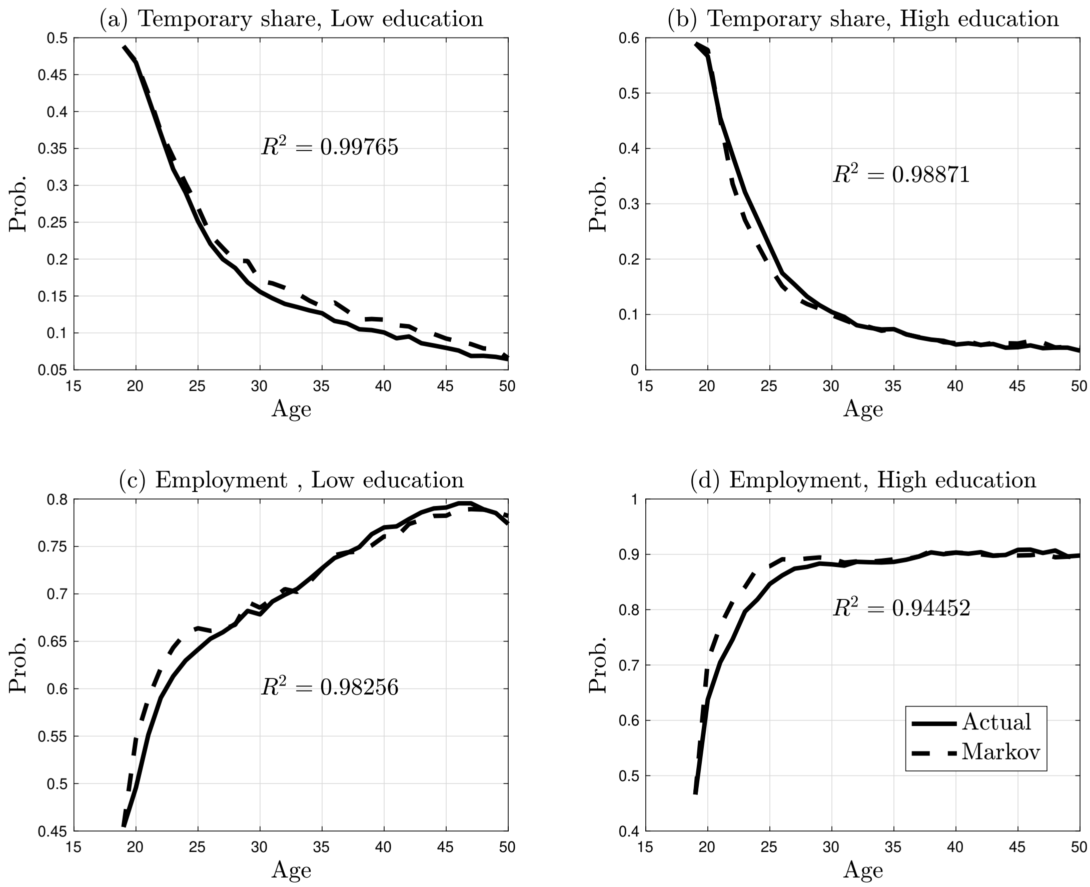
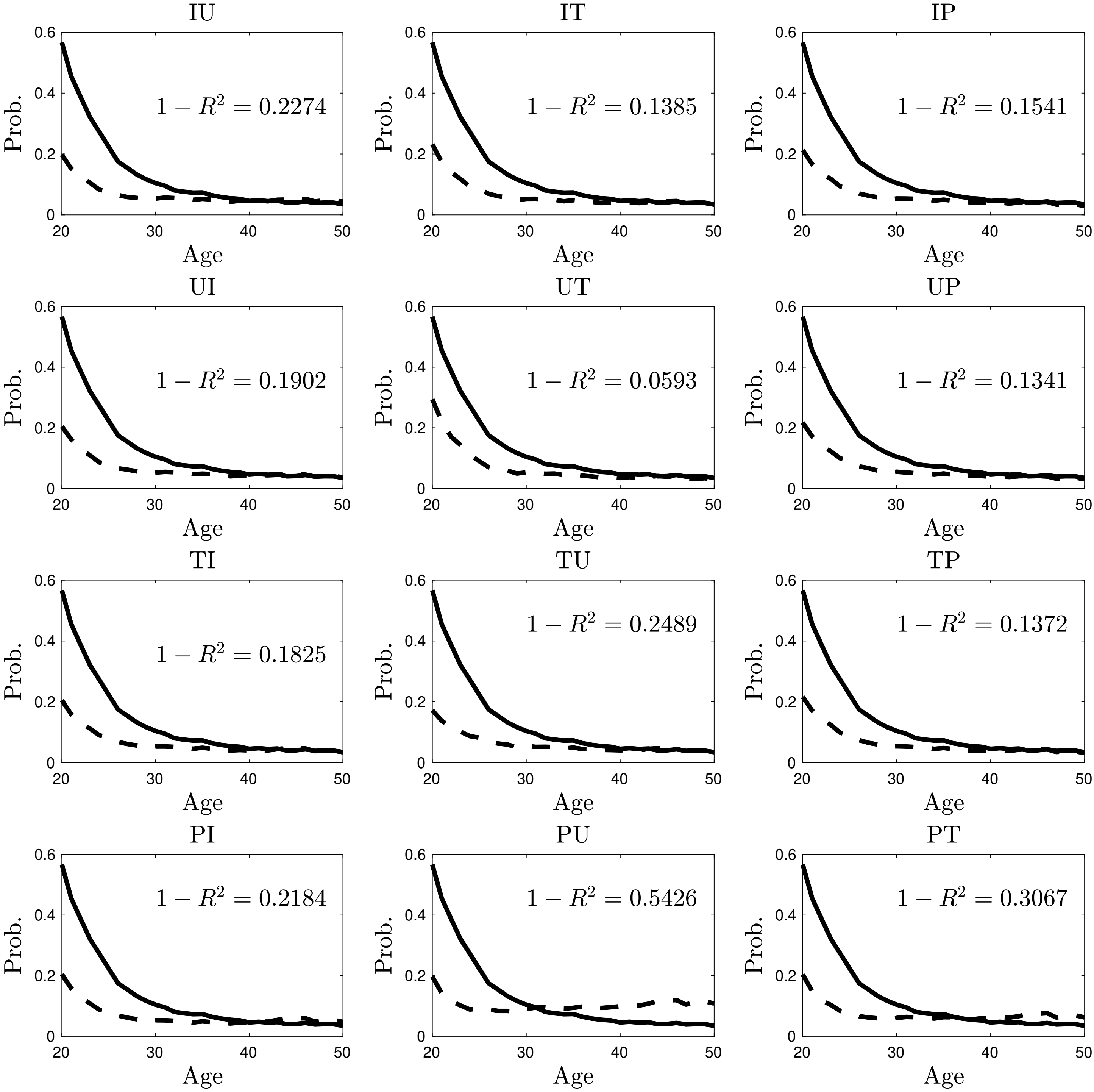
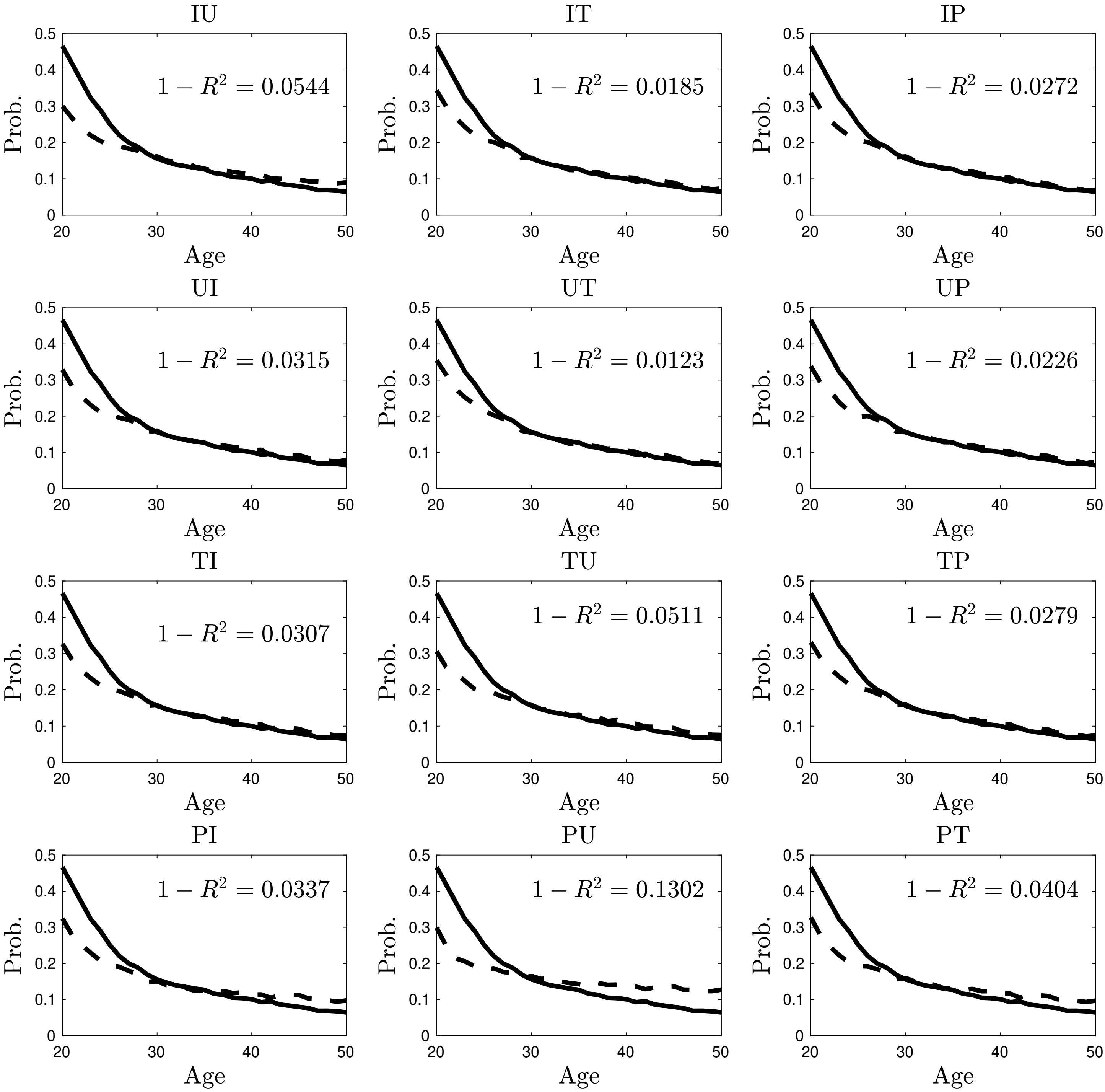


Figure B6: AB1C Decomposition of the importance of Flows: temporary employment share, High education (4 states)



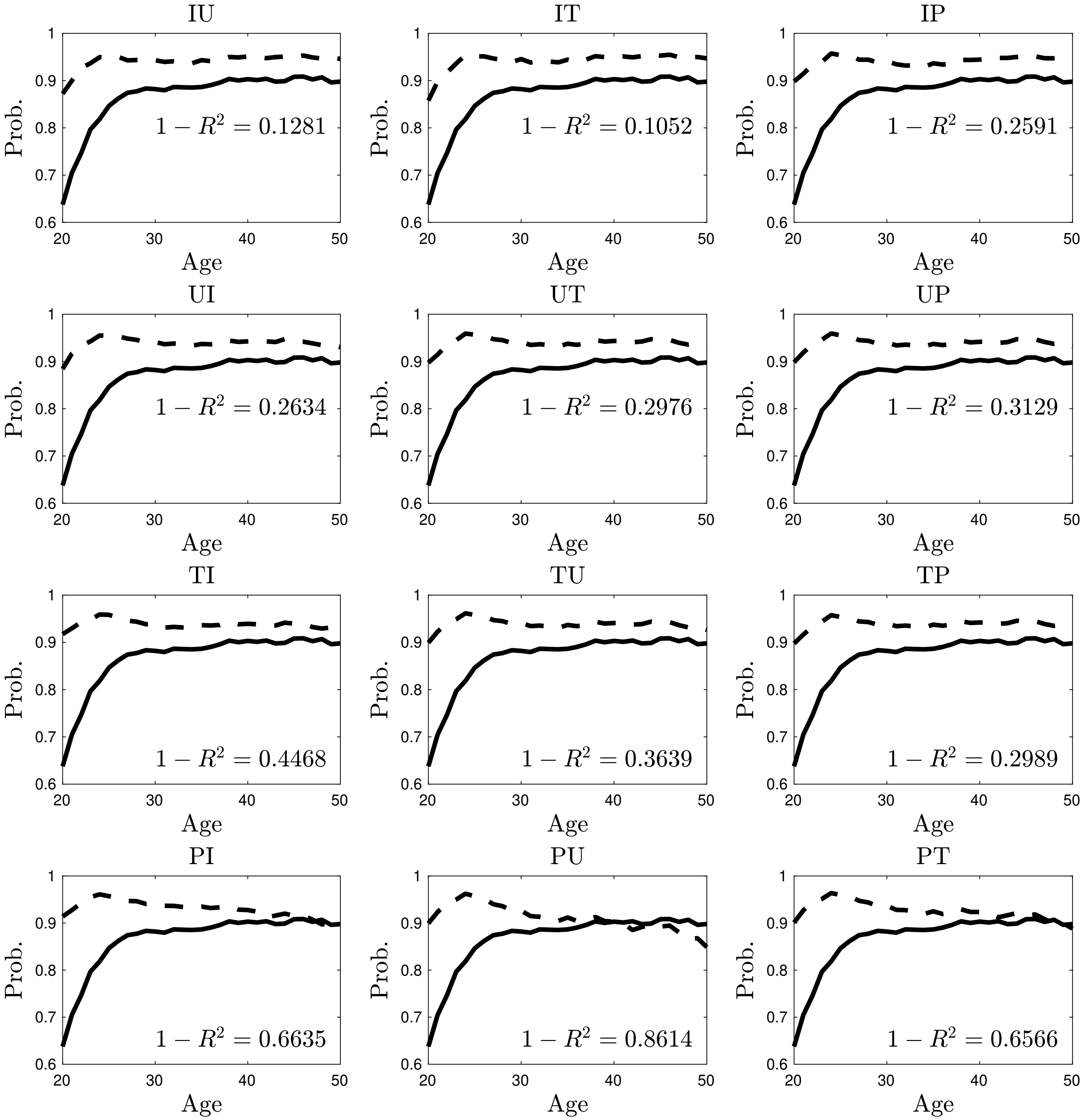
Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

Figure B7: AB1C Decomposition of the importance of Flows: temporary employment share, Low education (4 states)



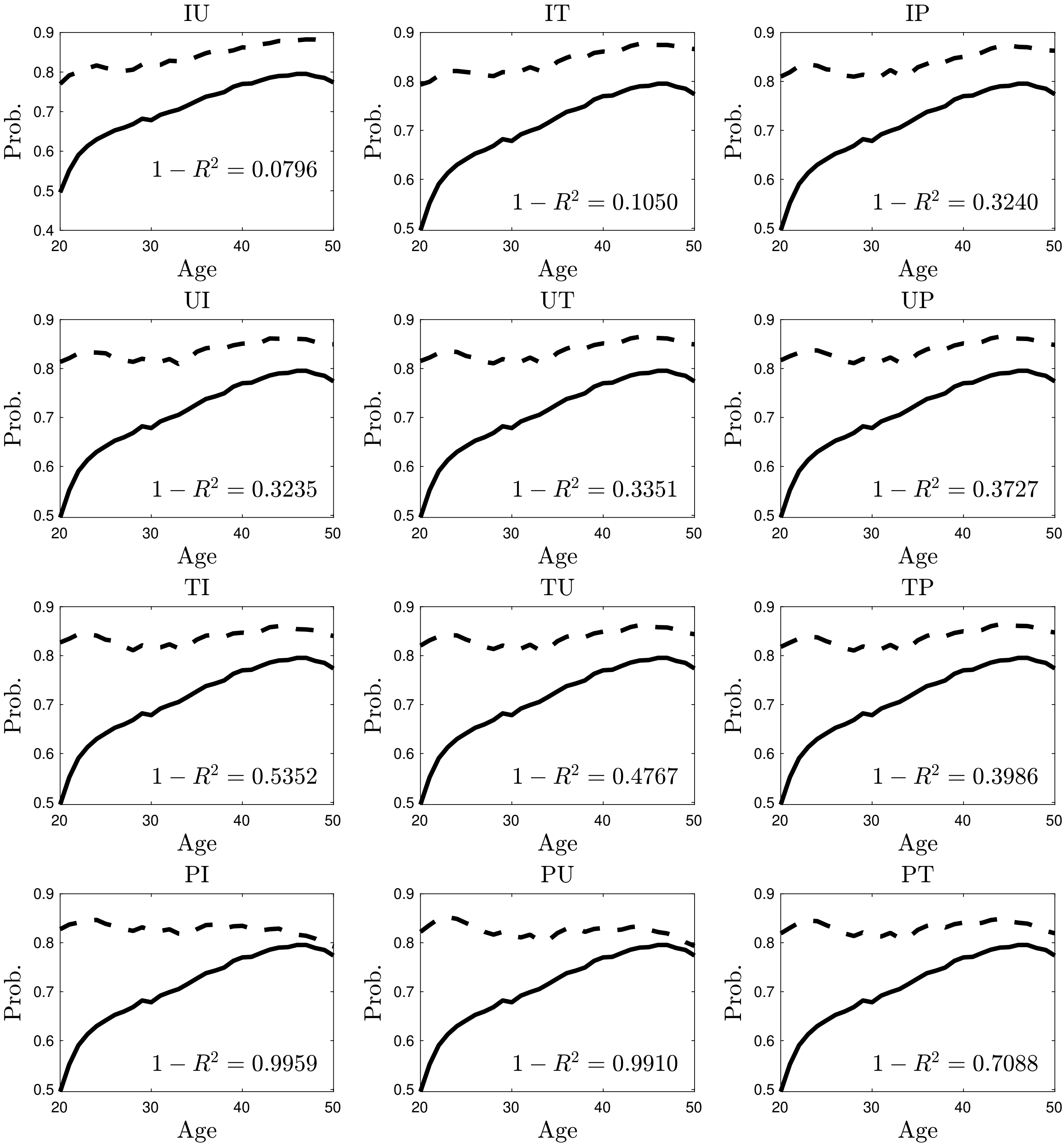
Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

Figure B8: AB1C Decomposition of the importance of Flows: employment-High education (4 states)



Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

Figure B9: AB1C Decomposition of the importance of Flows: employment- low education (4 states)



Note: The solid lines represent the actual profile derived from the data and the dashed represent the estimated Markov counterpart

C Appendix for chapter 3

C.1 Tables and figures

Figure C10: Climate performance and capital stock, manufacturing sector

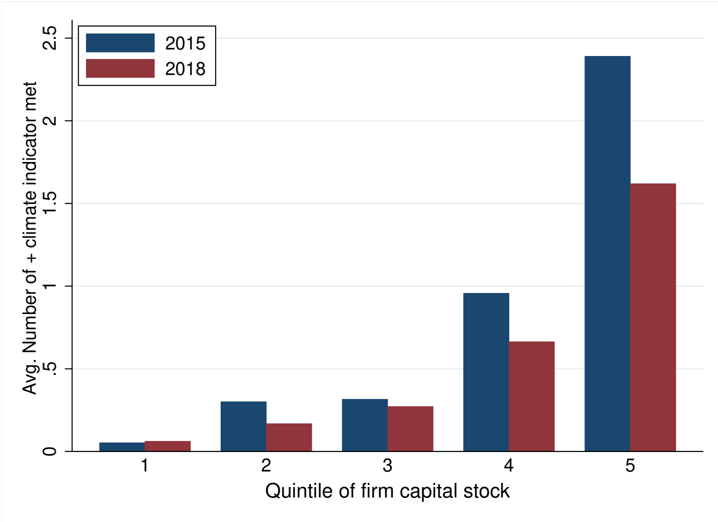


Figure C11: Climate performance and capital stock, transport sector

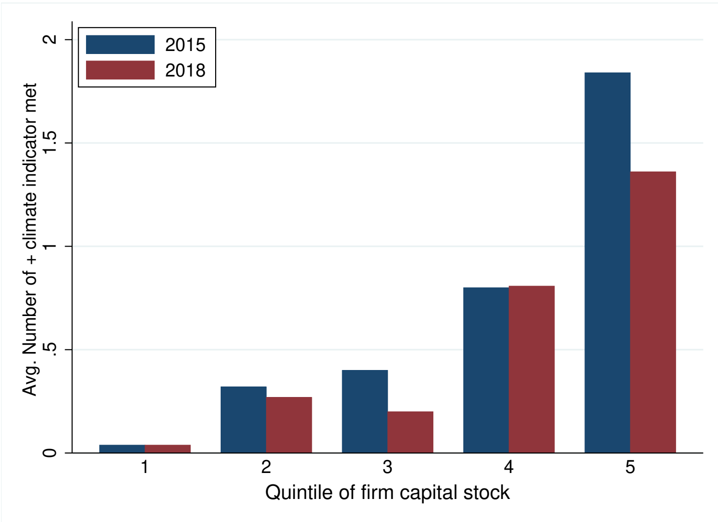


Table C12. Some E indicators form MSCI

Positive Environment Performance Indicators	**Data Set Column Headers**
Environmental Opportunities - Clean Tech	ENV-str-A
Waste Management - Toxic Emissions and Waste	ENV-str-B
Waste Management - Packaging Materials & Waste	ENV-str-C
Climate Change - Carbon Emissions	ENV-str-D
Environmental Management Systems	ENV-str-G
Natural Resource Use - Water Stress	ENV-str-H
Natural Resource Use - Biodiversity & Land Use	ENV-str-I
Natural Resource Use - Raw Material Sourcing	ENV-str-J
Natural Resource Use - Financing Environmental Impact	ENV-str-K
Environmental Opportunities - Green Buildings	ENV-str-L
Environmental Opportunities in Renewable Energy	ENV-str-M
Waste Management - Electronic Waste	ENV-str-N
Climate Change - Energy Efficiency	ENV-str-O
Climate Change - Product Carbon Footprint	ENV-str-P
Climate Change - Insuring Climate Change Risk	ENV-str-Q
Environment - Other Strengths	ENV-str-X

C.2 Data

The MSCI ESG KLD STATS dataset, provided by MSCI, is a comprehensive collection of environmental, social, and governance (ESG) research and ratings. It offers an extensive range of ESG indicators, focusing on the ESG performance of companies. These indicators provide insights into various aspects of environmental practices, social impact, and governance structures of publicly listed companies. The MSCI ESG KLD STATS data is widely utilized by investors, researchers, and organizations to evaluate the sustainability and ESG performance of companies and portfolios. It serves as a valuable tool for assessing and comparing the ESG profiles of different companies, aiding in the informed decision-making process for ESG-oriented investments. In the context of this study, the focus is specifically on the environmental (E) component of the ESG indicator. The dataset includes both positive and negative performance criteria related to environmental practices. However, the analysis in this study concentrates solely on the positive performance indicators, which capture the company's best management practices concerning environmental risks and opportunities. Within the dataset, there are 18 highlighted performance indicators, as presented in Table C12. For each indicator, a company is assigned a score of 1 if it meets the assessment criteria, and a score of 0 if it does not. An aggregate indicator is then constructed by summing up all the scores for each company. This provides a measure of the number of positive climate performance criteria fulfilled by a company.

Data regarding firm capital stock is computed using the Compustat-CRSP merged data. I also have information also on companies balance sheet. The resulting dataset, after merging the Compustat-CRSP and MSCI datasets, is a balanced annual panel dataset covering the period from 2015 to 2018 and consisting of 1,479 companies operating in the United States. I also exclude financial companies (SIC 6000-6999) and companies in the utilities sector (SIC 4900) are excluded from the analysis. As a result, the final sample comprises 1,151 publicly traded companies.

C.3 Proofs

C.4 Proof of Lemma 2

The lemma follows from the log-utility assumption and proceeds with a guess and verify strategy. See Moll (2014).

C.5 Proof of Lemma 3

The lemma follows from the linearity of the portfolio allocation problem.